ARTIFICIAL INTOLERANCE: The Disparate Impact of AI in Housing

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INTRODUCTION

[1] From the intentional displacement of Native Americans to the racially motivated redlining of cities across the country, housing discrimination has always been an issue in the United States.[1] Congress enacted the 1968 Fair Housing Act ("FHA") to eradicate the rampant discriminatory practices present in housing decision-making.[2] Since its enactment, courts have interpreted §§ 3604 and 3605 to not only hold housing providers directly responsible for their own policies, but have also applied this interpretation to a wide range of entities that provide housing-related services.[3] Additionally, because not all biases are intentional, or even recognizable at a cursory glance, the FHA has applied to and prohibited outwardly neutral policies with resulting discriminatory effects through disparate impact liability.[4] With technology evolving every day, the question we must consider is— how far will the FHA's disparate-impact liability extend, and how can regulation of AI fill in the gaps?

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[1] Danyelle Solomon et al., *Systemic Inequality: Displacement, Exclusion, and Segregation*, CTR. FOR AM. PROGRESS (Aug. 7, 2019), https://www.americanprogress.org/article/systemic-inequality-displacement-exclusion-segregation/ [https://perma.cc/9T8H-5RFN].

[2] Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmtys. Project, Inc., 576 U.S. 519, 539 (2015).

[3] *See* Swanson v. Citibank, N.A., 614 F.3d 400, 406 (7th Cir. 2010) (applying the FHA to lenders); NAACP v. Am. Fam. Mut. Ins. Co., 978 F.2d 287, 290 (7th Cir. 1992) (applying FHA to insurers); United States v. City of Black Jack, 508 F.2d 1179, 1184–85 (8th Cir. 1974) (applying FHA to state and municipal bodies); Balt. Neighborhoods, Inc. v. Rommel Builders, Inc., 3 F. Supp. 2d 661, 665 (D. Md. 1998) (applying FHA to developers).

[4] *Inclusive Cmtys.*, 576 U.S. at 521, 545 (explaining that disparate impact liability is meant to address the unintended discriminatory effects on protected class members that seemingly neutral policies may cause).

[2] This Article examines the unintended disparate impact of using AI in housing-related services, concentrating specifically on the case law regarding rental screening. To ensure that the use of algorithms in housing decisions does not perpetuate discriminatory patterns, companies offering algorithm-based screening services to housing providers should be subject to the FHA's non-discrimination laws. In addition, federal regulation of AI should begin by focusing on promoting the responsible development of algorithms in traditional civil rights sectors by requiring transparency from developers, regular independent auditing, and accountability under non-discrimination laws.

[3] Section I of the Article provides a background on how AI is developed and used in the housing sector. The section also explains how the FHA can be utilized to hold developers liable through disparate impact liability. Section II examines the current case law surrounding disparate impact liability as applied to developers of tenant-screening algorithms and examines the current federal legal landscape of AI regulation. In light of the severe lack of federal AI regulation, Section II continues by providing a public policy argument on the necessity of holding developers subject to the FHA, as well as an example of where AI has shown its potential for eradicating discrimination and making housing-related services more widely accessible.

[4] Section III concludes the Article by proposing a strategy to mitigate the harm caused by discriminatory algorithms and allow the use of AI in housing-related services to reach its full potential. This proposed strategy includes further research into the disparate impact of the use of certain data in tenant screening and the need to establish federal regulation that requires higher levels of transparency and accountability from AI developers.

I. AI, HOUSING, AND THE DISPARATE IMPACT ANALYSIS

[5] This section provides a brief background of how AI is developed and applied in various aspects of the housing industry. This section then

discusses, on the one hand, the benefits that AI developers hope to see from the use of AI in housing, and on the other hand, the unintended discriminatory effects perpetuated through the use of algorithms. This section then goes on to explain the steps of the disparate impact analysis and concludes with a discussion of how criminal background checks and credit screening have been found to produce discriminatory effects.

A. The Development & Uses of AI in Housing

[6] Artificial Intelligence ("AI") encompasses a wide range of technologies from simple predictive analytics to completely automated decision-making systems.[5] Machine Learning ("ML"), a branch of AI, involves the development of mathematical algorithms and models that learn patterns from data and respond to these patterns by creating rules which can then be applied to new datasets.[6] Developers begin the process of creating a self-learning algorithm by using large databases to develop an initial model.[7] Contrary to popular belief, for every desired prediction problem, there are multiple ways of analyzing the same factors that will result in different determinations depending on how the factors are analyzed, in what order, and with different weights assigned.[8] The more factors involved in a prediction problem, the more possibilities for alternative algorithms.[9]

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[5] *Artificial Intelligence and Housing: Exploring Promise and Peril: Hearing Before the S. Comm. on Banking, Hous., and Urb. Affs.*, 118th Cong. 2 (2023) [hereinafter *Promise and Peril*] (statement of Nicholas Schmidt, CTO, SolasAI).

[6] *Id.*

[7] *See* Sarah Brown, *Machine Learning, Explained*, MITSLOAN (April 21, 2021), https://mitsloan.mit.edu/ideas-made-to-matter/machine-learning-explained [https://perma.cc/VG8S-FCD3].

[8] *See generally* Emily Black et al., *Less Discriminatory Algorithms*, 113 GEO. L. J. 53 (2024).

[9] *Id.*

[7] Once a model is chosen, developers slowly feed it more data, allowing the computer to train itself to find patterns and make predictions.[10] Throughout the development process, programmers can tweak the model by changing parameters and adding in datasets showing specific patterns.[11] Because of its reliance on human-created data, these algorithms represent a sociotechnical system; essentially incorporating technical capabilities with societal components.[12]

[8] These algorithmic models are used in a variety of ways within the housing industry including in rental screening, mortgage lending, marketing, and appraisals. In rental screening, algorithms are used to efficiently conduct criminal background and credit checks to determine whether an applicant would serve as a good tenant.[13] In mortgage lending, algorithms run similar credit checks and determine what specific interest rate an applicant should be approved for.[14] In marketing, real estate professionals use algorithms to target advertisements toward the potential buyers who are most likely to have interest.[15] Lastly, AI appraisal

[10] *Promise and Peril*, *supra* note 5, at 3.

[11] *Id.*

[12] *Artificial Intelligence and Housing: Exploring Promise and Peril: Hearing Before the S. Comm. on Banking, Hous., and Urb. Affs.*, 118th Cong. 4 (2024) (statement of Lisa Rice, President, National Fair Housing Alliance).

[13] *The Benefits of AI Tenant Screening*, 3 OPTIONS REALTY (Nov. 30, 2022), https://www.3optionsrealty.com/the-benefits-of-ai-tenant-screening [https://perma.cc/7P66-5SR5].

[14] Robert Bartlett et al., *Consumer-Lending Discrimination in the Fintech Era*, 143 J. FIN. ECON. 30, 40 (2022).

[15] *12 Ways AI Is Shaping the Future of Real Estate Marketing*, REALSPACE, https://www.realspace3d.com/blog/12-ways-ai-is-shaping-the-future-of-real-estate-marketing/ [https://perma.cc/7ZMG-2L34].

technology has been used to rapidly analyze data and determine property values more quickly and cost-effectively than ever before.[16]

B. The Ups & Downs of AI in Housing

[9] AI developers and fair housing advocates alike are excited at the possible benefits AI could bring to the housing industry, especially in light of the affordable housing crisis the United States is currently facing due to inflation and an overall shortage of available housing.[17] AI systems have the potential to lower costs and streamline the entire process by determining locations in need of new development, gathering permits, optimizing construction, and ultimately helping housing providers run background checks on potential tenants.[18]

[10] Having an automated system do the decision-making instead of a person might also seem like a great way to mitigate the risk of human bias, but so far these systems have unfortunately proven to be just as much of a flawed system. By design, Machine Learning always involves a "form of statistical (and therefore seemingly rational) discrimination" picked up from whatever data is used.[19] Due to decades of discriminatory choices made in the United States in the housing industry, the source of discrimination of greatest concern is the societal bias arising from the training data itself.

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[16] *See* Tony Gilbert, *Real Estate Appraisals with AI: Changing the Appraisal Industry*, HYPEWIRED DIGIT. MKTG. (Sept. 28, 2023), https://www.hypewired.com/real-estate-ai-appraisals [https://perma.cc/2VQF-LVKW].

[17] *See Using AI to Promote Equitable and Affordable Housing*, PD&R EDGE (Feb. 20, 2024), https://www.huduser.gov/portal/pdredge/pdr-edge-featd-article-022024.html [https://perma.cc/4AK5-5BYT].

[18] *Id*.

[19] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms, and Machine Learning May Undermine Housing Justice*, 52 Colum. Hum. Rts. L. Rev. 251, 259 (2020); Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 Cal. L. Rev. 671, 677 (2016).

Although algorithms use an unbiased mathematical approach to reach their conclusions, when the data used to teach these algorithms is riddled with discrimination, the algorithms replicate and perpetuate the discriminatory patterns.

C. The Disparate Impact Analysis

[11] Disparate impact liability under the FHA is meant to address the issue of unintended discriminatory effects on protected class members in seemingly neutral policies and practices.[20] In *Texas Dept. of Housing & Community Affairs v. Inclusive Communities Project*, the Supreme Court held that disparate impact liability claims are consistent with the central purpose of the FHA, which "was enacted to eradicate discriminatory practices within a sector of our Nation's economy."[21]

[12] Under the burden-shifting framework of the disparate impact analysis, a plaintiff must first prove that the challenged practice or policy has caused or will predictably result in a discriminatory effect on a particular class.[22] Depending on the nature of the alleged claim, a disparity can be proven using statistical evidence ranging from the local to national level.[23] After proving a discriminatory effect, the burden then shifts to the defendant who may rebut the claim by showing that the practice is "justified" or necessary to achieve a "substantial, legitimate,

[20] *Inclusive Cmtys.*, 576 U.S. at 521.

[21] *Id*.

[22] 24 C.F.R. § 100.500 (2024).

[23] U.S. DEP'T OF HOUS. & URB. DEV., OFFICE OF GENERAL COUNSEL GUIDANCE ON APPLICATION OF FAIR HOUSING ACT STANDARDS TO THE USE OF CRIMINAL RECORDS BY PROVIDERS OF HOUSING AND REAL ESTATE-RELATED TRANSACTIONS 3 (2016) [hereinafter HUD GUIDANCE], https://www.hud.gov/sites/documents/HUD_OGC GUIDAPPFHASTANDCR.PDF [https://perma.cc/DVK3-BSKR].

nondiscriminatory interest" of the housing provider.[24] This interest must be more than purely speculative or hypothetical.[25] If such an interest is found, the burden shifts back to the plaintiff who, in order to prevail, must show that the defendant's interest could be served by another less discriminatory practice.[26]

D. Disparate Impact of Criminal & Credit Background Screening

[13] Tenant background screening, which usually involves some combination of criminal, credit, and eviction histories, has been found to have a disparate impact on minorities.[27] Criminal background checks have a disparate impact on African Americans and Hispanics, who due to racial profiling tend to have more interactions with the criminal justice system and therefore are arrested, convicted, and incarcerated at disproportionate rates.[28] As for credit checks, minority communities who historically were denied wealth-building opportunities and affordable financial services, are more likely to have lower credit scores than white non-Hispanic applicants.[29] Although nondiscriminatory reasons exist for using these factors to assess tenants, these pre-existing racial gaps make examining tenant screenings for unintentional discriminatory effects imperative.

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[24] *Inclusive Cmtys.*, 576 U.S. at 527.

[25] HUD GUIDANCE, *supra* note 23, at 4.

[26] 24 C.F.R. § 100.500(c) (2024).

[27] *See* HUD GUIDANCE, *supra* note 23, at 1–2.

[28] *Id.*

[29] Abby Boshart, *How Tenant Screening Services Disproportionately Exclude Renters of Color from Housing*, HOUS. MATTERS (Dec. 21, 2022), https://housingmatters.urban.org/articles/how-tenant-screening-services-disproportionately-exclude-renters-color-housing [https://perma.cc/WHZ2-J7HC].

[14] In 2016, the U.S. Department of Housing and Urban Development ("HUD") released guidance on the application of FHA standards regarding the use of criminal records in housing-related transactions.[30] Having a criminal record can substantially affect one's access to safe and affordable housing, which serves as a critical part of reentry into society after serving prison or jail time.[31] Not only are criminal record screenings a serious barrier, but they are also largely unnecessary; studies have proven that in most instances having certain types of criminal records, such as arrests without convictions, does not impact one's ability to be a good tenant.[32]

[15] When considering the disparate impact analysis as applied to the use of criminal background checks, the underlying "substantial, legitimate, and nondiscriminatory interest" that most housing providers point to is ensuring the protection and safety of other residents and the property itself.[33] While a court is likely to accept this interest as substantial, the housing provider must also prove that basing housing decisions on an applicant's criminal history truly assists in furthering this interest.[34] The housing provider must use reliable evidence, and not simply rely on generalizations and stereotypes that applicants with a criminal history tend to pose a greater risk.[35] Under this "non-speculative" standard, a housing provider with a policy of excluding applicants based on arrests without convictions cannot satisfy its burden of showing the policy is justified.[36] Accordingly, HUD

[30] HUD GUIDANCE, *supra* note 23, at 1.

[31] *Id.*

[32] *Id.* at 5.

[33] *Id.* at 4–5.

[34] *Id.* at 5.

[35] HUD GUIDANCE, *supra* note 23, at 5.

[36] *Id.*

advises housing providers of the potential for disparate impact liability per the FHA should these providers choose to implement the policy of denying tenants based on arrests without convictions.[37]

[16] Similarly, the substantial nondiscriminatory interest cited to defend the use of credit and eviction history checks is the landlord's interest in ensuring tenants will pay rent.[38] However, credit scores reveal and perpetuate inequities from the past.[39] Early credit reporting systems relied on an accumulation of subjective and frequently biased observations to determine someone's trustworthiness.[40] Today, the different inputs for credit scoring calculations regularly lead to lower scores for individuals in communities of color.[41]

II. ACCOUNTABILITY FOR DEVELOPERS: FHA & AI REGULATIONS

[17] From the moment *Inclusive Communities* was handed down in 2015, courts across the country have tested the limits of the FHA disparate impact liability in a variety of situations, including whether it will extend to the use of algorithms. A recent set of cases inquires whether AI developers can be held liable for the disparate impact of their tenant-screening software when used by landlords. The following cases, *CoreLogic* and *SafeRent*, involve the use of algorithmic screening to determine whether to accept or deny a rental applicant based on criminal background and credit background,

[37] *Id.* at 8.

[38] Nate Van Duzer, *The Discriminatory Impact of Credit Scores*, PUB. JUST. (Apr. 4, 2023), https://www.publicjustice.net/the-discriminatory-impact-of-credit-scores/ [https://perma.cc/E6VD-7G9L].

[39] *Id.*

[40] *Id.*

[41] *Id.*

respectively.[42] In both cases, plaintiffs alleged that the defendants violated § 3604(a) of the FHA, which makes it unlawful to "make unavailable or deny, a dwelling to any person because of race, color … or national origin." [43] In light of the lack of federal regulation of AI development, the section continues by providing a brief analysis of the public policy arguments discussing the importance of FHA liability.

A. Connecticut Fair Housing Center v. CoreLogic

[18] In *CoreLogic*, the district court first denied the defendant's motion for summary judgment, concluding that CoreLogic's CrimSAFE AI screening software could form the basis of a disparate impact claim.[44] At trial, however, the court reversed their previous decision and held that CoreLogic was not subject to the FHA, as CoreLogic was not responsible for the ultimate decision to reject the tenant and had no more than a tenuous connection to the actual decision-maker.[45] CoreLogic is a nationwide tenant screening company that offers an AI-based criminal background screening software, CrimSAFE, which matches criminal records to applicants and generates reports accepting or denying applicants to housing providers.[46] The case arose after Carmen Arroyo's apartment complex denied her application to move her severely disabled son, Mikhail, into her home. The apartment complex ran his background check using CrimSAFE and

[42] *See* Conn. Fair Hous. Ctr. v. Corelogic Rental Prop. Sols., LLC, 2023 U.S. Dist. LEXIS 125000, at *3, *5 (D. Conn. July 20, 2023), *appeal docketed*, No. 23-1118 (2d Cir. Aug. 4, 2023); Louis v. SafeRent Sols., LLC, 685 F. Supp. 3d 19, 25–26 (D. Mass. 2023).

[43] 42 U.S.C. § 3604.

[44] CoreLogic, 2023 U.S. Dist. LEXIS 125000, at *39–40.

[45] *Id.* at *4.

[46] *Id.* at *6–7.

received a "rejection" reading.[47] After months of back and forth with CoreLogic, the company finally informed Ms. Arroyo that the reason for her son's rejection was an arrest for minor retail theft for which he was never convicted.[48]

[19] HUD's guidance concerning the use of criminal background screening and disparate impact liability was released prior to Mikhail Arroyo's rejection by CoreLogic and the apartment complex.[49] CoreLogic was well aware of this guidance and not only relayed the information to their clients using their tenant-screening software, but also admitted that CoreLogic itself may need to rework the algorithms in response.[50]

[20] At the initial hearing in 2020, the court denied CoreLogic's motion for summary judgment and held that CoreLogic's CrimSAFE software could form the basis of a disparate impact claim and allowed the lawsuit to move forward.[51] Before running through the disparate impact analysis, the court first considered whether CoreLogic was subject to the FHA in the first place, asking whether they had denied or otherwise made housing unavailable.[52] The plaintiffs offered two theories for liability, both relying on the lack of an individualized assessment of the applicant.[53] Specifically, plaintiffs argued that because CoreLogic automatically reports an applicant's disqualification and CrimSAFE prevents housing providers

[47] *Id.* at *2.

[48] *Id*. at *30.

[49] CoreLogic, 2023 U.S. Dist. LEXIS 125000, at *24 (discussing HUD Guidance in Section I.D. above).

[50] *Id*. at *25–26.

[51] *Id.* at *40.

[52] *Id*. at *44–45.

[53] *Id.* at *47.

from conducting individualized assessments, CoreLogic should be held responsible for making housing unavailable.[54]

[21] The court found that the apartment complex had sole authority when denoting whether an applicant qualified for housing since the complex independently decided who received the full criminal reports, which criminal records were relevant, how the records were reviewed, and ultimately, whether to accept the tenant.[55] Additionally, the court held that the defendant's involvement in the decision-making process was merely "tenuous."[56] Therefore, the court held that CoreLogic did not deny or otherwise make housing unavailable pursuant to § 3604(a) of the FHA and accordingly could not be held liable for a disparate impact claim.[57]

[22] The plaintiffs in CoreLogic have since appealed the court's decision.[58] In an amicus brief filed in support of the appeal, the DOJ asserts that although the court acknowledged that theoretically, a "non-ultimate decision-maker" could be liable under the FHA, the court's rationale in rejecting the plaintiff's claims essentially shuts down any chance of liability against a non-housing provider that does not directly control the housing provider's final decision.[59] This reasoning does not align with the purpose

[54] CoreLogic, 2023 U.S. Dist. LEXIS 125000, at *47.

[55] *Id.* at *60.

[56] *Id.* at *56 (explaining the requirement for more than a tenuous connection was first declared in Mhany Management); Mhany Mgmt., Inc. v. Cnty. of Nassau, 819 F.3d 581, 621 (2d Cir. 2016) (holding a county to have a tenuous connection to the city and therefore not liable for the city's conduct).

[57] CoreLogic, 2023 U.S. Dist. LEXIS 125000, at *60.

[58] Brief for the U.S. as Amicus Curiae Supporting Appellants, Conn. Fair Hous. Ctr. v. CoreLogic Rental Prop. Sols., LLC, 2023 U.S. Dist. LEXIS 125000, at *1.

[59] *Id.* at 12.

of the FHA or previous caselaw construing § 3604.[60] Instead, the DOJ argues that the court should have employed traditional principles of causation to examine CoreLogic's actions.[61] Specifically, rather than limit liability to direct actors, § 3604(a)'s prohibition of "otherwise making housing unavailable" extends liability based on "prohibited acts."[62] The following case illustrates this line of reasoning.

B. Louis v. SafeRent

[23] At the same time *CoreLogic* was being heard, a strikingly similar case began making its way through the courts with not only the same issue, but also the same defendant. In *Louis v. SafeRent*, plaintiffs alleged that a tenant-screening service operated by SafeRent, which also does business as CoreLogic, violated §3604(a) of the FHA.[63] At the summary judgment hearing, the court held that SafeRent was subject to the FHA, not because it is the ultimate decision-maker in making housing unavailable, but because of its "prohibited acts" that contributed to an FHA violation.

[24] Instead of assessing the criminal history of an applicant like in *CoreLogic*, the SafeRent tenant-screening software analyzed several factors including credit history, payment performance, and eviction history, to calculate a score that measured the applicant's "lease performance risk" and then issued either an accept or decline decision to the housing provider.[64] Plaintiffs argued that by basing the calculation largely on credit history and failing to consider housing vouchers, income, or assets in their

[60] *Id.*

[61] *Id.*

[62] *Id.* at 13.

[63] SafeRent, 685 F. Supp. 3d at 25.

[64] *Id.* at 26.

determination, SafeRent scores disproportionately affect Black and Hispanic applicants.[65]

[25] The defendant filed a motion to dismiss, arguing in part that SafeRent is not subject to the FHA because SafeRent does not have the authority to make housing decisions.[66] In response, the court reiterated that the FHA does not limit liability to entities that have the authority to make housing decisions but instead, the language of the FHA is meant to broadly focus on prohibited acts.[67] Therefore, the court concluded that because SafeRent had sole discretion to control the calculation of scores and that determination may disqualify otherwise qualified applicants, SafeRent is subject to the FHA and thus potentially liable for the disparate impact caused.[68]

[26] In summary, while the court in *CoreLogic* held that the defendant could not be held liable under the FHA since it was not responsible for making housing unavailable, the *SafeRent* court instead focused on prohibited acts, rather than who is ultimately responsible for making the decision.[69] *SafeRent* continues to be litigated on its merits while *CoreLogic* has been appealed. Whatever their outcomes, these cases will no doubt have a profound impact on the degree of care that AI developers take in ensuring their algorithms are complying with the FHA and HUD guidelines.

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[65] *Id.* at 27.

[66] *Id.* at 25, 34.

[67] *Id.* at 35–36; Trafficante v. Metropolitan Life Ins. Co. 409 U.S. 205, 209 (1972).

[68] SafeRent, 685 F. Supp. 3d at 35–36.

[69] *See generally* SafeRent, 685 F. Supp. 3d; CoreLogic, 2023 U.S. Dist. LEXIS 125000, at *59–61; *see also* Marianna Wharry, *Rental Applicants Reach $2.28M Settlement Agreement for Discriminatory AI-Powered Screening Tool*, LAW.COM (Apr. 30, 2024, 10:41 AM), https://www.law.com/2024/04/30/rental-applicants-reach-2-28m-settlement-agreement-for-discriminatory-ai-powered-screening-tool/ [https://perma.cc/NY5J-GEY2].

C. Public Policy Support for FHA Liability

[27] Currently, there is a lack of comprehensive AI-related federal regulation that AI developers can look to.[70] Without requirements, many AI developers may fail to self-regulate and conduct bias-auditing on their own initiative. Because of this severe lack of regulation, there is strong public policy support to hold AI developers accountable under the FHA for the discriminatory harm caused by their algorithms.

[28] Plaintiffs who suffer housing discrimination due to an algorithm's decision-making should be able to prevail on an FHA claim, and neither housing providers themselves, nor the entities that create the algorithms, should be able to escape liability since both are partly responsible for the resulting discriminatory impact. The question should not be on whom to cast the blame, but how to split liability. Public Knowledge, a consumer advocacy focused think tank, commented that providing FHA immunity to providers for claims based on algorithmic discrimination was "in tension with the growing legal precedent that people should be able to challenge the accuracy of technological systems used to their detriment."[71]

[29] Although it is essential to make sure AI developers are subject to the FHA's discriminatory laws through litigation measures, another important way of ensuring the responsible development of algorithms, in housing and beyond, is to enshrine this guidance in federal law.

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[70] Victor Li, *What Could AI Regulation in the US Look Like?*, AM. BAR ASS'N (June 14, 2023), https://www.americanbar.org/groups/journal/podcast/what-could-ai-regulation-in-the-us-look-like/ [https://perma.cc/X4HL-LDUX].

[71] Valerie Schneider, *Locked Out by Big Data: How Big Data, Algorithms and Machine Learning May Undermine Housing Justice*, 52.1 COLUM. HUM. RTS. L. REV. 251, 264 (2020).

D. AI's Potential Shown In Lending

[30] There is no point in trying to stop the ever-increasing use of AI across industries and for good reason—AI can make processes faster and cheaper, and although it might seem doubtful, algorithmic decision-making does have the potential to decrease the amount of bias, particularly in markets prone to implicit face-to-face discrimination.[72] Algorithmic decision-making is already proving its potential by diminishing the amount of face-to-face implicit bias in mortgage lending and making services more accessible.[73]

[31] Under the disparate impact analysis, an entity can continue to analyze specific factors even when a discriminatory effect is proven, if the factors have a legitimate business necessity.[74] Courts have held that, in the lending industry, the act of scoring credit risk is a legitimate business necessity and have thus allowed lenders to discriminate based on creditworthiness.[75] However, face-to-face lenders tend to reject African American and Hispanic applicants approximately 6% more often than similarly-situated non-minority applicants for both purchase and refinancing loans.[76] This implicit bias that arises from face-to-face interactions is something that cannot easily be pointed to in a policy and is even harder to hold lenders liable for.

[32] However, a 2019 Berkely study about discrimination in FinTech lending, which involves using algorithms to determine pricing for

[72] Robert Bartlett et al., *Consumer-Lending Discrimination in the FinTech Era*, 143 J. FIN. ECON. 30, 31 (2022).

[73] *Id.* at 55.

[74] *Id.* at 31.

[75] *Id.* at 31.

[76] *Id.* at 31–32.

borrowers with no face-to-face human interaction, found that FinTech lenders overall discriminate about one-third less than other lenders, which is consistent with the removal of face-to-face interactions that lead to discrimination between originators and borrowers.[77] While celebrating this finding, the study also notes that discrimination is still very much present in FinTech lenders.[78] Therefore, although algorithm-based systems work to remove the discrimination due to face-to-face bias, algorithmic lending as a whole continues to contribute to discriminatory effects.[79]

[33] This decrease in discrimination due to the use of AI shows the potential impact that algorithmic screening can have in eradicating housing decision discrimination. With effective regulation, this potential may be fully realized.

III. PROPOSAL FOR FEDERAL REGULATION

[34] Although applying the FHA and other non-discriminatory laws to AI developers provides a pathway for consumers and advocates to recover from algorithmic discrimination, consumers should not be the only ones holding entities accountable. Implementing federal AI regulations is a starting point that states can expand from and would benefit everyone involved.

[35] One of the main reasons for the lack of comprehensive AI regulation is because of the newness of the technology and concerns that regulation

[77] Robert Bartlett et al., *Consumer-Lending Discrimination in the FinTech Era*, 143 J. FIN. ECON. 30, 32 (2022).

[78] *Id*. at 55.

[79] *Id.* at 31.

might stifle innovation and slow progress in the field.[80] Because of these concerns, federal AI regulation should begin in the areas where decisions have the greatest impact on people's civil rights and livelihoods: housing, healthcare, policing, and employment. Regulation in these areas to limit the discriminatory effects of AI should focus on promoting transparency throughout the development process and ongoing accountability from AI developers through independent auditing and federal limits on allowable risk levels.

A. The Need for Transparency

[36] One of the main principles that regulators should focus on is ensuring reasonable transparency from AI developers. Requiring that entities maintain a reasonable level of transparency with regulators, independent evaluators, and the consumers affected by the algorithms is essential. As we are in the beginning stages of AI usage and regulation, leaders must be cognizant of the basic underlying principles and potential of AI. Understanding how AI decisions are made is essential to creating fair and effective regulation.[81]

[37] Federal regulation should also require AI developers to conduct independent auditing. Short of demanding open-source AI, which is too risky for developers and even harder to regulate, regulation could require that developers allow for the independent evaluation of their automated

[80] Natasha Allen & Louis Lehot, *What to Expect in Evolving U.S. Regulation of Artificial Intelligence in 2024*, FOLEY & LARDNER LLP (Dec. 7, 2023), https://www.foley.com/insights/publications/2023/12/us-regulation-artificial-intelligence-2024/ [https://perma.cc/6K2F-A45M].

[81] *Promise and Peril*, *supra* note 5, at 2–3, 10–11.

systems.[82] However, in sectors where privacy concerns are an issue, developers should be responsible for reporting and when possible publicly disclosing the results of their own routinely made algorithmic impact assessments.[83] Independent evaluators should audit both the coding itself and the training data used at each stage of development. Although there is no federal regulation requiring independent evaluation, certain localities have begun implementing stricter guidelines for the usage of AI.

[38] In 2021, New York City led the country in passing the first local law requiring employers using AI-enabled employment decision tools ("AEDTs") to conduct bias audits.[84] The audits are conducted by independent evaluators, and the results of the auditor's report must be made publicly available on the employer's website.[85] In allowing for the routine assessment of discriminatory effects, the algorithms are constantly being enhanced to produce the least possible discriminatory version and results. Although this law seems promising, it has shown itself to be less effective in practice.[86] A recently conducted study by researchers at Cornell found that only 18 out of a group of 391 employers using AEDTs complied with

[82] David Evan Harris, *Open-Source AI Is Uniquely Dangerous*, IEEE SPECTRUM (Jan. 12, 2024), https://spectrum.ieee.org/open-source-ai-2666932122 [https://perma.cc/77AN-YGBZ]; Press Release, White House Off. Sci. & Tech. Pol'y, Blueprint for an AI Bill of Rights, https://www.whitehouse.gov/ostp/ai-bill-of-rights/algorithmic-discrimination-protections-2/ [https://perma.cc/3BFE-5MQP].

[83] *See* Blueprint for an AI Bill of Rights, *supra* note 82.

[84] *US State-by-State AI Legislation Snapshot*, BCLP, https://www.bclplaw.com/en-US/events-insights-news/2023-state-by-state-artificial-intelligence-legislation-snapshot.html [https://perma.cc/DP5V-FA2D] (last visited Feb. 12, 2024).

[85] *Id.*

[86] Roy Maurer, *New York City AI Law Is a Bust*, SHRM (Feb. 18, 2024), https://www.shrm.org/topics-tools/news/technology/new-york-city-ai-law [https://perma.cc/7GZW-Q6JR].

posting audit reports.[87] This lack of reporting is because, during the latter stages of passing the law, the definition of AEDTs was narrowed down significantly. The narrowed definition made it so that if there is even the slightest bit of human oversight in the AEDT process, the audit requirement no longer applies.[88]

[39] Although human oversight should be encouraged and ultimately helps cut down on the risk of bias, future attempts at federal regulation should not compromise on a broad inclusion of all types of algorithmic software, regardless of the possibility of human intervention. The Biden Administration's Blueprint for an AI Bill of Rights identifies five principles that should guide the design and use of automated systems: (1) promoting safe and effective systems, (2) algorithmic discrimination protections, (3) data privacy, (4) notice and explanation, and (5) human alternatives and considerations.[89] The section on algorithmic discrimination protections set expectations that all AI models should be developed using representative data previously assesed for bias. Additionally, developers should test AI models for disparities before implementation and should continue to test the models regularly throughout their usage.[90]

[40] Lastly, in the spirit of full transparency, consumers should be notified in advance of the use of an automated system and informed of which factors are used in the assessment and how those factors were weighed. New York City's Local Law 144 attempted to implement this by requiring employers using AEDTs to provide each applicant with notice of the AEDTs and to disclose which specific job qualifications and characteristics will be used in the assessment.[91] NY Local Law 144 goes a

[87] *Id.*

[88] *Id.*

[89] Blueprint for an AI Bill of Rights, *supra* note 82.

[90] *Id.*

step further and informs applicants of their right to request an alternative means of evaluation or accommodation.[92] While it may be unrealistic to require all providers of algorithmic software in every industry to provide consumers with alternative means, in areas where an alternative is reasonable, like in employee evaluation or tenant screening, developers should be required to make an accommodation. A reasonable accommodation could range from something as simple as human oversight of the assessment to conducting the assessment without the algorithm at all. In all instances of algorithmic decision-making, access to an escalated appeals process for consumers who suspect an error or disparate impact should be available. Not only does this limit the harm caused to the consumer, but it also allows for a remedy outside of litigation, thus freeing up the court system.

[41] Altogether, transparency towards regulators, independent auditors, and consumers is fundamental in eradicating AI discrimination and bias. Consumers should have the right to be informed of the use of their information in algorithmic decision-making and be able to in turn hold entities accountable for discrimination when it occurs.

B. The Need for Accountability & Less Discriminatory Alternatives

[42] In addition to transparency, AI developers should be held accountable when discriminatory harms are found. As discussed in Section II.D., developers of tenant-screening software should be subject to the FHA's non-discriminatory laws. Additionally, AI developers should be held

[91] Maurer, *supra* note 86.

[92] April A. Goff & Chris Katsimagles, *New York City Adopts Final Rules for Law Governing Automated Employment Decision Tools*, PERKINSCOIE (May 16, 2023), https://perkinscoie.com/insights/update/new-york-city-adopts-final-rules-law-governing-automated-employment-decision-tools [https://perma.cc/R2EJ-WHDG].

accountable for maintaining specified levels of risk and searching for less discriminatory algorithms throughout the development process.

[43] In addition to conducting bias audits, regulators should hold entities accountable for maintaining low levels of risk, which may vary depending on the possibility of harm in the specific industry the algorithm is used. The National Institute of Science and Technology ("NIST") developed an AI Risk Management Framework ("AI RMF") which acknowledges the fact that most AI risks arise from already existing real-world issues, not coding difficulties, and sets forth a list of risk management principles and characteristics of a trustworthy AI model.[93] AI RMF offers the "best of both worlds" solution, by minimizing potential impacts while allowing the maximization of positive impacts, thus leading to trustworthy AI systems.[94] According to the NIST, risk tolerance, which refers to the actor's readiness to bear certain types of risk in pursuit of its goals, is largely influenced by regulatory or legal requirements.[95] This recognizes the reality that most AI developers will not put in the work to lower the risk of bias unless required to. Regulators should work together with entities to determine what levels of risk are acceptable and hold entities accountable for staying below the line.

[44] The main goal behind responsible algorithm development is to achieve a less discriminatory algorithm ("LDA"). As discussed in Section I. A., there are always several variations of an algorithm to choose from when trying to solve the same prediction problem.[96] This model municipality phenomenon suggests that when a disparate impact is

[93] *AI Risk Management Framework*, NIST (July 26, 2024), https://www.nist.gov/itl/ai-risk-management-framework [https://perma.cc/3ABN-JDZ2].

[94] *Id.*

[95] *Id.*

[96] *See* Black, *supra* note 8, at 61–70.

displayed by an algorithm, there may be an alternative model that performs just as well but with less of a discriminatory impact—meaning no need to sacrifice accuracy for fairness.[97] Federal regulation should place a duty on algorithm developers to conduct a reasonable search for LDAs and implement them during the development process.

[45] Returning to the disparate impact analysis of algorithms, the availability of LDAs would come into play during the last step, where the burden shifts back to the plaintiff to prove that the defendant's legitimate business objective can be achieved using a less discriminatory solution.[98] Without regulations requiring entities to search for and implement LDAs, it is much harder for plaintiffs to prove the existence of an LDA without having access to the algorithm itself, which can lead to increased discovery costs and litigation.[99] Developers reporting on the existence and implementation of LDAs would also help insulate AI developers from unnecessary litigation by having this information available from the beginning.[100]

CONCLUSION

[46] Overall, the emergence of algorithms and machine learning in housing-related services is a promising change. Yet the aforementioned discriminatory effects must be restricted and regulated before the technology continues to be incorporated in the housing sector. This Article provided an overview of some of the major uses of self-learning algorithms in housing-related services and examples of how discrimination can be exacerbated using these algorithms. In order to eradicate the risk of

[97] *Id.*

[98] 24 C.F.R. § 100.500(c)(1)–(3) (2023).

[99] *See* Black, *supra* note 8, at 59, 109–10.

[100] *See* Black, *supra* note 8, at 113, 115–20.

algorithmic discrimination in housing, developers of tenant-screening algorithms should be subject to the FHA.

[47] While Artificial Intelligence remains a relatively new and untested tool, concerns over stifling technology should not restrain regulation from removing discrimination from the equation. Federal regulation of AI should begin in the traditional civil rights domain, which includes housing-related services, and should require developers to be transparent with regulators and consumers about how the algorithms work, what data is used to train the models, and which consumer attributes are analyzed. Developers should also be required to search for and implement LDAs throughout the development process, adhere to pre-determined allowable levels of risk for bias, and allow for routine inspections and bias audits by independent evaluators, the results of which should be publicly available. Through regular auditing, transparency, and accountability under non-discrimination laws already on the books, we can take the intolerance out of AI.