

**Congressional Testimony  
for the  
House Financial Services Task Force on  
Artificial Intelligence's Hearing**

**Equitable Algorithms: How Human-Centered AI Can Address Systemic Racism and Racial  
Justice in Housing and Financial Services  
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**Introduction**

*“Equality is not a concept. It's not something we should be striving for. It's a necessity. Equality is like gravity. We need it to stand on this earth as men and women... We need equality. Kinda now.”*

*— Joss Whedon, co-founder of Bellwether Pictures*

Algorithmic-based systems impact every area and aspect of our lives either providing access to key services that can open the doors of opportunity or blocking our ability to take advantage of critical amenities that we need to survive and live successful lives. Algorithms can determine whether consumers will have access to housing, get a living wage job, access quality credit, get released on bail after an arrest, or serve a prison sentence. Algorithms even determine whether a sick patient will receive needed healthcare or even whether a homeowner will get a refinance loan.

The math and science behind the development of algorithms are neither good nor bad. However, how these systems are designed, the data used to build them, the subjective renderings applied by the scientists creating the models, and other components of the systems can create or further entrench structural racism and other forms of inequality.

It is imperative that we hastily work to eliminate bias from these systems. Studies reveal that structural inequality, including the harms perpetuated by unfair tech, are not only having a deleterious impact on individuals and communities, but it is stifling the nation's economic progress.

Many innovations have been made in the use of algorithms and Artificial Intelligence (AI) such that they can be used to mitigate against biases innate in legacy tech systems. Much as scientists used the coronavirus, a deadly germ that has killed millions of people in the world, to develop

live-saving vaccines, we can use AI to detect, diagnose, and cure harmful technologies that are extremely harmful to people and communities.

## **Part I – History of Housing/Banking Bias**

### **Algorithmic Systems Can Perpetuate Injustice and Discriminatory Outcomes**

Algorithmic systems can create, manifest, amplify, and systemize bias creating harmful impacts for millions of people. This is largely because the data used to build models is deeply flawed, scientists and mathematicians developing the systems are not educated about how technology can render discriminatory outcomes, and regulators are not equipped to sufficiently handle the myriad manifestations of bias generated by the technologies we use in financial services and housing.

While AI, including Machine Learning (“ML”) systems, may be relatively new innovations, the building blocks for the models these tools create are tainted with historical bias. Algorithmic-based systems are not developed in a vacuum. They are crafted in a polluted environment that embeds particles of inequality into systems that appear to be facially neutral and innocuous. They carry with them and are imbued with a centuries-long legacy of discriminatory actions and unfair policies that still impact our society.

Throughout the entire history of the U.S., our housing and lending policies were written or implemented in ways that were intentionally discriminatory. In fact, many of our laws – Indian Removal Acts, Slave Codes, Fugitive Slave Acts, Repatriation Acts, Chinese Removal Act, Black Codes, Sundown Ordinances, Japanese Internment Act, Racially Restrictive Covenants, and much more - were explicitly and purposefully designed to provide opportunities to Whites and to simultaneously deny opportunities to people of color.

Even laws that appeared to be racially neutral were implemented with racialized policies. For example, the Home Owners Loan Corporation (“HOLC”) Act was passed during the Great Depression for the purpose of saving homeowners from foreclosure, but in implementing the law, the federal government institutionalized a structure for redlining communities of color that was widely adopted by the financial services and real estate industries.<sup>1</sup> The HOLC systemized the association between race and risk, a connection that still exists today.

The National Housing Act of 1934 created the Federal Housing Administration (“FHA”). However, the FHA, building off of the HOLC’s racialized method of redlining communities of color, developed race-based underwriting guidelines that not only promoted residential segregation but described people of color as “incompatible racial elements” and “inharmonious

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<sup>1</sup> Gregory D. Squires, *The Fight for Fair Housing: Causes, Consequences, and Future Implications of the 1968 Federal Fair Housing Act* (2018). For an in-depth discussion of the myriad ways the federal government institutionalized redlining and lending discrimination see Chapter 6, entitled *The Fair Housing Act: A Tool for Expanding Access to Quality Credit*.

racial groups.”<sup>2</sup> The FHA encouraged the use of racially restrictive covenants and required them in exchange for supporting the bevy of new housing developments built throughout the nation’s suburban communities. Even after the Supreme Court declared that racially restrictive covenants were not enforceable, the FHA gave preferential treatment to developers that adopted them.<sup>3</sup> From 1934 to 1962, the federal government backed over \$120 billion in mortgages but the FHA’s race-based policies meant that less than 2 percent of loans went to people of color.

Many other laws, seemingly racially neutral, were implemented with the use of discriminatory policies including the National Highway Acts, Fair Labor Standards Act, Tax Codes, Housing Act of 1949, Social Security Act, Anti-Drug Abuse Act of 1986, and local zoning ordinances. Moreover, hundreds more laws have been passed with no outright ill-intention, but because the laws were implemented with no consideration for the deep levels of inequality in our society, they produced disparate outcomes. The CARES Act, passed in response to the COVID-19 pandemic, is a prime example. The Paycheck Protection Program when initially rolled out excluded roughly 95% of Black-owned, 91% of Latino-owned businesses, 91% of Native Hawaiian or Pacific Island-owned businesses, and 75% of Asian-owned businesses. Business owners who were already well-connected with mainstream banks and business and financial experts were much more likely to access PPP loans, even if they did not have dire need for assistance.<sup>4</sup>

This bevy of laws, regulations and policies created structural inequities and systemic bias that is still being manifest in our society. Residential and school segregation, the inextricable link between place and opportunity, the dual credit market, the inequitable health ecosystem, the patchwork of exclusive and restrictive zoning systems, and additional structurally unfair systems all stem from a long stream of laws that were either explicitly racist, implemented with racialized policies, or produced disparate impacts on communities of color. The effect of these policies was to steepen the racial wealth, income, and homeownership gaps.

These systems are still performing their originally intended function, perpetuating disparate outcomes and generating tainted, bias-laden data that serves as the building blocks for algorithmic-based utilities like tenant screening selection, credit scoring, insurance rating, risk-based pricing, digital marketing, and automated underwriting systems. The scalability power and reinforcement effect of AI algorithms could make them bad agents that amplify discriminatory outcomes if they are not controlled.

While we have passed civil rights statutes designed to stop discrimination; we have not designed laws to dismantle the systems of inequality that are still producing biased impacts. Laws like the Fair Housing Act of 1968 or the Equal Credit Opportunity Act of 1974 prohibit housing and financial services providers from considering race, national origin or gender when making a housing related decision. But we have done little to nothing to remedy or rectify the

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<sup>2</sup> Lisa Rice, [Missing Credit: How the U.S. Credit System Restricts Access to Consumers of Color](#), Testimony before the U.S. House Committee on Financial Services (Feb. 26, 2019).

<sup>3</sup> Richard Rothstein, *The Color of Law: A Forgotten History of How Our Government Segregated America* (2017).

<sup>4</sup> Brian Thompson, [Getting Help for Minority-Owned Businesses Shut Out of PPP Loan Relief](#), Forbes (May 12, 2020)

discriminatory structures that we created from centuries of discriminatory laws. For example, though the Fair Housing Act does contain a provision for dismantling systemic inequality – the Affirmatively Furthering Fair Housing mandate – it has never been enforced.

## **Part II - How Algorithms Can Manifest Bias**

### **Data Risks**

#### *Introduction: Data and Technology are Not Innocuous*

Data is tainted. Computers and technology are not color- or gender-blind. In fact, much of the data used to build algorithmic systems is covered in a patina of bias. We all know the adage that bad inputs equal bad outputs. Well, the same holds true here. Biased data in equals biased outcomes. All the technologies we use in housing, employment, health, credit, law enforcement, advertising, and other sectors contain bias because the systems were created with tainted data.

#### *The Data Can Be Under-Inclusive*

Building fair AI systems requires the use of quality, reliable, robust data that truly reflects the patterns and behaviors of the people the models are designed to assess. For example, one challenge is that a disproportionate amount of data used to build models in the housing and financial services space is generated from information housed with the credit repositories. However, credit repository data can be very limiting because not all information about consumer behavior is reported to the credit reporting agencies. Moreover, the data that is reported is reflective of the structural biases replete throughout our society.

In many instances, BIPOC (Blacks, Indigenous, and People of Color) consumers are disproportionately missing from the data. AI systems can only see the patterns that are existent in the data. Because people of color disproportionately access data outside of the financial mainstream, they are underrepresented in datasets used to build financial services systems. Moreover, because BIPOC consumers are disproportionately rejected for credit, their consumer patterns are under-represented in the data. For example, many BIPOC consumers live in credit deserts and disproportionately access financial services from non-traditional, alternative credit providers such as payday lenders, check cashers and title money lenders. These non-traditional credit providers do not report consumers' timely payments to the credit repository system. Thus, consumers who are accessing credit outside of the financial mainstream and who pay their obligations as they should are not reaping the benefit of their good behavior simply because it is not reported. These consumers are essentially invisible to most scoring systems used in the housing and financial services space. This in no way means that these consumers are poor risks or are not responsible. It simply means that the data used to build traditional algorithmic financial services models is not representative of underserved groups.

As a result, AI systems built using unrepresentative data will not be able to score underserved consumers at all since these consumers register as credit invisible, or the systems will

inaccurately score underserved consumers likely assessing them as more risky than they really are.

Finally, AI systems are sometimes built with data sets that are over-weighted with certain features or lack critical information that can better inform the algorithm. The data collection itself might be biased. An example of this is when Amazon’s recruitment [AI system disadvantaged women](#). The system was built with Amazon’s own database of senior executives who were disproportionately White men. The system learned that men were preferable applicants. Rather than solely relying on a candidate’s qualifications, the system penalized applicants whose resumes contained the word “women” and downgraded graduates of all-women’s universities.<sup>5</sup> Another example is when [facial recognition technology](#) mis-reads women or people of certain racial or ethnic groups because the data used to train the system did not include enough examples of women and people of color.<sup>6</sup>

### *The Data Can Reflect Historical Bias*

Discrimination in the marketplace taints the data collected by credit repositories thus data can be extremely harmful. Discrimination in the employment, housing, credit, health and other sectors impacts the type and quality of data reflected in our credit repository system. How that data is ultimately used by credit modelling agencies can exacerbate disparities. Although discrimination is a common occurrence<sup>7</sup>, it is not accounted for in the way credit data is collected or utilized. When credit repositories gather data, they do not simultaneously ascertain if a consumer has obtained credit from a predatory, discriminatory or abusive debtor for the purposes of ameliorating any negative fallout. Data is captured as if it is innocuous and benign when the opposite is the case. Data is infused with the discrimination replete throughout our society. When credit repositories collect data, without any assessment of the quality or legitimacy of that data, they help perpetuate the inequities that harm under-served consumers.

Some have attempted to mitigate bias in our markets by moving toward automated systems lulled by the myth that data is blind. Data is not blind, nor is it harmless. It can be dangerous and toxic particularly when it manifests the discrimination inherent in our systems. For example, researchers at Berkeley have found that fintech lenders that rely on algorithms to generate decisions on loan pricing discriminate against borrowers of color because their systems “have not removed discrimination, but may have shifted the mode.”<sup>8</sup> It is estimated that borrowers of color are being overcharged by \$765 million per year. Similarly, concerns have been raised about AI systems based on appraisal data, which may reflect historical biases due to the HOLC maps and other forms of discrimination. A 2018 Brookings Institution study found that homes in

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<sup>5</sup> David Meyer, [Amazon Reportedly Killed an AI Recruitment System Because It Couldn’t Stop the Tool from Discriminating Against Women](#), Fortune (Oct. 10, 2018).

<sup>6</sup> James Vincent, [Gender and Racial Bias Found in Amazon’s Facial-Recognition Technology \(Again\)](#), The Verge (Jan. 25, 2019).

<sup>7</sup> There are over 4 million instances of housing discrimination each year. See National Fair Housing Alliance, [Defending Against Unprecedented Attacks on Fair Housing: 2019 Fair Housing Trends Report](#) (2020).

<sup>8</sup> Robert P. Bartlett, Adair Morse Richard H. Stanton, and Nancy E. Wallace, [Consumer Lending Discrimination in the FinTech Era](#), UC Berkeley Public Law Research Paper (Sept. 2019).

majority Black neighborhoods were appraised for 23 percent less than properties in mostly White neighborhoods, even after controlling for home features and neighborhood amenities, which raises questions about the appropriateness of the data. Finally, the data gleaned from credit reporting agencies that go into the credit scoring, risk-based pricing, and automated underwriting models do not exist in isolation. Each piece of information has appended to it other bits of data that is inherently connecting risk to race. In essence, these data systems manifest systemic and institutional racism.

*The Data Can Inappropriately Exclude Race/Gender Data Needed for Testing Outcomes*

Confusion exists regarding how to collect and use race or other protected class data or proxies. As a result, the data used to develop an AI system may not include the information needed to test outcomes based on race or other protected characteristics. However, while race or other protected class data may not be appropriate to use in the model, it may be critical to later evaluating the impact of the model's outcomes.

## **Model Risks**

*The Model Can Be Flawed and Discriminatory*

AI systems can be designed in a way that encourages biased outcomes. For example, systems that allow users to exclude certain racial or ethnic groups can cause discrimination against protected groups and even enhance the different ways in which users can discriminate against people. The National Fair Housing Alliance and several of its member organizations filed a legal challenge against Facebook over such an issue.<sup>9</sup> The company used to allow entities placing ads for housing, employment, and credit on Facebook's platform to target audiences based on protected class characteristics like gender, race, and national origin. Resolution of this case involved Facebook making eight meaningful and structural changes to its advertising platform including:

- Establishing a separate advertising portal for creating housing, employment, and credit ("HEC") ads on Facebook, Instagram, and Messenger that will have limited targeting options, to prevent discrimination.
- Creating a page where Facebook users can search for and view all housing ads that have been placed by advertisers for the rental, sale, or finance of housing or for real estate related transactions (such as appraisals and insurance), regardless of whether users have received the housing ads on their News Feeds.
- Requiring advertisers to certify that they are complying with Facebook's policies prohibiting discrimination and all applicable anti-discrimination laws.
- Providing educational materials and features to inform advertisers about Facebook's policies prohibiting discrimination and anti-discrimination laws.
- Meeting regularly with the Plaintiffs and their counsel to report on and discuss the implementation of the terms of the settlements.

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<sup>9</sup> See National Fair Housing Alliance, [Facebook Settlement](#) (March, 2019).

- Permitting the Plaintiffs to engage in testing of Facebook’s ad platform to ensure the reforms established under the settlements are implemented effectively.
- Working with NFHA to develop a training program for Facebook’s employees on fair housing and fair lending laws.
- Engaging academics, researchers, civil society experts, and civil rights/liberties and privacy advocates (including plaintiffs) to study the potential for unintended bias in algorithmic modeling used by social media platforms.

AI systems that use a scoring system to determine ad placement can also generate bias. Such might have been the case with a research project conducted using Google’s platform. A [Harvard researcher found](#) that Google searches for people with Black-identifying names turned up more ads suggestive of arrest records and/or criminal backgrounds than did ad searches using White-identifying names. Researchers recommended that by changing the quality score of ads to discount for unwanted bias, Google might be able to minimize bias on its platform. By measuring real-time unwanted discrimination in the way an ad is delivered, and then adjusting the score at auction, bias can be eliminated or minimized.<sup>10</sup>

#### *The Model Can Result in a Biased Feedback Loop*

If not carefully designed, AI systems can unduly amplify discriminatory information. For example, if an ad features an African American man, a digital platform registering the content of the ad might skew the ad’s delivery to men. As more men click on the ad, because they were historically more likely to see the ad, the digital platform might mis-perceive that men are more likely to be interested in seeing the ad than women and continue to over-skew the ad’s delivery to even more men.

As another example, predictive policing systems have been shown to discriminate against Black residents because of feedback loops that, because of historical discrimination in the criminal justice system, result in the targeting of people of color for heightened policing activity, even when no crime has been committed. The U.S. criminal justice system is notoriously biased, particularly when it comes to the area of substance abuse. The FBI’s criminal database shows that Blacks, Asian Americans, Latinos and Whites use and sell illegal substances to the same degree. Yet, [Blacks are 3-4 times more likely](#) than Whites to be arrested and almost 6 times more likely to be incarcerated for drug-related charges.<sup>11</sup> AI systems that rely on tainted data from the law enforcement system will reinforce discriminatory patterns.

Biased feedback loops exist in models used in financial services as well. The Berkeley study on bias in fintech offers a prime example. The study shows that risk-based pricing systems are likely overpricing Black and Latino borrowers to the tune of \$765M annually. Researchers posit that the systems may be optimized for profit and might be picking up on reduced shopping activity among Black and Latino borrowers. However, reduced levels of mortgage loan shopping among Black and Latino borrowers can be linked to the fact that these borrowers disproportionately live

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<sup>10</sup> Latanya Sweeney, [Discrimination in Online Ad Delivery](#), ACM Queue (Apr. 12, 2013).

<sup>11</sup> NAACP, [Criminal Justice Fact Sheet](#).

in credit deserts and have less access to banks. In this way, the structural inequities linked to residential segregation and the dual credit market serve as a biased feedback loop that results in borrowers of color being charged more for credit when they pose no greater level of risk.

*There Can be Failures in Adequately Testing Models for Discriminatory Outcomes*

If systems are not tested for bias, companies can use algorithms that unknowingly manifest discrimination. In other words, modelers may not see bias in an algorithm if they are not looking for it or have not been sufficiently trained to look for it. This is why testing is so important. For example, algorithms might have the incorrect optimization or unseen correlations that perpetuate or amplify an unintended bias. Data scientists must perfect the design of the algorithm to ensure that systems don't treat people unfairly. [CoreLogic has been challenged](#) on its CrimSafe tenant-screening system, which contains arrest information. The system can penalize people who have an arrest record but no convictions. This feature, of course, disproportionately discriminates against Blacks and Latinos<sup>12</sup> and no or insufficient testing of models for discriminatory impacts will result in reduced housing opportunities for underserved groups.

### **Part III - Recommendations for Mitigating the Risk of Algorithmic Bias**

There are significant risks of bias and discrimination in AI systems, but the risks are not insurmountable. Following are recommendations as to how lawmakers, regulators, housing providers, financial institutions, and tech companies can mitigate the risk of algorithmic bias.

#### **Integrate the Review of Racial and Other Bias into Every Phase of the Algorithm's Lifecycle**

Given the systemic discrimination that exists in almost every aspect of American life, there is a high risk that the data and models used for AI systems will reflect that systemic bias. Accordingly, it is imperative that equity and non-discrimination be top of mind at every phase of the algorithm's lifecycle. It is not enough to merely consider discrimination risk once the AI system is built or even deployed. Instead, the risk of bias must be considered and mitigated at every phase, from data selection to development to deployment to monitoring. Unfortunately, in many instances, regulators in the United States seem to view fair housing and fair lending risk as separate and apart from other AI risks. For example, the federal financial regulators recently issued a Request for Information regarding AI.<sup>13</sup> The section requesting comment on fair lending is relegated to the end of the questions, separate and apart from other AI concepts, such as explainability. Time and again, we see U.S. regulators considering fair housing and fair lending risk as somehow distinct from other risks, rather than as an integral and important part of all discussions of AI risk.

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<sup>12</sup> National Fair Housing Alliance, [Defending Against Unprecedented Attacks on Fair Housing: 2019 Fair Housing Trends Report](#) (2020).

<sup>13</sup> Board of Governors of the Federal Reserve System, Consumer Financial Protection Bureau, Federal Deposit Insurance Corporation, National Credit Union Administration, and Office of the Comptroller of the Currency, [Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, including Machine Learning](#), 86 Fed. Reg. 16837 (March 31, 2021).

By contrast, the European Union’s newly-released proposed regulation for AI (“EU Proposed Regulation”) clearly recognizes that AI systems that impact the evaluation of creditworthiness pose a high risk to fundamental rights, including the right to non-discrimination.<sup>14</sup> The proposed regulation creates a risk-based framework of three categories: (i) unacceptable risk, where the practices are prohibited (e.g., social scoring by public authorities); (ii) high-risk AI systems, which would need to comply with new requirements; and (iii) non-high-risk AI systems, which are encouraged to adopt voluntary codes of conduct. The appendix to the proposed regulations lists several high-risk AI systems, most notably, AI system that relate to the access to and enjoyment of essential private services and public services and benefits, including:

- **AI systems intended to be used to evaluate the creditworthiness of natural persons or establish their credit score.**

Importantly, the EU made this determination based on explicit recognition of (i) the importance of this benefit to fully participate in society or improve one’s standard of living and (ii) the high risk of discrimination. The preamble to the proposed regulation states:

Another area in which the use of AI systems deserves special consideration is the access to and enjoyment of certain essential private and public services and benefits **necessary for people to fully participate in society or to improve one’s standard of living**. In particular, AI systems used to evaluate the credit score or creditworthiness of natural persons should be classified as high-risk AI systems, since they determine those persons’ access to financial resources or essential services such as housing, electricity, and telecommunication services. AI systems used for this purpose may lead to discrimination of persons or groups and **perpetuate historical patterns of discrimination**, for example based on racial or ethnic origins, disabilities, age, sexual orientation, or **create new forms of discriminatory impacts**.

Thus, the EU recognizes that not all AI is the same and that AI systems that evaluate creditworthiness should be held to a higher standard given the far-reaching impact on consumers’ life options and the high risk of discrimination. The proposed regulation reflects this key premise by incorporating a review for discrimination risk in all aspects of the proposed requirements, from data governance to post-market monitoring.

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<sup>14</sup> European Commission, [Proposal for a Regulation Laying Down Harmonised Rules on Artificial Intelligence](#) (aka, the “Artificial Intelligence Act”) (April 21, 2021). It may also be instructive to review recent actions by the federal Food and Drug Administration (“FDA”) and the state of Virginia, both of whom have considered the use of AI with respect to high-risk scenarios. See FDA, [AI/ML Action Plan for AI/ML-based Software as a Medical Device](#) (Jan. 12, 2021); [Virginia Consumer Data Protection Act](#), Title 59.1, Ch. 52 (2021) (requiring data protection assessments for the processing of any personal data that is to be used for the purpose of profiling where there is a reasonable risk of unlawful disparate impact on consumers).

## Use Reliable Methods for Mitigating the Risk of Data Bias

### *The Reject Inference Pool Can Be Used for Equitable Credit Access*

Diverse peer-reviewed research works have shown that basing credit scoring solutions solely on the behaviours of approved customers or performances of approved loans can be detrimental to future loan applicants, especially the historically under-approved BIPOC applicants. As AI algorithms may only learn from patterns present in a dataset, declined applicants may never be scored fairly by an AI-credit scoring solution because their patterns are either missing or almost invisible in the data being used to train such scoring solutions. AI solutions are not magical; they can only see or detect what is already existent in the data. Thus, a credit scoring solution that has been historically trained on data exclusive of applicants that are thin-file, (undocumented) immigrants, or renters may continue to classify such borrowers as high risks since its training data lacks sufficient signals from these categories of applicants.

The Reject Inference (RI) is an inclusive method that augments data of approved loan applicants with data of declined applicants so that an AI algorithm trained on such inclusive data would be unbiased or less discriminatory towards under-approved applicants. RI is a collection statistical technique that tries to simulate what the reality could look like if declined loan applications were approved.

While it may be difficult to rigorously justify the fitness of counterfactual RI techniques such as fuzzy augmentation, simple augmentation, or any of their variants for credit scoring solutions, an (experimental) pool may be created for a fraction of the declined applicants so that the credit risks in this pool are shared (with some formula) by all lenders. Such a pool would provide real quality data that could be used to evaluate the accuracy of the original reject decision; augment training data on approved applicants without a need for theoretical, uncertain RI techniques; and, more importantly, present inclusive signals from underserved borrowers to AI algorithms.

### *Representative and Robust Datasets Should be Developed*

One way to address challenges with insufficient data is to augment more exclusive datasets with information from non-traditional sources as a means of building a more representative and robust dataset. Community Development Financial Institutions and state Housing Finance Agencies may be two sources of obtaining data that are more reflective of the practices of BIPOC and other underserved consumers.

Another means of building more robust dataset is to capture rental housing payment data. The Urban Institute conducted important research<sup>15</sup> regarding the efficacy of using rental housing payment information in financial services automated underwriting systems. Traditional credit scoring systems do not incorporate the use of rental housing payment information and this can be

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<sup>15</sup> Laurie Goodman and Jun Zhu, [Rental Pay History Should Be Used to Assess the Creditworthiness of Mortgage Borrowers](#), Urban Institute (Apr. 16, 2018).

harmful for consumers who access credit outside of the financial mainstream. But rental housing payment information may be able to significantly improve the ability of models to expand access to credit. The Urban Institute’s research found that borrowers who did not miss a housing payment for two years made on-time mortgage housing payments for the next three years. The analysis reveals that rental housing payment data would be a very strong predictor of mortgage risk.

*Protected Class Data Should be Collected and Used to Appropriately Build and Test Fairer Tech*

Although protected class data should not be used to create disparate treatment or disparate impacts, such data can be used responsibly to build and test AI systems. Here, the EU Proposed Regulation’s approach to data governance may be instructive. The preamble to the proposed regulation clearly states the importance of robust data governance with respect to fair AI systems: “High data quality is essential for the performance of many AI systems, especially when techniques involving the training of models are used, with a view to ensure that the high-risk AI system performs as intended and safely and it does not become the source of **discrimination** prohibited by [European] Union law.”<sup>16</sup> More specifically, the proposed regulation would require the review of data sets in view of possible bias.<sup>17</sup> In addition, the proposed regulation would allow the providers of high-risk AI systems to process special categories of personal data based on protected characteristics in order to protect the right of others from the discrimination that might result from the bias in AI systems.<sup>18</sup> Similarly, here in the U.S., protected class data should be used responsibly to build equitable AI systems and test for potentially discriminatory outcomes.

*A Publicly-available Dataset Should be Released for Research Purposes*

Congress should encourage and support public research that analyzes the impact of AI in housing and financial services for consumers of color and other protected classes. In particular, Congress should encourage the Consumer Financial Protection Bureau, the Federal Housing Finance Agency, Fannie Mae, Freddie Mac, and the Federal Housing Administration to release more loan-level data from the national mortgage survey and the national mortgage databases so researchers, advocacy groups, and the public can study bias in the housing and finance markets, including as that bias may relate to the use of AI.

**Ensure Models Undergo Robust Testing for Potential Discriminatory Outcomes**

We must develop methods to analyze and test our systems to understand better how multi-variate interactions in AI models might be manifesting bias and affecting consumers’ ability to fairly access products and services. For example, we can use AI to test the data we use in our systems

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<sup>16</sup> EU Proposed Regulation at Recital 44.

<sup>17</sup> *Id.* at Title III, Ch. 2, Art. 10.

<sup>18</sup> *Id.*

to determine if there are any discriminatory associations and then mitigate against them. We can also set the bar high for model validation with an eye toward diminishing bias in the systems.

Here again, the EU Proposed Regulation may be helpful. The EU's Proposed Regulation provides a robust regulatory framework for high-risk AI systems, which includes those systems that evaluate creditworthiness. In addition to the data governance requirements noted above, the proposed regulation would require providers to implement controls related to the following:

- Transparency,
- Human oversight,
- Risk and quality management systems,
- Security, and
- Post-market monitoring.<sup>19</sup>

Moreover, a provider of a high-risk AI system would need to conduct a conformity assessment and certify the system's conformity with the regulation *before* the system is released to the market to avoid consumer harm and the proliferation of discriminatory systems.<sup>20</sup> Penalties by regulators for non-compliance would be as high as 6% of the entity's total global earnings (before costs).<sup>21</sup> Although the EU's Proposed Regulation has been subject to criticism by some advocates for the over-reliance on provider self assessments and the lack of a private right of action,<sup>22</sup> it does provide a useful example of a robust regulatory framework. In particular, it is notable that the proposed regulation shows a clear commitment to fundamental rights, including the right to non-discrimination, that is integrated throughout the proposal.

## **Ensure Relevant Staff Receive Appropriate Fair Housing/Fair Lending Training and Reflect the Diversity of America**

### *Educate AI Stakeholders about Racial Inequality and Structural Racism*

All AI stakeholders – including regulators, housing providers, financial institutions, and tech companies - should be committed to ensuring that all of their staff receive fair housing and racial equity training. Trained professionals are better able to identify and recognize issues that may raise red flags; they are also better able to design solutions for debiasing tech and building fairer systems. In fact, recent innovations in developing mechanisms for debiasing tech has come from data scientists and engineers who were trained on issues of fairness. For example, employees at Google developed What-If<sup>23</sup>, a diagnostic tool for detecting various types of bias and ML-fairness-gym<sup>24</sup> a simulation tool to test the impacts of machine learning systems in different

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<sup>19</sup> EU Proposed Regulation at Titles III and VIII.

<sup>20</sup> *Id.* at Title III, Ch. 3 and 5.

<sup>21</sup> *Id.* at Title X, Art. 71.

<sup>22</sup> *See, e.g.*, Adam Satariano, [Europe Proposed Strict Rules for Artificial Intelligence](#), N.Y. Times (April 21, 2021).

<sup>23</sup> Google, <https://pair-code.github.io/what-if-tool/>

<sup>24</sup> Google, <https://github.com/google/ml-fairness-gym>

social environments. Employees at Microsoft developed Fairlearn<sup>25</sup>, a tool for diagnosing and debiasing machine learning systems. The more the field is educated about fairness and equity issues, the better tools will be created to expand opportunities for consumers.

### *Increase Diversity in the Tech Field*

Increasing diversity will lead to better outcomes for consumers. Research shows that diverse teams are more [innovative and productive](#).<sup>26</sup> Companies with [more diversity are more profitable](#).<sup>27</sup> Diverse teams can help bring broader ideas and solutions to the workplace and enhance morale. Moreover, in several instances, it has been the people of color who were able to identify potentially discriminatory AI systems.<sup>28</sup>

### **Ask the General Accounting Office (“GAO”) to Review Federal Oversight of AI Bias**

Given the rapid proliferation of AI systems in the critically-important areas of housing and financial services, Congress should ask the GAO to immediately review federal supervision and enforcement of fair lending laws, particularly with respect to oversight of AI systems used by housing providers and financial institutions. The GAO last conducted this type of review 25 years ago (in 1996), which resulted in significant policy changes and renewed efforts for robust fair lending supervision and enforcement.<sup>29</sup> The time is right to conduct a new review of the federal banking regulators’ fair lending approaches and methodologies.

### **Conclusion**

We can all agree that discriminatory policies like the federal HOLC’s discriminatory redlining system and the FHA’s biased practices created a housing finance structure that had a long-lasting and detrimental effect on American society, limiting the life choices of millions of people of color for generations up through the present time. Right now, America is at a similar crossroads in determining whether to develop equitable AI systems that serve and uplift the whole of the national financial services market, or one that perpetuates and amplifies old discriminatory patterns. The time to act is now as the use of AI in financial services proliferates in every aspect of housing and consumer credit and has the potential for far-reaching adverse impacts for people of color that could overshadow even the devastation caused by the HOLC, FHA, and other entities that perpetuated discriminatory practices. Government, industry, and advocacy groups should work together to envision and create AI systems that support equitable, non-discriminatory housing and finance markets. Doing so will not just benefit individual consumers, it will advantage our whole society. Citigroup issued an analysis revealing that if racial

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<sup>25</sup> Microsoft, <https://fairlearn.org/>

<sup>26</sup> John Rampton, [Why You Need Diversity on Your Team, and 8 Ways to Build It](#), Entrepreneur (Sept. 26, 2019).

<sup>27</sup> David Rock and Heidi Grant, [Why Diverse Teams Are Smarter](#), Harvard Business Review (Nov. 4, 2016).

<sup>28</sup> Steve Lohr, [Facial Recognition is Accurate, if You’re a White Guy](#), N.Y. Times (Feb. 9, 2018) (explaining how Joy Buolamwini, a Black computer scientist, discovered that facial recognition worked well for her White friends but not for her).

<sup>29</sup> GAO, [Fair Lending: Federal Oversight and Enforcement Improved but Some Challenges Remain](#), GGD-96-145, Aug. 13, 1996).

inequality was eliminated, the U.S. GDP would increase by \$5 trillion over a 5-year period.<sup>30</sup> Advancing equitable algorithmic systems would lead to increased productivity and improve people's quality of life.

In some respects, the U.S. is behind the ball in advancing fair tech. If we want to retain our competitive edge in the global society, we should hasten to remove bias from existing technologies and take the necessary steps to ensure all systems going forward are fair and equitable.

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<sup>30</sup> Dana Peterson and Catherine Mann, [Closing the Racial Inequality Gaps](#), Citigroup (September, 2020).