



**AI Innovation Explored:
Insights into AI Applications in Financial Services and Housing**

Testimony of

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Introduction: AI Is the New Civil and Human Rights Frontier

Chairman McHenry, Ranking Member Waters, and other distinguished members of the House Committee on Financial Services, thank you for the opportunity to testify during the Committee's Hearing entitled, "AI Innovation Explored: Insights into AI Applications in Financial Services and Housing." My name is Lisa Rice and I am the President and CEO of the National Fair Housing Alliance® (NFHA™), which is the country's only national civil rights organization dedicated solely to eliminating all forms of housing and lending discrimination and ensuring equal opportunities for all people. As the trade association for over 170 fair housing and justice-centered organizations throughout the U.S. and its territories, NFHA works to dismantle longstanding barriers to equity and build resilient, inclusive, well-resourced communities where everyone can thrive.

We applaud the Committee for its comprehensive bipartisan review of the benefits and risks of AI.¹ AI holds great promise for improving systems, democratizing opportunities, lowering costs, and increasing productivity. Yet, it also holds great dangers for perpetuating bias, spreading mis-information, excluding people from necessary services, and generating other harms. In fact, we can think of AI as "the new civil and human rights frontier," which will determine whether America pursues a just and equitable society or simply perpetuates discriminatory and other patterns that exclude underserved people and communities. It is critical that Congress understands these risks and benefits, and establishes sound rules and guardrails that can help ensure the U.S. remains the world leader in innovation and technological advancement, and that the nation protects its residents against the perils AI can present. We thank the Committee for this opportunity to share our knowledge of the risks, benefits, and policy opportunities for the use of AI in housing and financial services.

NFHA's Evolution in Addressing Algorithmic and AI Bias & Description of NFHA's Responsible AI Program

NFHA has addressed harms associated with automated systems and AI since its inception in 1988. We first concentrated our efforts on prohibiting or restricting the use of discriminatory automated systems such as credit and insurance scoring, underwriting, and pricing models, in housing and financial services. Early settlements with entities like Prudential, State Farm, Nationwide, and Allstate addressed these discriminatory systems. Several years ago, while litigating a major case against then-Facebook, it became even more clear that technology, including AI, was the new civil and human rights frontier and, as a civil rights organization, we had to be a leader in this sector. Thus, we established our Responsible AI Team, which is comprised of scientists, researchers, engineers, policy experts, and attorneys committed to civil

¹ Bipartisan Working Group on Artificial Intelligence, House Committee on Financial Services, *AI Innovation Explored: Insights into AI Applications in Financial Services and Housing*, Staff Report (July 18, 2024) (HFSC Staff AI Report), https://financialservices.house.gov/uploadedfiles/bipartisan_working_group_on_ai_staff_report.pdf.

and human rights principles and is headed by one of the world's premier AI Research and Data Scientists, Dr. Michael Akinwumi. NFHA's Responsible AI Team has five workstreams founded on each of the following technical and policy research pillars:

- **Tech Equity:** We focus on developing and advocating for methodologies that ensure automated systems offer equitable access to housing opportunities.
- **Data Privacy:** We strive to test and promote technologies that balance consumer privacy with the need for data access to eliminate bias in automated systems.
- **Explainability:** We advocate for consumers' right to explanations for automated decisions and work to test and promote methodologies that clarify the reasoning or design behind automated systems.
- **Reliability:** We focus on testing and advancing techniques to ensure only safe and valid automated systems are used in housing applications.
- **Human-Centered Alternative Systems:** We work on advancing technical and policy solutions to determine when human-centered alternatives should take precedence over automated systems in housing decisions, particularly when data quality is poor, infrastructure is inadequate, or there is a lack of social awareness about harms of automated systems.

Since launching our Responsible AI work, NFHA has advocated for and contributed to responsible technology policy solutions, including the White House's AI Bill of Rights² and the White House Executive Order on Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence.³ NFHA's Responsible AI Team has also developed a state-of-the-art framework for auditing algorithmic systems.⁴

Part I - The Genesis of Artificial Intelligence

The term "artificial intelligence" was first used by Professor John McCarthy, a mathematics professor at Dartmouth, during a summer research workshop held at Dartmouth College in 1956.⁵ Professor McCarthy and three other colleagues penned "A Proposal For The Dartmouth Summer Research Project On Artificial Intelligence," that stated the purpose of the workshop was to "proceed on the basis of the conjecture that every aspect of learning or any other feature

² See White House, Office of Science and Technology Policy, *Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People* (Oct. 2022), <https://www.whitehouse.gov/wp-content/uploads/2022/10/Blueprint-for-an-AI-Bill-of-Rights.pdf>.

³ See White House, *Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence* (Oct. 30, 2023), <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/>.

⁴ See Michael Akinwumi, Lisa Rice, and Snigdha Sharma, *Purpose Process, and Monitoring: A New Framework for Auditing Algorithmic Bias in Housing and Lending*, National Fair Housing Alliance (2022), https://nationalfairhousing.org/wp-content/uploads/2022/02/PPM_Framework_02_17_2022.pdf.

⁵ See Dartmouth College, *Artificial Intelligence Coined at Dartmouth* (1956) <https://home.dartmouth.edu/about/artificial-intelligence-ai-coined-dartmouth>.

of intelligence can in principle be so precisely described that a machine can be made to simulate it.”⁶

Just two years after this pivotal workshop, Fair, Isaac and Company developed its Credit Application Scoring Algorithm, a rule-based decision management system that simulated human functions and intelligence.⁷ Since then, developers have created many different complex rule-based, statistical, computational models to streamline and standardize decisioning, improve efficiencies, and save costs for a host of transactions and activities in the housing and financial services sector.

Thus, concepts for creating AI systems were developed during a time when segregation and discriminatory practices and policies in the housing and lending sectors were the norm in our society. Some foundational concepts were also designed before the U.S. Congress passed critical anti-discrimination and civil rights laws and prior to a broad-based understanding in our society about how years of race-based laws and policies⁸ established macro-level systems that perpetuate unfair outcomes.

Now that we understand how data generated from decades of biased decisioning and transactions can be used to train and develop technologies that reflect, perpetuate, and mirror that bias, it is incumbent on us to create new tools and strategies that improve outcomes and make decisioning fairer for everyone.

The Definition of AI

AI focuses on creating machines capable of intelligent behavior. It involves the computational understanding and creation of artifacts that exhibit intelligent behavior.⁹ The scope of AI is broad, encompassing various aspects such as machine intelligence, cognitive functions, or intelligent agents. It also includes systems that mimic human behavior. To guarantee existing automated systems in the housing and financial services sectors are not overlooked in the pursuit of implementing AI that is secure, reliable, and free from discrimination, NFHA

⁶ J. McCarthy, M. L. Minsky, N. Rochester, and C. E. Shannon, *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*, Dartmouth College (Aug. 31, 1955), <http://jmc.stanford.edu/articles/dartmouth/dartmouth.pdf>.

⁷ See Fair, Isaac and Company Incorporated, *FICO Investor Relations*, Annual Report (Dec. 1998), <https://investors.fico.com/static-files/461a5d42-97be-45d8-a837-38cc25a0c267>.

⁸ Race-based laws and policies implemented over the years include all state-level Black Codes and Slave Codes, Fugitive Slave Clause of the U.S. Constitution, Fugitive Slave Acts, racially restrictive covenants, Jim Crow laws, Alien Land Acts, Indian Removal Act, Dawes Act, Chinese Exclusion Act, Immigration Act of 1924 (Johnson-Reed Act), various Executive Orders including EO 9066 (Japanese Internment EO), Home Owners Loan Act and the Residential Security Surveys and Maps, National Housing Act (establishing the Federal Housing Administration among other programs), Social Security Act, National Interstate and Defense Highways Act, Housing Acts, Urban Renewal Program, various tax codes, and many more.

⁹ S. Shapiro, *Artificial intelligence (AI)* (Jan. 2003), <https://dl.acm.org/doi/abs/10.5555/1074100.1074138>.

characterizes AI as a computerized mechanism capable of performing one or more of the following functions:

- Discerning patterns in data;
- Conducting exploratory, predictive, prescriptive, or diagnostic analyses based on data, logical reasoning, or established rules; or
- Generating patterns utilizing data, logic, or rules.

NFHA views a system as an amalgamation of algorithm, model tech infrastructure, and human elements. Fundamentally, for NFHA, AI represents a sociotechnical system, integrating technical capabilities with societal and human components. This practical definition is consistent with definitions used by federal agencies.¹⁰

Part II - How Artificial Intelligence Can Perpetuate Bias in Housing and Financial Services

Artificial Intelligence is the new civil and human rights frontier. America’s housing and financial services policies are built on a foundation of bias and, without appropriate guardrails, today’s technology will merely reflect historic and ongoing biases and perpetuate the homeownership and wealth gaps that are the realities of our society. For centuries, laws and policies enacted to create land, housing, and credit opportunities were race-based, denying critical opportunities to Black, Latino, Asian American and Pacific Islander (“AAPI”), and Native American individuals.¹¹ These policies were developed and implemented in a racially discriminatory manner despite our founding principles of liberty and justice for all. In particular, the 1930s New Deal’s federal Home

¹⁰ See White House, *Executive Order 14110 on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence* (Oct. 30, 2023), <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/> (“The term ‘artificial intelligence’ or ‘AI’ has the meaning set forth in 15 U.S.C. 9401(3): 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.”); Consumer Financial Protection Bureau, U.S. Department of Justice, Equal Employment Opportunity Commission, and Federal Trade Commission, *Joint Statement on Enforcement Efforts against Discrimination and Bias in Automated Systems* (2023), <https://www.eeoc.gov/joint-statement-enforcement-efforts-against-discrimination-and-bias-automated-systems> (“We use the term ‘automated systems’ broadly to mean software and algorithmic processes, including AI, that are used to automate workflows and help people complete tasks or make decisions.”).

¹¹ See Lisa Rice, *The Fair Housing Act: A Tool for Expanding Access to Quality Credit*, *The Fight for Fair Housing: Causes, Consequences, and Future Implications of the 1968 Federal Fair Housing Act* (Gregory Squires, 1st ed. 2017) (providing a detailed explanation of how federal race-based housing and credit policies promoted inequality).

Owners Loan Corporation (“HOLC”) codified the practice of “redlining,” which systematized the unfounded link between race and risk in the U.S. housing and financial services markets.¹²

The original housing and financial services policies are still performing their originally-intended function: perpetuating disparate outcomes and generating tainted, bias-laden data that serve as the building blocks for automated systems. America’s discriminatory history is captured in the data, which is then fed into the models that power the algorithms and artificial intelligence used to access housing and financial services today.¹³ Following are some examples of how, without appropriate safeguards, AI may perpetuate and even amplify the historical discriminatory patterns found in housing and financial services.

Marketing Systems and Digital Redlining

The use of AI and other algorithms have changed the face of the billion-dollar U.S. advertising industry from a market where ad content was posted broadly and easily accessible in the general media to a market that is limited to hyper-targeted, individualized ad placement that can exclude certain consumers and communities from important opportunities. This development has brought new risks that can lead to biased marketing and discriminatory access to housing and financial services.¹⁴

In 2016 and 2018, fair housing and civil rights groups challenged Facebook’s algorithm-driven digital advertising systems that manifested discrimination against protected groups. Facebook’s advertising practices initially drew attention from journalists when it was revealed that the company permitted advertisers to exclude groups of Facebook users with selected personal characteristics from viewing particular advertisements on the social media site.¹⁵ Facebook’s technology effectively allowed advertisers to show advertisements to certain users while excluding others based on sex or age, or on interests, behaviors, demographics, or geography that related to or were highly correlated to and associated with race, national origin,

¹² See University of Richmond, Virginia Tech, University of Maryland, and Johns Hopkins University, Mapping Inequality (documenting the maps and area descriptions created by the HOLC between 1935 and 1940), <https://dsl.richmond.edu/panorama/redlining/#loc=3/41.245/-105.469&text=intro>.

¹³ See generally, Federal Trade Commission (FTC) Press Release, *FTC Report Warns about Using Artificial Intelligence to Solve Online Problems* (June 16, 2022), <https://www.ftc.gov/news-events/news/press-releases/2022/06/ftc-report-warns-about-using-artificial-intelligence-combat-online-problems> (finding significant concerns that AI tools can be inaccurate, biased, and discriminatory by design).

¹⁴ See Carol Evans, Westra Miller, *From Catalogs to Clicks: The Fair Lending Implications of Targeted, Internet Marketing*, Federal Reserve Consumer Compliance Outlook (2019), <https://www.consumercomplianceoutlook.org/2019/third-issue/from-catalogs-to-clicks-the-fair-lending-implications-of-targeted-internet-marketing/>.

¹⁵ See Julia Angwin, Ariana Tobin, and Madeleine Varner, *Facebook (Still) Letting Housing Advertisers Exclude Users by Race*, ProPublica (November 21, 2017), <https://www.propublica.org/article/facebook-advertising-discrimination-housing-race-sex-national-origin>; Julia Angwin and Terry Parris Jr., *Facebook Lets Advertisers Exclude Users by Race*, ProPublica (October 28, 2016), <https://www.propublica.org/article/facebook-lets-advertisers-exclude-users-by-race>.

sex, age, or family status. Advertisers could turn off African-American, Hispanic, and Asian-American audiences. There was no option for turning off White audiences.¹⁶

Facebook's advertising platform also permitted advertisers to create custom audiences of Facebook users known as "affinity groups," who shared common characteristics with the advertiser's current customers or other desired groups that could exclude certain groups based on protected class characteristics.. In a 2019 settlement with NFHA and other groups, Facebook agreed to retool its advertising platform to prevent advertisers for housing, employment or credit from discriminating based on race, national origin, ethnicity, age, sex, sexual orientation, disability, family status, or other characteristics covered by federal, state, and local civil rights laws.¹⁷ In 2023, the DOJ also entered into a consent decree in which Meta (formerly Facebook) agreed to implement a digital ad platform variance reduction auditing system to reduce bias in the delivery of ad campaigns.¹⁸

NFHA's case against Redfin provides an example of modern-day "digital redlining."¹⁹ In 2020, NFHA and fair housing groups throughout the nation pursued a federal lawsuit against Redfin Corporation for alleged digital redlining because Redfin offered "No Service" for homes in non-White areas at a greater rate than for homes in White areas due to a minimum loan amount policy.²⁰ The complaint alleged that Redfin digitally redlined communities of color by setting minimum home listing prices in each housing market on its website under which it will not offer any real estate brokerage services to buyers or sellers. Under a settlement agreement, Redfin agreed to alter its minimum home price policy to be fairer in its business operations.²¹

¹⁶ See, *Facebook Settlement*, National Fair Housing Alliance (March 14, 2019), <https://nationalfairhousing.org/facebook-settlement/>

¹⁷ See Joint Statement from National Fair Housing Alliance et al., *Summary of Settlements between Civil Rights Groups and Facebook* (March 19, 2019), <https://www.aclu.org/documents/summary-settlements-between-civil-rights-advocates-and-facebook>. See also *Vargas et al., v. Facebook*, No. 21-16499, Mem. Op. (9th Cir. 2023), <https://cdn.ca9.uscourts.gov/datastore/memoranda/2023/06/23/21-16499.pdf> (reversing the district court and holding that a Latino plaintiff had who alleged that that Facebook's 'targeting methods' used when the plaintiff was searching for housing in 2018-2019 discriminated against protected classes had stated a claim under the Fair Housing Act and state law); *Vargas et al., v. Facebook*, Amicus Brief of the National Fair Housing Alliance et al., (Jan. 26, 2022), [https://www.aclu.org/cases/vargas-v-facebook-inc?document=Vargas-et-al-v-Facebook-amicus-brief- .](https://www.aclu.org/cases/vargas-v-facebook-inc?document=Vargas-et-al-v-Facebook-amicus-brief-)

¹⁸ See DOJ Press Release, *Justice Department and Meta Platforms, Inc. Reach Key Agreement as They Implement Groundbreaking Resolution to Address Discriminatory Delivery of Housing Advertisements* (Jan. 9, 2023), <https://www.justice.gov/opa/pr/justice-department-and-meta-platforms-inc-reach-key-agreement-they-implement-groundbreaking>.

¹⁹ See *Redfin Investigation*, National Fair Housing Alliance. <https://nationalfairhousing.org/issue/redfin-investigation/>

²⁰ See NFHA Press Release, *NFHA Files Federal Discrimination Lawsuit to Stop Redfin's Real Estate Redlining* (Oct. 29, 2020), <https://nationalfairhousing.org/nfha-files-federal-discrimination-lawsuit-to-stop-redfins-real-estate-redlining-2/>.

²¹ See NFHA Press Release, *National Fair Housing Alliance and Redfin Agree to Settlement that Greatly Expands Access to Real Estate Services in Communities of Color* (April 29, 2022),

Federal agencies have recently issued guidance to mitigate the risks of digital redlining. For example, in August 2022, the CFPB issued an interpretive rule stating when digital marketers are involved in the identification or selection of prospective customers or the selection or placement of content to affect consumer behavior, they are typically service providers under the Consumer Financial Protection Act.²² When their actions, such as using an algorithm to determine who to market products and services to, violate federal consumer financial protection law, they can be held accountable. Just recently, the U.S. Department of Housing and Urban Development (HUD) issued a communication entitled, “Guidance on the Application of the Fair Housing Act to the Advertising of Housing, Credit, and Other Real-Estate Related Transactions through Digital Platforms.”²³ The guidance addresses the increasingly common use of automated systems, such as algorithmic processes and AI, to facilitate advertisement targeting and delivery, and the risks presented by such methods. The guidance emphasized that such targeting and delivery may be permissible in other contexts, but risks violating the Fair Housing Act when used for housing-related ads.

As AI continues to shape changes in the advertising markets and access to housing and financial services, it is imperative that stakeholders across the tech field consider the potential for discriminatory outcomes of their systems and implement ongoing monitoring audits of these platforms.

Tenant Screening Systems

Issues with automated tenant screening systems are ever increasing. To evaluate applicants, some landlords purchase AI-powered or automated tenant screening systems that “score” or “decision” a rental applicant. These tools raise fair housing and consumer protection concerns for at least three reasons. First, erroneous data can be used to develop the models, and neither the consumer nor the landlord are made aware of the faulty data. Second, there is a lack of transparency regarding the tenant screening algorithms’ predictiveness, design, development, testing process, and data inputs. The algorithm is often a “hidden box” that is difficult to

<https://nationalfairhousing.org/national-fair-housing-alliance-and-redfin-agree-to-settlement-which-greatly-expands-access-to-real-estate-services-in-communities-of-color-%EF%BF%BC/>.

²² CFPB Press Release, *CFPB Warns that Digital Marketing Providers Must Comply with Federal Consumer Finance Protections* (Aug. 10, 2022),

<https://www.consumerfinance.gov/about-us/newsroom/cfpb-warns-that-digital-marketing-providers-must-comply-with-federal-consumer-finance-protections/>.

²³ HUD, *Guidance on the Application of the Fair Housing Act to the Advertising of Housing, Credit, and Other Real-Estate Related Transactions through Digital Platforms* (April 29, 2024),

https://www.hud.gov/sites/dfiles/FHEO/documents/FHEO_Guidance_on_Advertising_through_Digital_Platforms.pdf.

understand, leaving the consumer with no means to challenge a decision. Finally, there are significant concerns about the quality of risk management efforts pertaining to these systems.²⁴

Tenant screening selection systems have been a focal point of federal regulators, enforcement agencies, and housing advocates for the past several years. In 2022, the Consumer Financial Protection Bureau (CFPB) effectively laid out the landscape of the tenant screening market.²⁵ At the time, the CFPB noted that there has yet to be independent verifications of the predictability of reports produced by tenant screening systems. The CFPB found the reports relied on out-of-date and erroneous data. Moreover, a critical factor such as a renter's prior payment data was not reflected in the reports. Finally, tenants lack a useful ability to have errors in the reports corrected.

In May 2023, NFHA submitted extensive comments in response to the Federal Trade Commission's (FTC) and CFPB's Request for Information on Tenant Screening.²⁶ In those comments, NFHA cited research supporting its assertion that tenant screening practices that screen for criminal background, credit history, and eviction history have an unfair and outsized negative impact on historically underserved populations, including people of color, immigrants, public housing voucher recipients, and renters with disabilities. These factors are particularly problematic when there is no evidence that they are actually predictive of whether the consumer will pay the rent. Additionally, we noted that landlords are increasingly relying on algorithmic models that may perpetuate bias and make it harder for consumers to understand why they are being denied a housing opportunity.

Just recently, HUD issued a communication entitled, "Guidance on the Application of the Fair Housing Act to the Screening of Applicants for Rental Housing."²⁷ The guidance describes the type of information that should be considered by an AI model when making rental decisions. In this document, HUD underscores the importance of nondiscrimination in housing based on race, color, religion, sex, familial status, national origin, or disability. The guidance also states that applicants should be given the opportunity to correct inaccuracies in their records and be provided clear reasons for denial.

²⁴ The lack of risk management is a recurring theme in the use of AI. See, e.g., Federal Trade Commission (FTC) Press Release, *Rite Aid Banned from Using AI Facial Recognition after FTC Says Retailer Deployed Technology Without Reasonable Safeguards* (

²⁵ CFPB, *Tenant Background Checks Market Report and Consumer Snapshot: Tenant Background Checks* (Nov. 2022), https://files.consumerfinance.gov/f/documents/cfpb_tenant-background-checks-market_report_2022-11.pdf.

²⁶ NFHA, *Comment to the FTC regarding the Request for Information on Tenant Screening* (May 30, 2023), <https://www.regulations.gov/comment/FTC-2023-0024-0585>.

²⁷ HUD, *Guidance on the Application of the Fair Housing Act to the Screening of Applicants for Rental Housing* (April 29, 2024), https://www.hud.gov/sites/dfiles/FHEO/documents/FHEO_Guidance_on_Screening_of_Applicants_for_Rental_Housing.pdf.

Recent cases have also highlighted the risks of tenant screening systems. For example, in the case of *Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions LLC*, the court held that the company was not liable for discrimination, but the case showed how CoreLogic's automated tenant screening software tool ("CrimSAFE") played a role in denying a mother the right to move her disabled son into her apartment so she could care for him. The son had been arrested for an offense. The arrest was dismissed and the young man was never convicted of any crime. The arrest occurred before the plaintiff's son became disabled and unable to care for himself.²⁸ By contrast, in the case of *Louis v. SafeRent Solutions, LLC*, the court denied a motion to dismiss where the tenant screening system provided a score that was based in part on criminal records but was ultimately unexplainable.²⁹ In that case, the DOJ submitted a Statement of Interest to explain the Fair Housing Act's application to algorithm-based tenant screening systems.³⁰

In May of 2024, NFHA and fair housing advocates filed a lawsuit against Tenant Turner, Inc. alleging that its tenant screening software discriminates based on race by generating listings that display a refusal to rent to people who use Housing Choice Vouchers, including veterans whose incomes have not kept up with rising housing costs.³¹ Finally, last month, a court denied Jacksonville Wealth Builders' motion to dismiss in a case alleging that the landlord discriminated against Black renters by using faulty tenant screening algorithms that cause some rental applicants to be denied based on mistaken identities or outdated information.³²

The tenant screening industry makes billions of dollars in revenue each year despite being plagued by numerous complaints of privacy violations and bias related to these systems. Concerns about these systems must be addressed as they will likely impact, in one form or another, nearly all of the 100 million+ renters in the U.S., who are disproportionately Black and Latino.

²⁸ *Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions LLC*, No. 3:18-cv-705-VLB, 2023 U.S. Dist. LEXIS 125000 (D. Conn. July 20, 2023). See also Cohen Milstein case summary at <https://www.cohenmilstein.com/case-study/connecticut-fair-housing-center-et-al-v-corelogic-rental-property-solutions/>.

²⁹ *Louis v. SafeRent Solutions, LLC*, No. 22-CV-10800-AK, 2023 U.S. Dist. LEXIS 128909 (D. Mass. July 26, 2023).

³⁰ DOJ Press Release, *Justice Department Files Statement of Interest in Fair Housing Act Case Alleging Unlawful Algorithm-Based Tenant Screening Practices* (Jan. 9, 2023), <https://www.justice.gov/opa/pr/justice-department-files-statement-interest-fair-housing-act-case-alleging-unlawful-algorithm>.

³¹ NFHA Press Release, *NFHA and Fellow Fair Housing Advocates File Complaint against National Tenant Screening Software System* (May 14, 2024), <https://nationalfairhousing.org/nfha-and-fellow-fair-housing-advocates-file-complaint-against-national-tenant-screening-software-company/>.

³² Charlie McGee, *Judge Rules JWB Must Face Trial over Alleged Algorithms against Black Renters*, The Tributary (June 10, 2024), <https://jaxtrib.org/2024/06/10/judge-rules-jwb-must-face-trial-over-alleged-use-of-algorithms-against-black-renters/>.

Dynamic Rental Pricing Systems and Rent-Setting Technology

In the rental housing market, dynamic pricing systems and rent-setting technology based on AI have become a widespread feature. The technology can change rent prices daily, weekly, or more frequently, based on any number of factors that are hidden from consumers. This makes it profoundly difficult for prospective tenants to plan ahead and to understand why they are being charged a certain rate. ProPublica broke this story by reporting that the company (RealPage) that produces the leading rental pricing software (YieldStar) feeds its client landlords' proprietary data into an algorithm that recommends what rents to charge.³³

Evidence shows dynamic pricing systems cause rental price increases even when apartment complexes have high vacancy rates.³⁴ Critics have charged that the algorithms are adding to a crisis of housing availability and affordability. Following this revelation, the U.S. Government Accountability Office (GAO) reported that rental rates had increased 24% in the last three years.³⁵ More recently, Attorney General Brian Schwalb of the District of Columbia sued the company and 14 of the largest landlords in the district,³⁶ the DOJ filed a Statement of Interest in the antitrust litigation against RealPage,³⁷ and Senators introduced a bill to make the practice illegal.³⁸

In addition, dynamic rental pricing powered by AI can be a barrier to housing for Housing Choice Voucher recipients as rent prices potentially fluctuate above HUD fair market rent amounts. This can negatively impact low wealth groups who are disproportionately single, female-headed families with children and people with disabilities³⁹ as well as people who live in rural

³³ Heather Vogell, *Rent Going Up? One Company's Algorithm Could Be Why*, ProPublica (Oct. 15, 2022), <https://www.propublica.org/article/yieldstar-rent-increase-realpage-rent>.

³⁴ *Id.*

³⁵ U.S. Government Accountability Office (GAO), *The Affordable Housing Crisis Grows While Efforts to Increase Supply Fall Short* (Oct. 2023), <https://www.gao.gov/blog/affordable-housing-crisis-grows-while-efforts-increase-supply-fall-short>.

³⁶ Danielle Kaye, *Lawsuits Mount over Software Used by Landlords to Set Rents*, The New York Times (July 19, 2024), <https://www.nytimes.com/2024/07/19/business/economy/rent-prices-realpage-lawsuit.html>.

³⁷ DOJ Statement of Interest, *In re Real Page: Rental Software Antitrust Litigation (II)*, Case No. 3:32-MD-3071, (Nov. 15, 2023), <https://www.justice.gov/d9/2023-11/418053.pdf>.

³⁸ Heather Vogell, *We Found That Landlords Could Be Using Algorithms to Fix Rent Prices. Now Lawmakers Want to Make the Practice Illegal*, ProPublica (Jan. 30, 2024), https://www.propublica.org/article/senators-introduce-legislation-stop-landlords-algorithm-price-fixing?utm_campaign=trueanthem&utm_medium=social&utm_source=linkedin.

³⁹ See Claudia D. Solari et al., *Housing Insecurity in the District of Columbia*, Urban Institute (Nov. 16, 2023), <https://www.urban.org/research/publication/housing-insecurity-district-columbia>; Sharon Cornelissen, *The Pandemic Aggravated Racial Inequalities in Housing Insecurities: What Can It Teach Us about Housing Amidst Crisis?*, Harvard Joint Center for Housing Studies (July 12, 2023), <https://www.jchs.harvard.edu/blog/pandemic-aggravated-racial-inequalities-housing-insecurity-what-can-it-teach-us-about-housing>.

communities.⁴⁰ Congress should seek to fully understand the role dynamic pricing systems play in impacting rental housing affordability and any possible violations of law, including the Fair Housing Act.

Credit Scoring Systems

Credit scoring systems are algorithmic models that attempt to predict a borrower's risk of prepayment or default. They are often used as part of a lender's decisions on underwriting and pricing.

Concerns about the potential for credit scoring models to perpetuate bias against certain groups have been raised over the decades. Both the data and the model can reflect bias. The data reported to the three main credit reporting agencies (CRAs) of Equifax, Transunion, and Experian often reflects bias within the credit and housing markets.

Credit scoring models are largely comprised of factors that present systemic challenges for underserved consumers, include the following:

- Number and type of credit accounts
- Timely payment of bills
- Amount/percentage of available credit
- Collection actions
- Amount of outstanding debt
- Age of accounts

Each of the above components can reflect bias, particularly for those living in urban and rural credit deserts.⁴¹ For example, because of the U.S. dual credit market,⁴² mainstream lenders and banks are hyper-concentrated in predominantly White communities. Conversely, non-traditional lenders like subprime lenders, payday lenders and check cashers, are concentrated in communities of color.⁴³ As a result, borrowers of color disproportionately access credit with

⁴⁰ See Irina Ivanova, *Inflation is Hurting Rural Americans More Than City Folks - Here's Why*, CBS MoneyWatch (Dec. 2, 2021),

<https://www.cbsnews.com/news/inflation-rural-households-non-college-grads-hardest/>.

⁴¹ Trulia and NFHA, *50 Years After the Fair Housing Act – Inequality Lingers* (April 19, 2018),

<https://www.trulia.com/research/50-years-fair-housing/>.

⁴² For more information about the U.S. dual credit market, see the National Fair Housing Alliance's webpage on Access to Credit, available at <https://nationalfairhousing.org/issue/access-to-credit/>.

⁴³ This dynamic is not a function of economics. In fact, banks are closing their branches at a higher rate in affluent, high-income Black neighborhoods than they are in low-income non-Black communities. See Zach Fox, Zain Tariq, Liz Thomas, Ciaralou Palicpic, *Bank Branch Closures Take Greatest Toll on Majority-Black Areas*, Standard and Poor Global (July 25, 2019),

<https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/bank-branch-closures-take-greatest-toll-on-majority-black-areas-52872925#:~:text=Since%202010%2C%20the%20branch%20footprint,disparity%20in%20net%20closure%20rates.>

non-traditional lenders that often do not report positive financial data to the CRAs. Accordingly, the information that would demonstrate their ability to repay their financial obligations is not included in the dataset used to build credit scoring models. This also results in people of color being disproportionately credit invisible or un-scoreable. Roughly one-third of Black and Latino people do not have credit scores because they disproportionately access credit outside of the financial mainstream.⁴⁴ Moreover, because of the nation's exclusionary housing policies and practices, families of color have less wealth. As a result, typically they have higher credit utilization rates, which can result in lower scores as the credit utilization rate accounts for 30 percent of the overall credit score.⁴⁵

Additionally, consumers impacted by historical discrimination are negatively impacted by these factors because they have less access to mainstream credit. For example, creditworthy people of color disproportionately were steered to predatory subprime loans that carried abusive terms and conditions. As a result, these consumers disproportionately experienced collection actions not because these consumers were not creditworthy, but rather, because they were targeted by predatory lenders with discriminatory practices who placed consumers in bad, unsustainable loans.⁴⁶

Moreover, when people experience discrimination in lending markets or are unfairly declined for a loan, they are forced to apply for multiple loans from other lenders. This causes an increase in the number of inquiries that appears in the credit repository data and lowers the consumer's credit score.

Recently, regulators and researchers have acknowledged the risks of outdated credit scoring models and data that is not predictive, which can have a disparate impact on people of color. For example, because they can rely on outdated, incomplete, or inaccurate information, credit

⁴⁴ CFPB, *Who Are The Credit Invisibles?* (Dec. 2016), https://files.consumerfinance.gov/f/documents/201612_cfpb_credit_invisible_policy_report.pdf.

⁴⁵ See Megan Leonhardt, *Black and Hispanic Americans Often Have Lower Credit Scores—Here's Why They're Hit Harder*, CNBC (Jan 28 2021), <https://www.cnbc.com/2021/01/28/black-and-hispanic-americans-often-have-lower-credit-scores.html>; Michelle Singletary, *Credit Scores Are Supposed To Be Race-Neutral. That's Impossible.*, The Washington Post (Oct. 16, 2020), <https://www.washingtonpost.com/business/2020/10/16/how-race-affects-your-credit-score/>.

⁴⁶ See Will Douglas Heaven, *Bias Isn't the Only Problem with Credit Scores—and No, AI Can't Help* (June 17, 2021), https://www.technologyreview.com/2021/06/17/1026519/racial-bias-noisy-data-credit-scores-mortgage-loans-fairness-machine-learning/?truid=&utm_source=weekend_reads&utm_medium=email&utm_campaign=weekend_reads.unpaid.engagement&utm_content=06.26.21.subs&mc_cid=aad1663503&mc_eid=eea_d1c58a0; Megan Leonhardt, *Democrats and Republicans in Congress Agree: The System That Determines Credit Scores Is "Broken,"* CNBC (Feb. 27, 2019), <https://www.cnbc.com/2019/02/27/american-consumer-credit-rating-system-is-broken.html>; Lisa Rice and Deidre Swesnik, *Discriminatory Effects of Credit Scoring on Communities of Color*, Suffolk University Press (June 2012), <https://nationalfairhousing.org/wp-content/uploads/2021/12/NFHA-credit-scoring-paper-for-Suffolk-NCL-C-symposium-submitted-to-Suffolk-Law.pdf>.

scoring systems may not be as effective as other tools in measuring consumer risk. To an extensive degree, credit scores do not include rental housing payment data which is highly predictive in determining a borrower's willingness to pay their mortgage obligation.⁴⁷ Moreover, a detailed analysis of consumer cash-flow data reveals that using more detailed information about how consumers manage and pay all their obligations (cash-flow) can be a better predictor of risk than using traditional credit scores alone. The research also suggests that cash-flow analysis can be a better tool than traditional credit scores for expanding access to credit for underserved groups.

48

In October 2022, the Federal Housing Finance Agency (FHFA) approved two new credit score models for use by lenders: FICO 10T and VantageScore 4.0.⁴⁹ Among other things, the new models will be more inclusive by including new payment history information such as rent, utilities, and telecom payments. Similarly, the CFPB has proposed to ban medical bills from credit reports because, among other things, medical bills have little to no predictive value.⁵⁰

In other words, when a person is discriminated against in their efforts to access the credit markets, the data and models become tainted. As Federal Reserve Vice Chair of Supervision Michael Barr stated, "Artificial Intelligence...relies on the data that is out there in the world and the data...is flawed. Some of it is just wrong. Some of it is deeply biased...Information we have on the Internet is imperfect...if you train a Machine Learning device, if you train a Large Language Model on imperfect data, you're going to get imperfect results."⁵¹

Insurance Scoring, Underwriting, Rating, and Claims Systems

Insurance scoring systems are algorithmic models built using actuarial data designed to predict the likelihood of a consumer experiencing a risk-related event such as filing a homeowners insurance claim or filing an auto claim. Insurance scoring systems can be built using data from the CRAs; however, model developers also rely on proprietary company data and information

⁴⁷ Laurie Goodman and Jun Zhu, *Rental Pay History Should be Used to Assess the Creditworthiness of Mortgage Borrowers*, Urban Institute (April 17, 2018), <https://www.urban.org/urban-wire/rental-pay-history-should-be-used-assess-creditworthiness-mortgage-borrowers#:~:text=Considering%20the%20comparability%20of%20monthly.indication%20for%20credit%20risk%20purposes>.

⁴⁸ *The Use of Cash-Flow Data in Underwriting Credit*, FinRegLab (July 2019), https://finreglab.org/wp-content/uploads/2023/12/FinRegLab_2019-07-25_Research-Report_The-Use-of-Cash-Flow-Data-in-Underwriting-Credit_Empirical-Research-Findings.pdf

⁴⁹ FHFA Press Release, *FHFA Announces Validation of FICO 10T and VantageScore® 4.0 for Use by Fannie Mae and Freddie Mac* (Oct. 24, 2022), <https://www.fhfa.gov/news/news-release/fhfa-announces-validation-of-fico-10t-and-vantagescore-4.0-for-use-by-fannie-mae-and-freddie-mac>.

⁵⁰ CFPB Press Release, *CFPB Proposes to Ban Medical Bills from Credit Reports* (June 11, 2024), <https://www.consumerfinance.gov/about-us/newsroom/cfpb-proposes-to-ban-medical-bills-from-credit-reports/>.

⁵¹ See Federal Reserve Board of Governors Vice Chair Michael Barr, *Setting the Foundation for Effective Governance and Oversight: A Conversation with U.S. Regulators*, NFHA Responsible AI Symposium (January 19, 2024), https://www.youtube.com/watch?v=HbM_zD0esDo.

purchased from data providers that reflect consumers' claims experiences, weather-related data, and other information. Unlike credit scoring systems, insurance scoring models are not typically designed to determine whether a consumer will pay their insurance premium, but rather, the consumer's risk profile related to an event that would present a monetary exposure for the insurance company. The score can be used to help underwrite business and/or determine the price a consumer should pay for insurance.

Insurance scoring systems, like other AI systems, can perpetuate bias in myriad ways.⁵² NFHA has challenged discriminatory provisions in insurance scoring systems, most specifically in a matter brought against the Prudential Insurance Company.⁵³ NFHA's investigation, research, and expert witness analysis revealed the company's insurance scoring system presented a disproportionate discriminatory impact on Black consumers in the price they paid for homeowners insurance. The differences in premiums between Black and White insureds was not explainable, based on NFHA's analysis, by appropriate risk factors. Instead, we alleged the model the company utilized was contributing to disparate outcomes. Moreover, our expert was able to devise a way to yield a less discriminatory outcome than the one generated by the model used by Prudential.

Additionally, the Casualty Actuarial Society (CAS) acknowledged that algorithmic bias can manifest in systems used in the insurance sector including underwriting, pricing, and claims models.⁵⁴ The CAS issued reports highlighting examples of discrimination in the insurance market over the decades and various analyses of whether certain variables used to assess risk or affix insurance rates presented unfair discrimination. Factors such as zip code, address, educational level, credit scores, and occupation have raised serious concerns about their propensity for manifesting discrimination. CAS' research pointed out that "fully or semi-automated systems...are...inherently capable of introducing unfairness into the process and thus have direct consequences to individuals affected by these models. Bias is all around us, and it can creep into the decision-making paradigm in subtle ways, whether it is the

⁵² AI systems can manifest discrimination by using biased or unrepresentative data sets, and by other means. For a detailed discussion about the many ways AI can perpetuate discrimination, see Testimony of Lisa Rice, *Hearing on Equitable Algorithms: How Human-Centered AI Can Address Systemic Racism and Racial Justice in Housing and Financial Services before the U.S. House Financial Services Task Force on Artificial Intelligence* (May 7, 2021), <https://nationalfairhousing.org/wp-content/uploads/2022/01/Lisa-Rice-House-Testimony-on-AI-5-7-21.pdf>.

⁵³ See *National Fair Housing Alliance v. Prudential Ins. Co.*, 208 F. Supp. 2d 46 (D.D.C. 2002), <https://casetext.com/case/national-fair-housing-alli-v-prudential-ins-co>.

⁵⁴ See Ronda Lee, *AI Can Perpetuate Racial Bias in Insurance Underwriting*, Yahoo!Money (Nov. 1, 2022), <https://finance.yahoo.com/news/ai-perpetuates-bias-insurance-132122338.html>.

subjectivity of human judgment, prejudice, historical inequities baked into the data, or faulty algorithms.”⁵⁵

Recently, the New York State Department of Financial Services adopted final guidance to prevent discrimination in the use of AI in insurance.⁵⁶ The agency noted that the use of external consumer data and information sources (“ECDIS”) and AI can benefit insurers and consumers by simplifying and expediting insurance underwriting and pricing processes, however, it is critical that insurers who utilize such technologies establish a proper governance and risk management framework to mitigate the potential harm to consumers. The guidance outlines DFS’s expectations for how all insurers authorized to write insurance in New York State develop and manage the integration of ECDIS, AI, and other predictive models.

Automated Valuation Models

The use of Automated Valuation Models (AVMs) for some portion of the home valuation process has been growing more popular. Some see the use of AVMs as a potential remedy to multiple complaints of consumers of color having to “whitewash” their home by removing all indications of their race and ethnicity to receive a fair value through traditional appraisals.⁵⁷ By statute, an AVM is defined as a “computerized model used by mortgage originators and secondary market issuers to determine the collateral worth of a mortgage secured by a consumer’s principal dwelling.”⁵⁸

In some cases, a secondary market issuer or lender may use an AVM in place of a human appraiser; in other cases, the human appraiser may develop the opinion of value using an AVM; and in still other cases, a secondary market issuer or lender may use an AVM as a check on the human appraiser. The AVM may be faster, cheaper, more consistent, and less prone to bias, but AVMs pose at least two problems.

First, the AVM still relies on the traditional sales comparison approach in which the home valuation is based on recent sales of comparable homes in a comparable neighborhood. Because of America’s long history of redlining, segregation, and consideration of race in valuing

⁵⁵ Roosevelt Mosley, FCAS, and Radost Wenman, FCAS, CAS Research Paper Series on Race and Insurance Pricing: *Methods for Quantifying Discriminatory Effects on Protected Classes in Insurance*, *Casualty Actuarial Society* (2022), https://www.casact.org/sites/default/files/2022-03/Research-Paper_Methods-for-Quantifying-Discriminatory-Effects.pdf?utm_source=Landing&utm_medium=Website&utm_campaign=RIP+Series.

⁵⁶ NYDFS Press Release, *DFS Superintendent Harris Adopts Insurance Guidance to Combat Discrimination in Artificial Intelligence* (July 11, 2024), https://www.dfs.ny.gov/reports_and_publications/press_releases/pr20240711241.

⁵⁷ See, e.g., Julian Glover and Mark Nichols, *Our America: Lowballed*, ABC (2022), <https://abc7news.com/feature/our-america-lowball-home-appraisal-racial-bias-discrimination/12325606/>. See also, HUD Press Release, *HUD Appraiser, Appraisal Management Company, and Lender with Race Discrimination* (July 15, 2024), https://www.hud.gov/press/press_releases_media_advisories/HUD_No_24_181.

⁵⁸ 12 U.S.C. § 3354(d).

properties and neighborhoods, the AVM is likely using historical data that undervalues homes in communities of color.⁵⁹ For example, research has shown that in 2021, homes in White neighborhoods were appraised at values nearly 250% higher than similar homes in similar Black neighborhoods and nearly 278% higher than similar homes in similar Latino neighborhoods.⁶⁰ Further research reveals that, because of societal and industry bias, the homes of people who live in predominately Black communities are undervalued on average by 43%. That amounts in \$162 billion in lost equity.⁶¹ These disparities then generate data points used by the AVM, which can perpetuate the disparity in future transactions.

Second, using AVMs may create a bifurcated valuation system. AVMs tend to work best in neighborhoods with similar homes that generate multiple data points, which means the models excel in suburban subdivisions, which tend to be majority-White and comprised of homes that are very similar to one another. AVMs do not work as well in neighborhoods of color, which tend to have older properties with varied types of homes and architecture. Also, consumers of color tend to stay in their homes longer, which means fewer sales data points for the AVM. Fannie Mae and Freddie Mac have begun accepting the AVM value and waiving the traditional appraisal in certain situations.⁶² The risk is that a bifurcated valuation system will develop in which consumers of color are more likely to be burdened with the cost of a traditional appraisal, which in turn tends to undervalue their home.

In June 2023, NFHA hosted a hackathon designed to investigate whether bias existed in AVMs. Hackathon teams identified several critical issues, including 1) disproportionate errors in property valuation affecting communities of color; 2) calcification of historical discrimination patterns in current appraisal practices; and 3) lags in recognizing value increments due to gentrification, leading to undervaluation in predominately Black and Latino neighborhoods. In fact, because of these systemic flaws, in some cases AVMs had only a 15% rate of accuracy in Black communities. Teams participating in the Hackathon proposed several ideas for mitigating bias in AVMs including:

1. Implementing data preprocessing and exploratory data analysis to identify and mitigate biases.

⁵⁹ See NFHA and National Consumer Law Center, *Comment to FHFA, CFPB, Federal Reserve, FDIC, OCC, and NCUA regarding Quality Control Standards for Automated Valuation Models* (Aug. 21, 2023), <https://www.fdic.gov/resources/regulations/federal-register-publications/2023/2023-quality-control-standards-for-automated-valuation-models-3064-ae68-c-010.pdf>.

⁶⁰ See Junia Howell and Elizabeth Korver-Glenn, *Appraised: The Persistent Evaluation of White Neighborhood as More Valuable Than Communities of Color*, Eruka (2022), https://static1.squarespace.com/static/62e84d924d2d8e5dff96ae2f/t/6364707034ee737d19dc76da/1667526772835/Howell+and+Korver-Glenn+Appraised_11_03_22.pdf.

⁶¹ Jonathan Rothwell and Andre Perry, *How Racial Bias in Appraisals Affects the Devaluation of Homes in Majority-Black Neighborhoods*, Brookings, December 5, 2022. <https://www.brookings.edu/articles/how-racial-bias-in-appraisals-affects-the-devaluation-of-homes-in-majority-black-neighborhoods/>

⁶² See, e.g., Fannie Mae, *Delivering Effective, Efficient, and Impartial Home Valuations Across America*, <https://singlefamily.fanniemae.com/valuation-modernization>.

2. Developing Machine Learning classifiers to predict and evaluate AVM errors across different demographics.
3. Proposing algorithm modifications to reduce reliance on biased historical data.

Recently, the federal financial regulators issued a final rule to help ensure the integrity of AVMs.⁶³ Under the final rule, the regulators will require institutions that engage in certain transactions secured by a consumer's principal dwelling to adopt policies, practices, procedures, and control systems designed to:

- ensure a high level of confidence in estimates,
- protect against data manipulation,
- seek to avoid conflicts of interest,
- require random sample testing and reviews, and
- comply with nondiscrimination laws.

However, the rule does not create a private right of action, so consumers will need to rely on the regulators to supervise institutions and enforce compliance with the rule.

Automated Underwriting Systems and Risk-Based Pricing Systems

Automated underwriting systems and risk-based pricing systems manifest and perpetuate bias as well. These systems rely on and are built using data contained in the CRAs. The data captured by CRAs is under-representative as it is missing critical information, like rental housing payment data, that can accurately reflect a borrower's willingness and ability to pay financial obligations. Data captured by the CRAs also includes information tainted by bias against underserved groups. Unfortunately, redlining and housing discrimination are still everyday occurrences⁶⁴ and when consumers experience discrimination, that bias is reflected in the data captured by the CRAs.

In some instances, the models themselves can reflect discrimination. For example, researchers at University of California-Berkeley found that fintech lenders that rely on algorithms to generate

⁶³ See CFPB Press Release, *Agencies Issue Final Rule to Help Ensure Credibility and Integrity of Automated Valuation Models* (July 17, 2024), <https://www.consumerfinance.gov/about-us/newsroom/agencies-issue-final-rule-to-help-ensure-credibility-and-integrity-of-automated-valuation-models/>.

⁶⁴ See DOJ, *Recent Accomplishments of the Housing and Civil Enforcement Section*, (Oct. 5, 2023), <https://www.justice.gov/crt/recent-accomplishments-housing-and-civil-enforcement-section>; Zillow Research, *What Modern-Day Housing Discrimination Looks Like: A Conversation with the National Fair Housing Alliance* (Feb. 4, 2019), <https://www.zillow.com/research/modern-housing-discrimination-22898/>; NFHA, *Fair Housing Solutions: Overcoming Real Estate Sales Discrimination* (Dec. 2019), <https://nationalfairhousing.org/wp-content/uploads/2019/12/Fair-Housing-Solutions-Overcoming-Real-Estate-Sales-Discrimination-2.pdf>.

decisions on loan pricing discriminate against borrowers of color because their systems “have not removed discrimination but may have shifted the mode.”⁶⁵ The study revealed that Black and Latino borrowers were overcharged by \$765 million per year. That is, Black and Latino borrowers were disproportionately charged a rate that is higher than their commensurate level of risk because of biased risk-based pricing systems. Further the same research shows that the lenders selling loans to the Government Sponsored Enterprises use risk-based pricing to drive profitability rather than for accurate risk assessments, which can result in disproportionate cost burdens for people of color.⁶⁶

Finally, concerns have been raised about the impact of underwriting and pricing models’ lack of transparency and explainability.⁶⁷ For example, in 2023, the CFPB clarified that when lenders use AI or complex credit models, they may not rely on the checklist of reasons provided in CFPB sample forms for adverse action notices if those sample reasons do not accurately or specifically identify the reasons for the adverse action. The CFPB further clarified adverse action notice requirements apply equally to all credit decisions, regardless of whether the technology used to make them involves complex or “black-box” algorithmic models, or other technology that creditors may not understand sufficiently to meet their legal obligations.

Large Language Models and Consumer Interactions

Large Language Models (LLMs) are a type of AI model designed to understand and generate human language. They are trained on vast amounts of text data, learning to predict the next word in a sentence based on the context of the previous words. LLMs are a significant advancement in natural language processing (NLP) and AI. These models are characterized by their ability to process and generate human-like text. Some of their capabilities are:

1. Capabilities in Language Generation: LLMs offer unparalleled capabilities in language generation, which opens exciting opportunities for interaction design. They are highly context-dependent and can adapt to a wide range of linguistic styles and nuances.⁶⁸
2. Importance in Psycholinguistics: While LLMs are not precise models of human linguistic processing, their success in language modeling makes them significant in the field of

⁶⁵ 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), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3063448.

⁶⁶ See Michelle Aronowitz, Edward L. Golding, and Jung Hyun Choi, *The Unequal Costs of Black Homeownership*, MIT Golub Center For Finance And Policy (Oct. 1, 2020), <https://mitsloan.mit.edu/sites/default/files/inline-files/Mortgage-Cost-for-Black-Homeowners-10.1.pdf>.

⁶⁷ See CFPB, *Adverse Action Notification Requirements and the Proper Use of the CFPB’s Sample Forms Provided in Regulation B*, CFPB Circular 2023-23, <https://www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/>.

⁶⁸ Mina Lee, Percy Liang, and Qian Yang, *Designing a Human-AI Collaborative Writing Dataset for Exploring Language Model Capabilities* (2022), <https://doi.org/10.1145/3491102.3502030>.

psycholinguistics. They serve as practical tools for exploring language and thought relationships.⁶⁹

3. **Enhancing Creativity:** AI LLMs have contributed to creative writing, including newspaper articles, novels, and poetry. These models can generate creative and original text, demonstrating their potential in diverse creative applications.⁷⁰

In summary, LLMs represent a significant leap in AI's ability to interact with and understand human language. They are crucial for a variety of applications, from enhancing creative writing to contributing to the understanding of human language processing, despite facing challenges in certain aspects of language comprehension.

LLMs also pose newfound risks and civil rights and consumer protection concerns, especially in highly deterministic contexts, such as housing and financial services. Due to representation imbalances,⁷¹ dataset biases, and lack of red-teaming efforts, the discriminatory use cases of LLMs are highly probable.⁷² For example, earlier this year, Open Communities settled a case against Harbor Group, for the use of an AI chatbot which automatically rejected applicants who used Housing Choice Vouchers.⁷³ While LLMs offer promising opportunities for innovation in housing and financial services, addressing challenges related to data security, bias, regulatory compliance, and public trust will be key to their successful implementation and acceptance.⁷⁴

Part III: Using AI to Promote Fairer Outcomes in Housing and Financial Services

While AI poses certain risks, AI also can significantly assist in the identification and mitigation of the risk of discriminatory practices in housing and financial services. This potential is

⁶⁹ Conor J. Houghton, N. Kazanina, and Priyanka Sukumaran, *Beyond the Limitations of Any Imaginable Mechanism: Large Language Models and Psycholinguistics* (2023), <https://doi.org/10.48550/arXiv.2303.00077>.

⁷⁰ See *id.*

⁷¹ See Angelina Wang, Jamie Morgenstern, John P. Dickerson, *Large Language Models Cannot Replace Human Participants Because They Cannot Portray Identity Groups* (Feb. 2024) <https://arxiv.org/pdf/2402.01908> (demonstrating that LLMs will misportray and flatten the representations of demographic groups due to LLMs use of existing online text for training data and loss function).

⁷² See Ondrej Linda, et al., *Navigating Fair Housing Guardrails in LLMs*, Zillow (Jan. 16, 2024), <https://www.zillow.com/tech/navigating-fair-housing-guardrails-in-llms/> (discussing the potential of a LLM-powered, conversational experience in the real estate market, the challenges of discriminatory/offensive content, and the guardrails needed to enforce good behavior).

⁷³ Open Communities Press Release, *Open Communities Reaches Accord in Case Addressing Artificial Intelligence Communications with Prospective Tenants* (Jan. 31, 2024), <https://www.open-communities.org/post/press-release-open-communities-reaches-accord-in-case-addressing-artificial-intelligence-communicat>.

⁷⁴ For a discussion of the risks of complex chatbots using LLMs, see CFPB, *Chatbots in Consumer Finance* (June 2023), https://files.consumerfinance.gov/f/documents/cfpb_chatbot-issue-spotlight_2023-06.pdf.

explored through various tools, including dataset analysis,⁷⁵ internet or website crawling,⁷⁶ and other enforcement-based AI tools, including those that use Natural Language Processing (NLP).⁷⁷

Using Fairness Techniques at Each Stage of the AI Model Lifecycle

Algorithmic fairness techniques play a crucial role in mitigating biases and ensuring equitable outcomes in AI systems. These techniques can be categorized into pre-processing, in-processing, and post-processing methods, each addressing biases at different stages of the AI model lifecycle.

1. Pre-processing Techniques: These techniques focus on the initial stages of AI development, where the primary goal is to rectify biases present in the training data before it is fed into the model. By identifying and modifying biased data, pre-processing methods aim to prevent the AI system from learning and perpetuating these biases.⁷⁸
2. In-processing Techniques: These are applied during the model training phase and involve modifying the learning algorithm to incorporate fairness. This might include adjusting the model's objective function to balance accuracy with fairness criteria. One approach is the integration of fairness constraints directly into the training process, as discussed by some researchers in their exploration of unified data and algorithm fairness through adversarial data augmentation and adaptive model fine-tuning.⁷⁹
3. Post-processing Techniques: These methods are applied after the model has been trained. They adjust the output of the model to ensure fairness, often through recalibration of decision thresholds for different groups. This approach is particularly useful in scenarios where modifying the training process is not feasible or when dealing with legacy systems.

In summary, algorithmic fairness techniques are integral to developing AI systems that are equitable and unbiased. These methods, spanning from the initial data preparation to the final model output, help in creating AI solutions that are not only effective but also fair and just.

⁷⁵ See Rie Kamikubo, Lining Wang, Crystal Marte, Amnah Mahmood and Hernisa Kacorri, *Data Representativeness in Accessibility Datasets: A Meta-Analysis* (2022), <https://doi.org/10.1145/3517428.3544826>.

⁷⁶ Internet or website crawling tools can allow users to search for discriminatory phrases and comments that can impede access to fair housing and lending opportunities.

⁷⁷ See Paula Reyer Lobo, *Bias in Hate Speech and Toxicity Detection* (2022), <https://doi.org/10.1145/3514094.3539519>; Eirini Ntoutsi et al., *Bias in Data-Driven AI Systems: An Introductory Survey* (Jan. 14, 2020), <https://arxiv.org/abs/2001.09762>.

⁷⁸ Nengfeng Zhou, Zach Zhang, Vijay Nair, Harsh Singhal, and Jie Chen, *Bias, Fairness and Accountability with Artificial Intelligence and Machine Learning Algorithms* (2022), <https://doi.org/10.1111/insr.12492>.

⁷⁹ N. V. Berkel, Jorge Gonçalves, D. Russo, S. Hosio, and M. Skov, *Effect of Information Presentation on Fairness Perceptions of Machine Learning Predictors* (2021), <https://doi.org/10.1145/3411764.3445365>.

Expanding Inclusive and Equitable Housing and Financial Services Opportunities

Using AI to Deepen Research

AI can significantly enhance the depth and effectiveness of housing and financial policy and research. For example, AI can be instrumental in analyzing vast datasets to identify trends and patterns that might indicate discriminatory practices in housing and lending. The analysis can focus on various aspects, such as loan approval rates, interest rates charged, and geographical distribution of loans. These insights are critical for shaping fair housing policies and for enforcing anti-discrimination laws. The work by Wyly and Holloway, on the disappearance of race in mortgage lending, highlights the importance of data analysis in understanding and addressing issues in housing markets.⁸⁰

Using AI to Fix the Non-representative/Under-representative Data Problem

AI can be used to identify and rectify biases in non-representative or under-representative datasets, which is crucial for ensuring equitable housing and lending practices. The work of Jain and Verma highlights the importance of AI in making the credit underwriting process more accurate.⁸¹ By refining data to be more representative, AI can help lenders make fairer and more equitable decisions.

Leveraging AI to Design Equitable Systems

AI technologies can analyze alternative data sources, such as cash-flow underwriting data and rental housing payment histories, which are particularly beneficial for individuals with limited credit histories. Consumers can often have limited or non-existent credit histories because they cannot access traditional, mainstream credit markets, live in a credit desert, or have limited information about how mainstream credit markets function. AI and big data can capture weak signals in creditworthiness assessments, thereby improving financial inclusion and access to credit for traditionally underserved borrowers.⁸²

⁸⁰ See Elvin K. Wyly and S. Holloway, *The Disappearance of Race in Mortgage Lending*, *Economic Geography* (2002), <https://doi.org/10.1111/j.1944-8287.2002.tb00181.x>.

⁸¹ See Aastha Jain and Deval Verma, *Making Credit Underwriting Process More Accurate using ML* (2022), <https://doi.org/10.1109/ICACCM56405.2022.10009117>.

⁸² See Hicham Sadok, Fadi Sakka and Mohammed El Hadi El Maknouzi, *Artificial Intelligence and Bank Credit Analysis: A Review*, *Cogent Economics & Finance* (2022), <https://doi.org/10.1080/23322039.2021.2023262>.

The Use of Cash-Flow Data in Underwriting Credit: Market Context & Policy Analysis, FinRegLab (February 2020)
https://finreglab.org/wp-content/uploads/2023/12/FinRegLab_2020-03-03_Research-Report_The-Use-of-Cash-Flow-Data-in-Underwriting-Credit_Market-Context-and-Policy-Analysis.pdf

One way financial service providers are using AI to expand access to credit is by incorporating rental housing payment and cash-flow data into underwriting models. These two data points help lessen the reliance on credit scoring systems, loan-to-value ratios, and debt-to-income ratios. These three measures are not the best arbiters of risk and reflect a borrower's wealth and not necessarily their willingness or ability to pay debt obligations. However, as described above, research shows that rental housing payment information and cash-flow data can do a better job of assessing risk for underserved groups including people long impacted by discrimination in our housing and lending markets.

Using AI to Fix Zoning Challenges

Exclusive and restrictive zoning policies have been used over the decades to generate residential segregation, reduce affordable housing options, and thwart fair housing efforts.⁸³ Innovators are using AI and other technologies to address zoning challenges to overcome the housing shortage. For example, some scholars and urban planners are examining the idea of using AI to automate the process of developing zoning codes.⁸⁴ Using AI to develop and analyze zoning codes may make it easier and quicker to identify provisions in the ordinances that present barriers to fair housing and affordable housing. This would, in turn, enable legislators to address potential discrimination risks. Using AI in this way can also help jurisdictions meet their Fair Housing Act obligation to Affirmatively Further Fair Housing.⁸⁵

AI can also be used to analyze and fix unfair patterns or barriers presented by restrictive or over-burdensome zoning and permitting policies. For example, AI can detect instances where parking limits, lot-size, and other requirements can drive up the cost of housing and restrict the building and development of affordable housing units. AI can also identify other problematic conditions such as "blood-only" or "relative-only" requirements that limit the ability of people to move into a community unless they are related by blood to someone already living in the jurisdiction. AI can be used to detect other restrictive or discriminatory provisions and provide suggestions for how to amend ordinances so they are fairer and promote the development of affordable housing.

Optimizing Privacy Protections through AI Techniques

⁸³ See Fair Share Housing Center, *Dismantling Exclusionary Zoning: New Jersey's Blueprint for Overcoming Segregation* (April 2023), https://www.fairsharehousing.org/wp-content/uploads/2023/04/Dismantling-Exclusionary-Zoning_New-Jerseys-Blueprint-for-Overcoming-Segregation.pdf

⁸⁴ Norman Wright, AICP, *Using Generative AI to Draft Zoning Codes*, American Planning Association (Oct. 2023), <https://www.planning.org/publications/document/9277441/>

⁸⁵ Jurisdictions receiving federal funds for a housing or community development purpose must ensure all their laws, programs, and services are implemented in compliance with the Federal Fair Housing Act and in a manner that Affirmatively Furthers Fair Housing. This means zoning policies must not perpetuate discrimination, segregation, or other anti-fair housing principles. See National Fair Housing Alliance, *Affirmatively Furthering Fair Housing*, <https://nationalfairhousing.org/issue/affirmatively-furthering-fair-housing/>.

Privacy-enhancing techniques are essential in AI to ensure the protection of consumer data while utilizing it for housing and lending purposes.⁸⁶ The work of Chen et al., shares lessons learned during the development of frameworks that aid in the correct use of privacy-enhancing technologies like homomorphic encryption and secure multi-party computation.⁸⁷ These technologies are vital for developing AI systems that are both effective and respectful of consumer privacy.

Part IV: Applying the Existing Legal Framework to AI

It is critically important to understand the existing legal framework governing AI before pursuing new policy recommendations. There are two key laws that prohibit discrimination in housing and financial services: the Fair Housing Act and the Equal Credit Opportunity Act (“ECOA”). The Fair Housing Act prohibits any entity from discriminating in housing and mortgage lending on the basis of race, color, religion, national origin, sex (including sexual orientation), disability, and familial status (also known as “protected characteristics” or “protected classes” or “prohibited bases”).⁸⁸ The Fair Housing Act also requires entities receiving federal funds for a housing or community development purpose to disseminate those funds, as well as implement their programs and services in a way that Affirmatively Furthers Fair Housing. This means entities receiving these funds cannot not discriminate and must examine how their policies and programs contribute to a person’s zip code determining their outcomes in life. If entities have policies or programs that distribute resources unfairly or in ways that build up some communities while allowing others to remain underserved, those entities may well be violating their obligation to Affirmatively Further Fair Housing.

The ECOA prohibits “creditors” from discriminating in lending on the basis of race, color, religion, national origin, sex (including sexual orientation), marital status, age, and source of income.⁸⁹ The prohibition on lending discrimination extends to ensuring creditors do not redline communities based on the characteristics of the persons living in those communities. Moreover, ECOA does allow creditors to design Special Purpose Credit Programs (SPCPs) for certain

⁸⁶ See Hannah Holloway, Snigdha Sharma, Samantha Gordon, and Dr. Michael Akinwumi, *Privacy, Technology, and Fair Housing – A Case for Corporate and Regulatory Action* (Aug. 22, 2023), <https://nationalfairhousing.org/privacy-technology-and-fair-housing-a-case-for-corporate-and-regulatory-action/>.

⁸⁷ See Huili Chen, S. Hussain, Fabian Boemer, Emmanuel Stapf, A. Sadeghi, F. Koushanfar and Rosario Cammarota, *Developing Privacy-preserving AI Systems: The Lessons Learned* (2020), <https://doi.org/10.1109/DAC18072.2020.9218662>.

⁸⁸ The Fair Housing Act: 42 U.S.C. § 3601, et seq.; HUD’s implementing regulation: 24 CFR Part 100.

⁸⁹ ECOA: 15 U.S.C. § 1619(a); CFPB’s Regulation B: 12 CFR Part 1002. Recently, an appeals court upheld the longstanding regulatory interpretation that ECOA prohibits discriminatory discouragement of prospective credit applicants. See Relman Colfax Press Release, *Major Victory in Fair Lending: Seventh Circuit Rules in CFPB’s Favor in CFPB v. Townstone Financial, Inc.* (July 7, 2024), <https://www.relmanlaw.com/news-561>. NFHA filed an amicus brief in this case.

protected class groups in limited instances. SPCPs are tool to help lenders develop necessary programs to overcome a critical barrier that thwarts people from being able to access credit.

Generally, there are two methods of proving discrimination under either the Fair Housing Act or ECOA: “disparate treatment” or “disparate impact.”⁹⁰ Disparate treatment occurs when an entity explicitly, overtly, or intentionally treats people differently based on prohibited characteristics, such as race, national origin, or sex. Disparate treatment can be proven through direct evidence or indirect (or “circumstantial”) evidence, for example comparator evidence, statistical evidence, or a pretextual explanation. Although disparate treatment is known as “intentional discrimination,” the law does not actually require showing prejudice, animus, or even an intent to treat someone worse because of a protected class; the differential treatment is enough to establish a violation of law.⁹¹ An example of potential disparate treatment discrimination would be an AI model that explicitly included a protected class (such as race) as a model variable, or that resulted in different, adverse outcomes on a prohibited basis (such as race) for similarly-situated individuals.

Disparate impact discrimination occurs when a (1) facially neutral policy or practice disproportionately harms members of a protected class, and either (2) the policy or practice does not advance a legitimate interest, or (3) a less discriminatory alternative to serve the legitimate interest exists. Disparities alone are not sufficient to impose disparate impact liability, and entities are not required to sacrifice legitimate business needs or ignore relevant business considerations. Disparate impact only requires entities to avoid considerations that disproportionately harm members of protected classes unnecessarily. An example of potential disparate impact discrimination would be an AI model that considers a mortgage applicant’s arrest record, which has a disproportionate adverse impact on people of color who are often hyper-policed⁹², but is not predictive of default risk.

Institutions should be aware that they need adequate Compliance Management Systems (CMS) to monitor and test AI models for potential discrimination, search for less discriminatory

⁹⁰ Based on legal precedent, the federal financial regulators have also based fair lending risk assessments on these theories of discrimination. See Federal Financial Institutions Examination Council, *Interagency Fair Lending Examination Procedures* (2009), <https://www.ffiec.gov/pdf/fairlend.pdf>.

⁹¹ See 12 C.F.R. Part 1002, 4(a)-1: “Disparate treatment on a prohibited basis is illegal whether or not it results from a conscious intent to discriminate.”

⁹² See, *Investigation of the Ferguson Police Department*, a report and analysis by the Department of Justice, as one example of a law enforcement agency that targeted Black people in the City of Ferguson for arrests, tickets, and fines in a manner that violated the 1st, 4th, and 14th amendments to the United States Constitution as well as federal laws. Because the police department’s policies were focused on revenue generation rather than public safety, the institutional character of the department was compromised. The report also highlights how the department and municipal court both had practices that exhibited racial bias.
https://www.justice.gov/sites/default/files/opa/press-releases/attachments/2015/03/04/ferguson_police_department_report.pdf

alternatives, and implement appropriate controls for fair lending or fair housing risk.⁹³ The federal financial regulators have made clear that existing laws, including civil rights protections, extend to the use of AI.⁹⁴ Moreover, federal agencies have long provided guidance informing institutions of their obligations for third party oversight.⁹⁵ Institutions should be aware that using a third-party AI model does not insulate them from liability.

Part V: Policy Recommendations to Mitigate the Risk of AI in Housing and Financial Services

Congress Should Ensure Compliance with Existing Civil Rights and Consumer Protection Laws

Congress should ensure that the federal agencies issue robust policies that remind institutions of their legal obligations under the Fair Housing Act and Equal Credit Opportunity Act to test housing- and credit-related AI models for potential disparate treatment or disparate impact discrimination. As stated in the bipartisan HFSC Staff AI Report: “Using AI does not exempt market participants from their obligations under the law, and regulators must leverage their oversight and enforcement authorities to ensure those obligations are met as well as examine alternative compliance processes, where appropriate.”

First, all of the federal agencies with responsibility for supervision and/or enforcement of the Fair Housing Act and/or ECOA (collectively, the Agencies)⁹⁶ should emphasize that discrimination in AI models is illegal, including AI models developed or deployed by third parties. In 2023, the DOJ, FTC, CFPB, and EEOC issued a joint statement regarding enforcement efforts to protect the public from bias in AI and automated systems.⁹⁷ The remaining federal agencies should immediately issue a similar announcement.

⁹³ See, e.g., Relman, Colfax, *Initial Report of the Independent Monitor, Fair Lending Monitorship of Upstart Network’s Lending Model* (April 14, 2021),

https://www.relmanlaw.com/media/cases/1086_Upstart%20Initial%20Report%20-%20Final.pdf.

⁹⁴ See ABA Banking Journal, *Regulators Say Banks Responsible for Ensuring AI Complies with Law* (Jan. 19, 2024),

<https://bankingjournal.aba.com/2024/01/regulators-say-banks-responsible-for-ensuring-ai-complies-with-law/>.

⁹⁵ The agencies recently replaced each of their separate policies dating as early as 2008 for joint guidance. See Federal Reserve, FDIC, OCC, *Interagency Guidance on Third Party Relationships: Risk Management*, 88 Fed. Reg. 37920 (June 9, 2023)

<https://www.govinfo.gov/content/pkg/FR-2023-06-09/pdf/2023-12340.pdf>.

⁹⁶ The DOJ and HUD have responsibility for enforcement of the Fair Housing Act. The DOJ and FTC have enforcement authority for ECOA. The FHFA, FDIC, Federal Reserve Board, FDIC, OCC, and NCUA have supervision and enforcement authority for certain financial institutions with respect to the Fair Housing Act and ECOA. The CFPB has regulatory, supervision, and enforcement authority for ECOA. The FHFA has supervisory authority for the Fair Housing Act and other civil rights statutes over the Government Sponsored Enterprises.

⁹⁷ CFPB, DOJ, EEOC, FTC, *Joint Statement on Enforcement Efforts against Discrimination and Bias in Automated Systems* (April 2023),

https://www.ftc.gov/system/files/ftc_gov/pdf/EEOC-CRT-FTC-CFPB-AI-Joint-Statement%28final%29.pdf.

Second, consistent with the Uniform Interagency Consumer Compliance Rating System⁹⁸ and the Model Risk Management Guidance,⁹⁹ the Agencies should ensure that financial institutions have appropriate Compliance Management Systems that effectively identify and control risks related to AI models, including the risk of discriminatory outcomes for consumers. Where a financial institution's use of AI indicates weaknesses in their Compliance Management System or violations of law, the Agencies should use all of the tools in their toolbelt to quickly address and prevent consumer harm, including issuing supervisory Matters Requiring Attention; entering into a non-public enforcement action, such as a Memorandum of Understanding; referring a pattern or practice of discrimination to the DOJ; or entering into a public enforcement action. The Agencies have already provided clear guidance (e.g., the Uniform Consumer Compliance Rating System) that financial institutions must appropriately identify, monitor, and address compliance risks, and the Agencies should not hesitate to act within the scope of their authority. When possible, the Agencies should explain to the public the risks that they have observed and the actions taken in order to bolster the public's trust in appropriate oversight, and provide clear examples to guide the industry.

The Agencies should clarify acceptable methods for AI testing so that institutions can align their methods accordingly.¹⁰⁰ Existing civil rights laws and policies provide a framework for the Agencies to analyze fair lending risk in AI and to engage in supervisory or enforcement actions, where appropriate. That said, the Agencies can be more effective in ensuring consistent and effective compliance by setting clear regulatory expectations regarding testing for the risk of discrimination. The Agencies have been in learning mode for some time. Indeed, the Agencies have yet to issue guidance even after receiving a robust response to their Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence in March of 2021.¹⁰¹

⁹⁸ Federal Financial Institutions Examination Council, *Uniform Interagency Consumer Compliance Rating System* (Nov. 14, 2016) <https://www.govinfo.gov/content/pkg/FR-2016-11-14/pdf/2016-27226.pdf>.

⁹⁹ See, e.g., FHFA, *Artificial Intelligence, Machine Learning Model Risk Management*, Advisory Bulletin 2022-02 (Feb. 10, 2022) (explicitly addressing fairness and equity), <https://www.fhfa.gov/SupervisionRegulation/AdvisoryBulletins/Pages/Artificial-Intelligence-Machine-Learning-Risk-Management.aspx>; Federal Reserve, OCC, *Guidance on Model Risk Management* (April 2011) <https://www.federalreserve.gov/supervisionreg/srletters/sr1107a1.pdf>.

¹⁰⁰ The Biden Administration's recent Executive Order 14110 encourages the CFPB to issue additional guidance requiring their regulated entities to use "appropriate methodologies including AI tools" to evaluate existing underwriting models, automated collateral valuation, and appraisal processes for bias. Exec. Order No. 14110, *Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence* (Oct. 30, 2023), <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/>.

¹⁰¹ CFPB, Federal Reserve, FDIC, OCC, and NCUA, *Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, including Machine Learning* (March 31, 2021) <https://www.govinfo.gov/content/pkg/FR-2021-03-31/pdf/2021-06607.pdf>. See also, NFHA et al., *Response to RFI re AI* (July 1, 2021), <https://nationalfairhousing.org/leading-civil-rights-consumer-and-technology-advocates-urge-the-federal-financial-regulators-to-promote-equitable-artificial-intelligence-in-financial-services/>.

Additionally, HUD, DOJ, CFPB, FTC, and other appropriate enforcement agencies must step up enforcement of the nation's fair housing and lending laws. Existing laws can and should be used to address AI bias. Given the exponential growth of AI in the housing and lending sectors, it is imperative that enforcement agencies work in lock-step with regulatory agencies as well as together to promote compliance with our laws. This means all agencies will need to hire and train staff to understand AI systems and increase the ability of agencies to formulate and undertake comprehensive investigations and prosecute cases. Moreover, agencies will need to equip themselves with the resources they need to undertake impactful enforcement actions.

To retain America's competitive edge in the global society, all appropriate Federal Agencies should move quickly to issue actionable policy statements that clearly state their commitment to consumer protection and civil rights laws, including fair lending laws; insight into their supervisory expectations and methods; and useful guardrails and best practices. The time to act is now as the use of AI proliferates in every aspect of housing and financial services and has the potential for far-reaching adverse impacts for consumers of color and other protected groups.

The United States Must Enact Comprehensive Legislation to Advance Responsible AI

While there are significant risks of bias and discrimination in AI systems, the risks are not insurmountable. The U.S. must play a leadership role in advancing Responsible AI principles and tech equity. Leading the world on these issues includes passing comprehensive legislation that forms the basis for sound policies, systems, practices, and frameworks for Responsible AI. While much of the world's technological innovations are developed in the U.S., other nations are significantly stepping up their efforts by building the infrastructure needed to spur AI innovations. The U.S. is behind the curve, and in some cases playing catch-up to other nations. The U.S. must lead the world in ensuring technologies are fair and beneficial; do not harm people and communities; and promote ideals of freedom, including ensuring robust privacy protections, equality, and equity. For these reasons, Congress should pass new legislation that mitigates the risk of algorithmic bias and ensures fairer structures by:

Ensuring Strong Civil and Human Rights Protections

Congress should develop AI legislation that reflects civil and human rights principles that are equitable and reflect America's ideals of freedom and equality. Civil rights, human rights, and consumer protection organizations lack the resources to fully ensure that technologies are beneficial and not harmful, which means Congress must increase federal funding and new programs to support effective oversight and accountability. Any loopholes in existing laws must be tightened up to prevent harms against people and our society. This includes ensuring full and complete corrective actions will be taken to stop and mitigate harmful practices and that those who are impacted can be made fully whole.

Ensuring Equitable Automated Systems

America is at a critical juncture in deciding whether to create equitable automated systems that uplift society or use automated systems that continue to perpetuate historical discriminatory practices. Research has clearly shown that AI systems generate bias not only in systems used in housing and lending, but other systems as well, including those used in health, criminal justice, employment, and education.

Any comprehensive legislation must include a provision that requires entities to examine their systems for bias and audit systems on a regular basis. The legislation must also require entities to regularly search for less discriminatory alternatives and to replace discriminatory systems with systems that are fairer. Systems must be regularly updated to ensure they remain viable and trustworthy.

Digital Access

Currently, access to broadband and other technologies is not available on an equitable basis.¹⁰² For example, rural areas and communities of color disproportionately do not have access to high-speed internet. These communities also have higher instances of cell phone dead zones. They also pay higher rates for inferior internet services. No service and slow-speed service results in children not being able to access critical learning courses and materials, patients not being able to access important medical treatment, and people not being able to access employment opportunities.

The legislation must include a provision to ensure access to technological solutions are equitable and nondiscriminatory, as its far-reaching impact could either benefit or continue to severely disadvantage underserved groups and society at large. All internet service providers should be required to shore up services they currently offer so everyone in the businesses service area has access to high-speed internet. The legislation should also make consumers that have been paying higher pricing for inferior service whole. Finally, Congress should authorize funding to provide for and support internet access in areas that currently lack service.

Public Data and Research

AI legislation should mandate public availability of key data, as the lack of such data hampers efforts to develop responsible automated systems in housing and financial services. This data

¹⁰² Leon Yin, Aaron Sankin, *Investigation Finds Lower Internet Speeds for Higher Prices in Poor, Less White U.S. Neighborhoods*, PBS News (October 19, 2022), <https://www.pbs.org/newshour/economy/investigation-finds-lower-internet-speeds-for-higher-prices-in-poor-less-white-u-s-neighborhoods>

Aallyah Wright, *What It's Like Living With Limited Access to Internet in the Black Rural South*, The Markup (December 6, 2023), <https://themarkup.org/still-loading/2023/12/06/digital-redlining-and-the-black-rural-south>

usage must rightly balance privacy rights with the need to protect civil and human rights.¹⁰³ For example, Congress should encourage the Consumer Financial Protection Bureau and the Federal Housing Finance Agency to release more de-personalized loan-level data from the Uniform Appraisal Dataset, National Survey of Mortgage Originations, and the National Mortgage Database so trusted researchers, advocacy groups, and the public can study potential discriminatory and inequitable outcomes in the housing and financial services sectors, especially as they relate to the use of AI. Congress should also support public research that analyzes the efficacy of specific uses of AI in housing and financial services and the impact of AI in financial services for consumers of color and other protected classes.

Consumer Data

Current AI practices in decision-making, such as those used in employment or mortgage screening, significantly lack informed consent, consumer agency, and the right to contest decisions. Disclosure and notice and consent requirements are insufficient means of providing consumers agency over their data used in housing and financial services decisions. For example, consumers being informed about the use of automated screening technologies and granted the option of withdrawal, must also be assured that opting out will not lead to exclusion or unfair treatment. Policies that lack this practical approach risk becoming mere liability checkboxes, failing to protect individuals who choose to safeguard their data and privacy from potential ostracism.

In addition to adequate privacy protections, consumers must be allowed to consent to how, where, when, and under what circumstances their personal data will be utilized. The European Union and certain states are currently leading in this space. Congress should learn from their examples, adopt these protections, and build upon them for using consumers' personal information. Legislation must clarify that consumers own their personal data. Data minimization frameworks coupled with discrimination testing must be required.

The legislation must also balance consumer data protections with the need of government to ensure effective compliance and research activities are not thwarted. This means protecting consumer data against misuse.

Privacy-Enhancing Technologies

Research has demonstrated that privacy can be preserved through various technical methodologies, such as federated learning, synthetic data generation, and differential privacy. AI systems must incorporate these methodologies to enhance privacy protections before

¹⁰³ To more fully understand NFHA's position on balancing civil rights with privacy in housing decisions, see NFHA and Tech Equity Collaborative, *Privacy, Technology, and Fair Housing - A Case for Corporate and Regulatory Action* (Aug. 2023), <https://nationalfairhousing.org/wp-content/uploads/2023/08/NFHA-TechEquity-Paper-final.pdf>.

deployment. The legislation should mandate ongoing evaluations and audits of existing technologies and models to ensure they adhere to robust security protocols and mitigate potential risks. These assessments should be thorough and frequent, addressing not only the technical safeguards in place but also the broader implications for user privacy and data protection. Regular audits will help identify vulnerabilities, adapt to evolving threats, and maintain public trust in the integrity of AI systems. Aligned with the AI Bill of Rights, NFHA's research¹⁰⁴ endorses the adoption of "privacy by design" legislation, where AI systems must undertake a phased review process to ensure privacy protections at every stage of the technology life cycle.

Congress can also consider providing incentives to entities that utilize appropriate privacy enhancing technologies. Incentives could include tax rebates and grant funding programs.

Safe, Accurate, and Effective Systems

Legislation must require entities to develop systems that are safe, accurate and effective. This means entities must employ diverse and highly trained people to develop their systems and use independent third parties and domain experts to develop the products. Protocols must be put in place to ensure the systems are being built using appropriate data and deployed for appropriate uses. Additionally, entities should take important steps to ensure systems are not being used inappropriately or in a manner that would harm people, communities, or our society. The legislation must ensure that poorly designed and ineffective systems will not be put in use.

Transparency, Notice, and Explainability

Legislation must also ensure that AI and automated decision-making is transparent, meaning there are explanations for automated decisions and work is conducted to test and promote methodologies that clarify the reasoning or design behind automated systems. In addition, the legislation should emphasize that AI systems delivering decision-making outcomes must be explainable, not only in technical terms, but also accessible language for the impacted public.

Congress should also ensure notices to the public about decisions based on automated and algorithmic systems provide people with a path to improve their outcomes.

Human Alternatives, Considerations, and Fallback

There will not be a technological solution for every circumstance and technology can often fail. There is no clearer example than the recent global IT outage as a result of Microsoft and CrowdStrike's computer software update failure. Planes were grounded throughout the world as

¹⁰⁴ NFHA and Tech Equity Collaborative, *Privacy, Technology, and Fair Housing - A Case for Corporate and Regulatory Action* (Aug. 2023), <https://nationalfairhousing.org/wp-content/uploads/2023/08/NFHA-TechEquity-Paper-final.pdf>.

broad failures brought systems to a halt. Medical hospitals throughout the world had to cancel surgical procedures and the provision of other critical medical treatment to patients. Banks and financial institutions were impacted, not being able to provide critical information or make transaction on behalf of consumers. 911 services were down across the state of Alaska disabling services to thousands of people.

The “defect” was “found in a single content update for Windows.”¹⁰⁵ Essentially, a corrupted file provided by cybersecurity firm, CrowdStrike, was included in a software update. The corruption was not detected and impacted all systems that had uploaded the update.

The outage caused nurses to switch to handwriting prescriptions and manually processing information for patients. Airline professionals had to opt for handwritten boarding passes. Businesses could not rely on pushing orders or information via computer and automated systems and had to switch to a very old-fashioned and manual process - picking up the phone and talking directly to people to get things done.

The global outage highlighted the real need for ensuring there are human alternatives and fallbacks for when technology fails or simply does not present the optimal option for a group of people. Legislation should ensure there are human options for people.

Technologies Developed Outside of the U.S.

Any legislation passed by Congress must ensure that foreign innovations adhere to U.S. civil rights and consumer protection standards to prevent violations through irresponsible AI. Congress should ensure there is a mechanism to make American citizens whole when a foreign entity violates our laws.

Integrate the Review of Racial Equity and Other Bias Mitigation in the Algorithm’s Lifecycle

Legislation must require Responsible AI innovation while implementing risk mitigation measures. Congress can ensure entities use tools like NIST’s Risk Management Framework¹⁰⁶ and NFHA’s AI auditing framework¹⁰⁷ to help protect consumers, communities, and the U.S. economy.

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.

¹⁰⁵ *Major Global IT Outage Grounds Flights, Hits Banks and Businesses Around the World*, NBC News (July 19, 2024), <https://www.nbcnews.com/news/world/live-blog/live-updates-it-outage-flights-banks-businesses-microsoft-crowdstrike-rcna162669>

¹⁰⁶ See NIST, *Artificial Intelligence Risk Management Framework*, U.S. Department of Commerce (Jan. 26, 2023), <https://nvlpubs.nist.gov/nistpubs/ai/NIST.AI.100-1.pdf>.

¹⁰⁷ See Michael Akinwumi, Lisa Rice, and Snigdha Sharma, *Purpose Process, and Monitoring: A New Framework for Auditing Algorithmic Bias in Housing and Lending*, National Fair Housing Alliance (2022), https://nationalfairhousing.org/wp-content/uploads/2022/02/PPM_Framework_02_17_2022.pdf.

Accordingly, it is imperative that safety 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.

Promote Effective Training for the Federal Workforce

Although the White House is making strides in training the federal workforce,¹⁰⁸ many federal workers do not have the requisite training needed to effectively test, monitor, and provide oversight over automated systems. To keep America safe, Congress should support comprehensive training on technology and AI bias for federal regulators and enforcement agencies and ensure the federal workforce has the equipment and resources needed to enforce U.S. laws and regulations. Training should include a focus on civil rights, human rights, and consumer protection laws and standards as well as standards for building and designing AI systems. 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.

Conclusion

It is imperative that the U.S. continue to lead the world in establishing policies and frameworks to advance technological innovations while ensuring these systems are fair, safe, transparent, explainable, and reliable; ensuring that these systems protect consumers' privacy; and ensuring that human alternatives are available when warranted. Technological innovations can provide great benefits to people and society as well as spur economic progress. Yet too many automated systems have been deployed without proper protocols, testing, and oversight. As a result, people have unfairly and inappropriately been denied housing, credit, other important opportunities and services. Researchers have found that racial inequality has cost the U.S. economy \$16 trillion over the past 20 years.¹⁰⁹ Congress must move with all haste to guarantee the U.S. can remain productive, strong, and viable and people residing in the U.S. can benefit from technological innovations.

¹⁰⁸ See Office of Management and Budget, *Advancing Governance, Innovation, and Risk Management For Agency Use of Artificial Intelligence* (March 28, 2024), <https://www.whitehouse.gov/wp-content/uploads/2024/03/M-24-10-Advancing-Governance-Innovation-and-Risk-Management-for-Agency-Use-of-Artificial-Intelligence.pdf>.

¹⁰⁹ See Dana Peterson and Catherine Mann, *Closing the Racial Inequality Gaps*, Citigroup (Sept. 2020), <https://www.citigroup.com/global/insights/citiqps/closing-the-racial-inequality-gaps-20200922>.