UCSD UNDERGRADUATE LAW REVIEW

MEHRI SADRI

Equal Protections in the Age of AI: Navigating Civil Rights in Housing with Machine Learning

ABSTRACT. As software becomes increasingly widespread, the data generated through bookkeeping and information transfers can be harnessed for the public good. The principle of data science, using forms of information to uncover insights or predict future outcomes, is dependent on inputs to fuel its function. For instance, large language models such as ChatGPT draw from massive datasets to respond to user questions with precision in the form of a large language model. What happens, however, when the data driving these technologies is inaccurate or biased? If flawed inputs lead to life-altering consequences, who should be held accountable? This paper challenges the efficacy of artificial intelligence algorithms used by housing corporations to identify "ideal" tenants. Through examining two recent court cases and outdated privacy legislation, I will identify inconsistencies in user data protection law and reevaluate them through a legal and technological lens. The paper argues that, to protect civil rights in the age of AI, both the data and the laws governing its use must be critically examined. By focusing on AI's role in national housing development, broader industries leveraging artificial intelligence may integrate similar safeguards to ensure fairness and accountability for the people they serve.

AUTHOR. Mehri Sadri is a graduating senior at UC San Diego, earning a B.S. in Economics with a minor in Data Science, publishing with the help of UCSD faculty member Dr. Germaine A. Hoston. Her public impact work, recognized by *Shoutout SoCal* and *The San Diego Union-Tribune*, reflects a deep commitment to using data science software tools for social equity. This marks her third undergraduate publication, complementing her data-driven initiatives on homelessness AI accountability, and product waste across San Diego County with her machine learning start-up, sr.cag, and full-time work in the public sector. In the fall, she will pursue an M.S. in Data Analytics for Public Policy at Carnegie Mellon University on scholarship.

INTRODUCTION

Society has transformed into a data-driven world, where hundreds of businesses and institutions are turning to technology. This directly affects workforce accounts, productivity, and reachability. As Artificial Intelligence, colloquially known as AI, becomes increasingly integrated into everyday functions, its potential to reshape industries becomes increasingly powerful. Integrating AI and machine learning techniques into various economic sectors has proven effective for smooth management and general administrative purposes, making individuals more productive at their jobs and giving clients improved, cheaper outcomes.

For example, the housing sector has promised greater efficiency in processes like tenant screening, mortgage lending, and property valuation, removing human bias from decision-making. Owning a home has typically been a pinnacle of the "American Dream", and rental corporations often serve as a stepping stone for young individuals saving money in the hopes of having funds for a future down payment. For many others, housing provides a sense of stability, and rational leasing agencies make this feasible. As of 2025, AI technologies are ingrained within this industry: predictive modeling for population forecasting, statistical analysis techniques for credit score analysis, and other techniques meant to bolster efficiency. All data science adjacent techniques rely on vast amounts of data, using historical numbers and statistical patterns to generate future value predictions.

Yet, the power of data shows us that these technologies are far from neutral. When evaluating how AI models function within the tenant industry– predictive algorithms designed to evaluate tenant eligibility, determine loan risk, or suggest housing options– often disproportionately disadvantage low-income and minority communities, reinforcing systemic inequalities. AI algorithms are shaped by the data they are trained on, generated by extracting millions of Gigabytes from Application Program Interfaces (APIs). When historical biases are embedded in those datasets through factors such as false records and inaccurate web resources, these AI algorithms may lead to negative results. However, much of the data extracted for AI creation comes from reputable sources, such as the United States Census, credit bureaus, and law enforcement. These sources are the backbone of preserving 'accurate' AI models, but there is no auditing source to ensure data is fully accurate. From faults such as selective reporting, over-policing, and historical discrimination, we cannot ensure full transparency of such numerical points.

Court cases like *Louis v. SafeRent Solutions* have highlighted how tenant screening algorithms unfairly penalize minority applicants, erecting new barriers to fair housing access.[1] These algorithms assign lower risk scores to voucher recipients based on factors such as income instability or lack of traditional credit history, despite their ability to pay rent through guaranteed government assistance. First, data inputted into these models could be inaccurate or misleading if systems are not thoroughly vetted. Additionally, Machine Learning (ML) firms may choose to prioritize financial metrics within their models that disadvantage low-income and minority renters. The perpetual usage of biased or skewed data reinforces systemic exclusion within AI-driven tools, disproportionately disqualifying applicants who have historically faced housing discrimination.

Similarly, *Connecticut Fair Housing Center v. CoreLogic* represents a case where algorithms flagged criminal records indiscriminately, disproportionately disqualifying applicants of color without considering the nature or relevance of their offenses.[2] A detailed analysis in Section 2 will underscore how AI can reinforce discriminatory practices, undermining civil rights protections established by foundational laws like the Fair Housing Act (FHA).

The United States housing sector and its internal affairs represent a critical intersection of technology, law, and equity. Access to housing is not just a basic human need but a gateway to economic opportunity, educational attainment, and overall well-being.[3] As machine learning (AI) tools are increasingly utilized in housing-related decisions, ensuring their fairness and accountability is essential to upholding civil rights protections and preventing further entrenchment of systemic inequities.[4] More importantly, it is critical to develop infrastructure within local, state, and federal legislation that promotes the usage of positive aspects of artificial intelligence. By focusing on discrimination in housing AI systems, this article seeks to contribute to the broader discussion on how 21st-century technology intersects with civil rights, advocating for legal frameworks that promote equity in the current climate.

This paper seeks to critically examine the intersection of artificial intelligence and

---

[1] *Louis et al. v. SafeRent et al.*, No. 1:22-cv-10800 (D. Mass. filed, Jan. 9, 2023).

[2] *Connecticut Fair Housing Center, et al. v. CoreLogic Rental Property Solutions*, No. 3:18-cv-00705 (D. Conn. 2023).

[3] Joydeep Roy et al., *The Hidden Costs of the Housing Crisis: The Long-Term Impact of Housing Affordability and Quality on Young Children's Odds of Success*, Pew Charitable Trusts, 2008, https://www.pewtrusts.org/~/media/legacy/uploadedfiles/wwwpewtrustsorg/reports/partnership_for_americas_economic_success/paeshousingreportfinal1pdf.pdf.

[4] Danya Sherbini, *AI is Making Housing Discrimination Easier Than Ever Before*, Feb. 12, 2024, https://kreismaninitiative.uchicago.edu/2024/02/12/ai-is-making-housing-discrimination-easier-than-ever-before/.

housing discrimination, focusing on whether existing civil rights frameworks are equipped to address the unique challenges posed by AI technologies. While current statutes are meant to provide equity for tenants and provide a foundation for combating discrimination, their application to algorithmic bias and artificial intelligence is limited and inconsistent. As enforcement often lags behind technological advancements, the usage of artificial intelligence is not yet held accountable by legislation, even as industry standards introduce new machine learning systems. By analyzing legal precedents through two court cases, regulatory gaps within federal law, and the underlying mechanics of AI systems, this paper argues for the urgent need to modernize both equitable housing actions and anti-discrimination laws. In Section 3, cohesive action items are proposed to promote accountability for AI developers and users without hindering incentives for AI innovation, as well as proposing the establishment of a regulatory body to oversee the deployment of algorithms in housing.

A. The Need For Legislative Modernization

As AI becomes an essential part of the housing sector, gaps in existing legislation become increasingly evident. For example, the Federal Housing Administration and Equal Credit Opportunity Act (ECOA) were designed to address human decision-making and reasoning.[5] Applying such legislation becomes difficult when the decision-making processes are instead created by a computer system. These statutes do not apply to AI technologies, as many were ratified before the implementation of such systems. Thus, companies are left to self-regulate, often resulting in inconsistent practices and limited accountability. The current legislation does not promote transparency in AI systems, making it difficult for individuals to challenge discriminatory outcomes in a litigation setting, despite evident wrongdoings.[6]

Courts and regulatory agencies are only beginning to grapple with algorithmic discrimination, often relying on outdated legal frameworks that fail to capture the complexities of AI decision-making. Individuals in the rental housing sector are often under-informed about AI used to run housing decision systems. This lack of

---

[5] US Department of Housing and Urban Development, *Federal Housing Administration History,* https://www.hud.gov/program_offices/housing/fhahistory (last visited Jan. 13, 2025).; U.S. Department of Justice, *Equal Credit Opportunity Act*, https://www.justice.gov/crt/equal-credit-opportunity-act-3 (last visited Jan. 13, 2025).

[6] Rowena Rodrigues, *Legal and Human Rights Issues of AI: Gaps, Challenges, and Vulnerabilities,* 4 Journal of Responsible Technology (Dec. 2020) (discussing how current AI algorithms often lack transparency).

understanding, coupled with legal loopholes, allows biased AI systems to operate largely unchecked once deployed to firms.

Companies deploying technological tools are not obligated to assess or mitigate potential biases before implementation due to the absence of standardized auditing requirements. This unchecked range risks the equity of the housing market. Discriminatory outcomes may persist undetected until challenged in court, affecting those with limited financial resources who are unable to combat these outcomes. Without proactive regulatory intervention, AI-driven housing tools risk exacerbating systemic inequities, leading to legal battles in which corporations or higher entities hold greater financial power.[7] To address these challenges, I believe that legislators must establish clearer mandates for algorithmic transparency, bias testing, and accountability mechanisms to ensure AI systems improve outcomes for all involved parties in the housing market.

The growing reliance on AI within the housing sector underscores the urgent need for legislative modernization of intelligent machinery. Thus, this paper will use the effects from cases and legislation analyzed in Sections 1 and 2 to draw out new regulations that address issues such as algorithmic transparency, accountability for biased outcomes, and the role of third-party developers in perpetuating discrimination.[8] Establishing independent regulatory bodies to oversee the use of AI in housing would provide a centralized mechanism for enforcement and redress. If implemented, these systems and regulations would require AI systems to undergo bias audits and mandate the disclosure of algorithmic decision-making criteria, ensuring compliance with anti-discrimination laws.[9]

---

[7] Arthur J. Goldberg, *Equal Justice for the Poor, Too; Far too often, money—or the lack of it—can be the deciding factor in the courtroom, says Justice Goldberg, who calls for a program to insure justice for all Americans*, N.Y. Times (Mar. 15, 1964), https://www.nytimes.com/1964/03/15/archives/equal-justice-for-the-poor-too-far-too-often-moneyor-the-lack-of.html.

[8] Notice Pasipamire & Abton Muroyiwa, *Navigating Algorithm Bias in AI: Ensuring Fairness and Trust in Africa*, 9 Frontiers in Research Metrics and Analytics, 4-5 (2024) (discussing the need for new regulations focused on addressing algorithmic bias).

[9] *Civil Rights Council Releases Proposed Regulations to Protect Against Employment Discrimination in Automated Decision-Making Systems*, Press Release, California Civil Rights Department (May 17, 2024), https://calcivilrights.ca.gov/2024/05/17/civil-rights-council-releases-proposed-regulations-to-protect-against-employment-discrimination-in-automated-decision-making-systems/.

I. THE GROWTH OF ARTIFICIAL INTELLIGENCE

The adoption of AI in the housing sector has accelerated over the past decade, reshaping how landlords, property managers, lenders, and real estate firms make decisions. From tenant screening algorithms to predictive property valuation tools, these systems are advertised as additions to large decision-making firms that increase efficiency, reduce human error, and optimize decision-making.[10] These tools often leverage vast amounts of data from varying sources, including credit scores, rental histories, employment records, and social media activity, to evaluate prospective tenants.[11] For example, some landlords use AI-driven tenant screening software that analyzes an applicant's credit report, history of evictions, and LinkedIn activity to predict their likelihood of making timely rent payments.[12] The information on a hypothetical candidate is then analyzed on data points related to the applicant's characteristics, such as rental payment patterns, employment status, and behavioral indicators extracted from online sources. These models operate by identifying correlations within historical datasets, assigning weights to different factors based on their predictive power, and generating a risk assessment score. AI streamlines decision-making by evaluating applicants against established criteria in real-time. While these advancements reduce human labor and standardize evaluations, they also raise concerns about algorithmic fairness, data privacy, and the risk of perpetuating historical biases embedded in training data.

Before delving into legal proceedings, this section will provide a comprehensive overview of the various components of outdated legislation that continue to influence judicial decision-making in the world of AI. The court case analysis follows a detailed explanation of the underlying mechanics of artificial intelligence and the principles of data efficacy that serve as the drivers of these models.

A. How AI Identifies the Best Candidates

AI-driven lending models not only calculate candidacy for housing but also assess potential borrowers' creditworthiness when looking to lease an apartment or purchase a home. These models go beyond traditional credit scores by incorporating alternative

---

[10] Sherbini, *supra* note 4.

[11] Jesse Anglen, *AI Agents Tenant Screening Workflow: Use Cases, Benefits, & Challenges*, https://www.rapidinnovation.io/post/ai-agents-tenant-screening-workflow (last visited Feb. 25, 2025).

[12] Alice Dodd, *Tenant Screening with AI: A Guide for Property Managers*, Mînut, Sept. 20, 2024, https://www.minut.com/blog/ai-in-tenant-screening.

data points, such as payment history for utilities, mobile phone bills, and even financial behaviors inferred from bank transaction records. For example, an applicant who regularly pays their rent and utility bills on time but lacks a strong credit history may be scored more favorably than someone with a higher credit score but inconsistent bill payments. AI systems analyze spending habits to gauge financial responsibility, flagging applicants with excessive debt accumulation or higher-risk borrowers. Additionally, natural language processing (NLP) can analyze applicant communication with lenders or landlords, identifying patterns indicative of financial instability. Some models incorporate geospatial and economic data, assessing factors such as neighborhood stability and local cost-of-living trends to further refine risk assessments. In cases where a candidate does not meet traditional approval criteria, the system may generate tailored recommendations, such as suggesting co-signers, offering alternative loan structures, or adjusting required deposits, to increase accessibility while maintaining financial security for lenders and property managers.

These technologies are intended to make housing and lending decisions objective, replacing subjective human judgments; however, it is unknown whether human bias is important when picking the best option for a tenant. Data may not have the ability to quantify all factors needed to make an informed decision on a potential renter.

The system used to analyze data is rarely exposed to applicants. Most companies using such algorithms are also unaware of their functionality. These AI models are known as "black boxes" and even developers struggle to fully understand how inputs are weighted to produce outcomes.[13] With little oversight and comprehensibility, questions are raised about whether this technology should be used for essential needs, particularly when AI systems perpetuate biases encoded in their training data.

B. How is Bias Perpetuated in AI?

If historical data reflects systemic inequalities, AI models trained on these datasets are likely to replicate inequities in their predictions. AI has transformed how the housing market functions, offering tools to streamline processes, analyze vast datasets, and reduce human error. However, these benefits quickly become overshadowed by the

[13] Vikas Hassija et al., *Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence*, 16 Cogn Comput. 45–74 (2024), https://doi.org/10.1007/s12559-023-10179-8 (discussing black box models and the lack of transparency in many AI systems).

risks of amplifying preexisting systemic biases in the housing sector.[14] These biases are transferred through training data that reflects patterns of housing discrimination, such as redlining, unequal mortgage approvals, and disproportionate denial rates for minority applicants, becoming the foundation for predictive algorithms.[15] As a result, instead of acting as a neutral source, AI systems frequently replicate these inequities, perpetuating cycles of exclusion and disadvantage for marginalized communities.

For instance, tenant screening algorithms often rely on proxies like credit scores, rental histories, and employment records, which can disproportionately penalize minority applicants and low-income individuals. While human decision-makers are also susceptible to bias, it is often easier to identify and challenge discrimination due to transparent reasoning and legal frameworks that govern fair housing practices. In contrast, AI models operate within complex systems where biases may be deeply embedded in training data or decision-making logic, making them harder to detect and regulate effectively. These models often intertwine with structural inequalities that limit access to credit or stable employment opportunities for certain groups. An individual denied housing may be facing the effects of past discriminatory practices, as data is populated from as early as the 20th century.[16] For example, mortgage-lending AI tools may assign lower creditworthiness scores to applicants from neighborhoods with historically lower property values, reproducing the long-outlawed practice of redlining under the perception of objectivity.

The "black box," or the unknown nature of AI systems, makes creating legislation to police these issues difficult. Often, developers cannot fully explain how an algorithm arrives at a decision. This lack of transparency creates significant barriers for affected individuals to challenge discriminatory outcomes. For instance, a tenant denied housing due to an algorithm's evaluation may never know the specific criteria used by the housing corporation to come to their final decision, regardless of whether those criteria were tainted by bias. This not only undermines accountability but also poses a

---

[14] *The AI Revolution in Real Estate: A New Era of Market and Property Insights*, CameronAcademy, Feb. 8, 2025, https://cameronacademy.com/the-ai-revolution-in-real-estate-a-new-era-of-market-and-property-insights/page/3/?srsltid=AfmBOoo9-gnQsQ4LCaqffMOYKVpiXcrCvs6-e5HJzUtMYkJNycOFSrGi.

[15] Neil Bhuta et al., *How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions*, 2022-067 FEDS Washington: Board of Governors of the Federal Reserve System 1 (2022) (discussing how predictive algorithms are sometimes shaped by racially biased data).

[16] Susan Dymling, *The Risks of Poor Data Quality in AI Systems*, Twoday, Apr. 30, 2024, https://www.twoday.com/blog/the-risks-of-poor-data-quality-in-ai-systems.

fundamental challenge to the enforcement of anti-discrimination laws like the FHA, explored in Section 2.[17]

Without clear insight into how decisions are made, it becomes impossible to determine whether AI systems comply with existing civil rights protections. This raises the question of whether an algorithm denying a housing application without a transparent explanation constitutes a violation of discriminatory practice prohibitions. Since AI-driven decisions rely on correlations rather than explicit rules, there is a risk that these systems could unintentionally reinforce exclusionary practices without violating the law. The question of who should manage decision-making power in AI systems creates a myriad of responsibilities among developers, landlords, and policymakers that they are not equipped to handle. Developers argue that biases in their systems are a reflection of historical inequities in the data, not the program they built, while landlords and lenders claim they are using "neutral" tools to make decisions while not understanding the ramifications of their resources. Regulators and courts struggle to apply traditional anti-discrimination statutes to these nebulous systems, leaving tenants and borrowers with limited recourse to challenge unfair outcomes.

II. CURRENT REFORMS

The rise of technological systems in the housing sector presents a challenge to existing anti-discrimination laws, which provide no background on how technology may cause undetected discrimination. The FHA of 1968 prohibits discrimination based on race, color, national origin, religion, sex, familial status, or disability in the sale, rental, and financing of housing.[18] This law was designed to prevent direct discrimination, such as landlords or lenders deliberately rejecting applicants based on visible characteristics such as race or gender. AI-driven housing algorithms do not "see" applicants the same way humans do, factually and emotionally. Instead, they rely on statistical indicators like credit scores, criminal records, and rental histories that are often shaped by systemic inequalities. While algorithms may not be programmed to discriminate, a negative feedback loop may still disproportionately filter out marginalized groups by reinforcing existing disparities. This raises concerns about

[17] David Beer, *Why Humans Will Never Understand AI*, British Broadcasting Corporation, Apr. 7, 2023, https://www.bbc.com/future/article/20230405-why-ai-is-becoming-impossible-for-humans-to-understand.

[18] Fair Housing Act, 42 U.S.C. §§ 3601–3619 (1968).

whether AI systems unintentionally undermine the protections the FHA was made to uphold. While the FHA has been instrumental in combating overt discrimination, its applicability to AI-driven practices in the 21st century is unclear.[19] Since most algorithms operate on a black box scale, they often fall into a legal gray area.[20] An example of this is demonstrated by tenant screening algorithms, as assigning lower scores to individuals does not explicitly violate the FHA, but still affects low-income and minority groups.

Additionally, mortgage algorithms that penalize applicants from historically underserved neighborhoods may unintentionally mirror the effects of "redlining," a practice the FHA was designed to eliminate.[21] Courts have begun to address these issues, but rulings remain inconsistent.

To address this problem, federal regulatory guidelines must be established to mandate transparency in AI-driven tenant screening and ensure compliance with fair housing principles. These regulations should require AI models to disclose which factors they consider, limit the weight of historically biased variables like credit scores or rental history, and implement fairness audits to detect discriminatory patterns. Rather than outright prohibiting these factors, the guidelines could mandate alternative indicators, such as verifiable income sources, government assistance, and consistent rent payments, to provide a more balanced assessment. Additionally, standardized impact assessments and third-party audits done by a federal agency– discussed in Section 4– could ensure that AI models do not disproportionately exclude marginalized groups.[22]

In *Louis v. SafeRent Solutions,* the plaintiffs successfully argued that an AI-powered tenant screening algorithm violated the FHA by disproportionately disadvantaging low-income and minority applicants. However, in *Connecticut Fair Housing Center v.*

[19] Fair Housing Act, 42 U.S.C., *supra* note 18.

[20] David N. Anthony et al., *HUD Issues Guidance on Applicability of the Fair Housing Act to Tenant Screening and Housing-Related Advertising That Relies Upon Algorithms and AI*, Troutman Pepper Locke: Consumer Financial Services Law Monitor, May 14, 2024, https://www.consumerfinancialserviceslawmonitor.com/2024/05/hud-issues-guidance-on-applicability-of-the-fair-housing-act-to-tenant-screening-and-housing-related-advertising-that-relies-upon-algorithms-and-ai/.

[21] Emily Peiffer, *The Ghosts of Housing Discrimination Reach Beyond Redlining*, Urban, Mar. 15, 2023, https://www.urban.org/stories/ghosts-housing-discrimination-reach-beyond-redlining#:~:text=For%20decades%2C%20until%20the%20Fair,race%2C%20ethnicity%2C%20and%20religion.

[22] Louis Au Yeung, *Guidance for the Development of AI Risk and Impact Assessments*, UC Berkeley Center for Long-Term Cybersecurity (2021), https://cltc.berkeley.edu/ai-risk-and-impact/.

CoreLogic, the courts have been more reluctant to hold AI developers accountable, shifting the responsibility to landlords and other end users.

Federal statutes, such as the ECOA of 1974 and Title VII of the Civil Rights Act of 1964, also intersect with AI-driven housing practices based on fair use.[23] However, similar to the FHA, these regulations were established before artificial intelligence. The ECOA prohibits discrimination in credit transactions, including for mortgages, but does not address algorithmic bias. Similarly, Title VII, which addresses workplace discrimination, has yet to be applied in housing bias contexts.[24] These laws provide a framework for addressing discrimination, but their language and enforcement mechanisms are often ill-suited to the complexities of AI systems.

The ECOA aims to prevent discrimination in lending decisions, yet challenges arise in its application to AI systems. AI-powered mortgage approval processes may unintentionally reproduce historical lending disparities. While lenders are required to provide adverse action notices explaining loan denials, AI-driven decisions lack clear reasoning. The Consumer Financial Protection Bureau (CFPB) has issued guidance emphasizing that financial institutions must provide "specific and accurate reasons" for credit denials, even when AI is involved, but enforcement remains inconsistent.

In this section, I summarize the absence of comprehensive legal safeguards in AI ethics beyond the housing market, as AI systems perpetuate discriminatory practices under the guise of efficiency and objectivity. While laws such as the FHA, ECOA, and Title VII of the Civil Rights Act provide a foundation for addressing discrimination, they were not designed to regulate the nuances of algorithmic decision-making. The gaps in these frameworks underscore the urgency of developing legislative and regulatory measures to ensure that AI technologies are used fairly and equitably, particularly in sectors as important as housing.

III. ANALYSIS & CONCLUSIONS OF RECENT LITIGATION

Due to AI and ML expansion, courts have interpreted laws such as the FHA to include disparate impact claims, finding that a neutral policy unintentionally harms protected groups. However, the burden of proof often falls on the plaintiff to demonstrate these discriminatory effects, a challenge made harder by the complexity of

---

[23] Equal Credit Opportunity Act, 15 U.S.C. §§ 1691-1691f (1974).; Title VII of the Civil Rights Act of 1964, 42 U.S.C. 2000e (1964).

[24] *Consumer Compliance Examination Manual: Section IV – Fair Lending*, Federal Deposit Insurance Corporation (Jun., 2024), https://www.fdic.gov/consumer-compliance-examination-manual.

black box AI systems. In this section, I will conduct a thorough examination of two recent court cases, *Louis v. Rent Safe Solutions* and *Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions*. My analysis will focus on evaluating whether the legal outcomes of these cases are fair, considering the complex and ambiguous nature of artificial intelligence.

Regulatory agencies like the Department of Housing and Urban Development (HUD) and the Federal Trade Commission (FTC) have expressed concerns about algorithmic discrimination. HUD recently took enforcement action against companies using biased tenant screening algorithms. However, without comprehensive federal legislation, enforcement remains incomplete. State and local governments have begun introducing AI accountability laws, but these efforts vary widely in scope and effectiveness. For example, while concerns regarding the safety of tenants are valid, not everyone with a criminal record poses an imminent threat to their community. Regulations should require AI models to differentiate between types of crime such that certain groups are not unfairly disadvantaged, ensuring housing decisions are based on relevant and equitable criteria. A more nuanced approach could involve technology that screens for the nature of a crime and the time elapsed since the offense, rather than definite exclusions.

A. Louis v. SafeRent Solutions

In *Louis v. SafeRent Solutions*, plaintiffs challenged the use of an AI-driven tenant screening system, arguing that it disproportionately harmed Black and Hispanic renters by assigning lower risk scores that correlated with minority race and socioeconomic status.[25] The lawsuit alleged that SafeRent's algorithmic model reinforced historical biases and violated the FHA, denying housing opportunities to minority applicants.[26] In November 2024, the parties reached a settlement exceeding $2.2 million, with SafeRent agreeing to modify screening practices to prevent future discrimination.[27] The case questioned whether AI-based tenant screening constitutes unlawful

[25] *SafeRent et al.*, No. 1:22-cv-10800, *supra* note 1.
[26] *Id.*
[27] Emma Roth, *AI Landlord Screening Tool Will Stop Scoring Low-Income Tenants After Discrimination Suit*, The Verge, Nov. 20, 2024, https://www.theverge.com/2024/11/20/24297692/ai-landlord-tool-saferent-low-income-tenants-discrimination-settlement.

discrimination, as the FHA predates algorithmic decision-making.[28] The court's handling of this case underscores the growing tension between civil rights protections and the expanding use of AI in housing markets.

Courts recognized the discriminatory impacts of AI tools in *Louis v. SafeRent Solutions*, but inconsistent rulings and a lack of comprehensive legal guidelines allowed for significant gaps in protection.[29] The legal landscape surrounding AI discrimination in housing remains fragmented, with existing legislation struggling to keep pace with rapid technological advancements. Concerning the legality of AI systems, the FHA prohibits discrimination in housing-related transactions based on race, color, religion, sex, disability, familial status, and national origin.[30] However, the case states that the FHA statute was written before algorithmic decision-making, leaving significant ambiguity in how it applies to AI-driven housing decisions.[31]

To address these gaps, policymakers must develop AI governance frameworks that incorporate fairness audits, algorithmic impact assessments, and mandatory explainability requirements. Strengthening existing civil rights protections to cover AI-driven discrimination and requiring greater transparency from developers and landlords are critical steps toward ensuring equitable access to housing.

B. Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions

The case of *Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions* provides an example of how AI-driven systems contribute to discriminatory housing outcomes,[32] exposing the limitations of current anti-discrimination laws in regulating algorithmic decision-making. CoreLogic's CrimSAFE tenant screening algorithm flagged rental applicants based on criminal history without considering the nature, relevance, or recency of the offenses. The plaintiffs argued that the algorithm violated

---

[28] Jesse Bedyan, *Class Action Lawsuit on AI-Related Discrimination Reaches Final Settlement*, AP News, Nov. 20, 2024, https://apnews.com/article/artificial-intelligence-ai-lawsuit-discrimination-bias-1bc785c24a1b88bd425a8fa367ab2b23.

[29] *SafeRent et al.*, No. 1:22-cv-10800, *supra* note 1.; Chiraag Bains, *The Legal Doctrine That Will Be Key to Preventing AI Discrimination*, The Brookings Institution, Sep. 13, 2024, https://www.brookings.edu/articles/the-legal-doctrine-that-will-be-key-to-preventing-ai-discrimination.

[30] Fair Housing Act, 42 U.S.C., *supra* note 18.

[31] Marie J. Fritz, *Federal Housing Administration*, Britannica, Mar. 7, 2025, https://www.britannica.com/topic/Federal-Housing-Administration.

[32] *CoreLogic Rental Property Solutions*, No. 3:18-cv-00705, *supra* note 2.

the FHA by disproportionately disqualifying Black and Hispanic applicants due to criminal history screenings.[33] However, the court ruled that CoreLogic, as a third-party provider, was not directly liable under the FHA.[34] Instead, the responsibility fell on the landlords who used the tool to make final decisions.

CoreLogic's CrimSAFE algorithm relied on publicly available criminal records to generate applicant recommendations.[35] While this might appear neutral, the algorithm failed to account for contextual factors, such as the age or severity of the offenses. This disproportionately excluded minority applicants because of longstanding racial disparities in the US criminal justice system. For example, the over-policing of predominantly Black and Hispanic neighborhoods has led to higher arrest rates, regardless of actual crime levels.[36] Relying on criminal history without contextualization causes the algorithm to perpetuate these biases, effectively automating discriminatory practices under the guise of efficiency.

The FHA prohibits housing discrimination based on race, color, religion, sex, familial status, or national origin. The plaintiffs argued that the algorithm violated the FHA by disproportionately disadvantaging minority applicants. The court's ruling highlighted a critical limitation of the FHA, as the act does not explicitly address liability for third-party algorithm providers. CoreLogic avoided responsibility, shifting the burden onto landlords who relied on the algorithm's recommendations.

One challenge in this case was the lack of transparency in how the CrimSAFE algorithm made decisions.[37] The proprietary nature of AI systems makes it difficult to understand how recommendations are generated, complicating efforts to identify and address discriminatory practices. Neither CoreLogic developers nor the landlord understood the algorithm's decision-making process, creating a significant obstacle in the plaintiff's ability to prove intent to discriminate. Without clear standards for transparency in algorithmic systems, it is difficult to hold developers accountable, allowing biased AI tools to influence housing decisions with little oversight.

---

[33] C*oreLogic Rental Property Solutions*, No. 3:18-cv-00705, *supra* note 2.
[34] *Id.*
[35] Lauren Kirchner, *Can Algorithms Violate Fair Housing Laws?*, The Markup, Sep. 24, 2020, https://themarkup.org/locked-out/2020/09/24/fair-housing-laws-algorithms-tenant-screenings#:~:text=Arroyo%20and%20her%20attorneys%20argued,mitigating%20circumstances%20through%20more%20detailed%2C.
[36] Susan Nembhard & Lily Robin, *Racial and Ethnic Disparities Throughout the Criminal Legal System* (Urban Institute Justice Policy Center, 2021).
[37] Vinhcent Le, Algorithmic Bias Explained: A Report by the Greenlining Institute (Bruce Mirken eds., Feb. 18, 2021).

To prevent this, policymakers should establish concrete measures, such as mandatory bias audits, impact assessments, and explainability requirements. Additionally, regulatory agencies could introduce certification processes for tenant screening algorithms, ensuring that models do not unfairly disadvantage protected groups. By enforcing these safeguards, policymakers can create an accountable system that prevents AI from reinforcing historical inequities while harnessing its efficiencies to improve housing access.

This case demonstrates the limitations of current anti-discrimination laws in addressing the challenges posed by AI-driven systems. A critical gap in legal protections was created when the court failed to hold CoreLogic accountable, exposing vulnerable populations to continued harm. As AI becomes increasingly integrated into decision-making processes, it is essential to modernize existing legal frameworks to ensure that these technologies promote fairness and equity rather than perpetuate systemic bias.

C. AI Infrastructure Expansion

The next part of this paper seeks to explain how AI infrastructure has rapidly expanded across various sectors, with significant implications not only for housing but also for employment, education, and lending. Analyzing their overall impact, I assess both the efficiencies created and the risks posed in creating systematic bias. Tenant screening platforms such as SafeRent, CoreLogic, and Zillow use AI-driven algorithms to assess prospective renters.[38] These systems take data from multiple online sources, using APIs to predict an applicant's likelihood of paying rent on time and adhering to lease terms. Mortgage lenders employ AI in loan underwriting processes, integrating traditional financial metrics with non-traditional data like employment patterns and digital footprints. Notably, credit-providing entities like Fannie Mae and Freddie Mac rely on automated underwriting systems (AUS) that utilize machine learning models to

[38] *AI in Property Markets: A Double-Edged Sword for Cybersecurity?*, Cotality, Oct. 25, 2024, https://www.corelogic.com/intelligence/ai-in-cybersecurity/.

expedite lending decisions.[39] These infrastructures are marketed as efficient and neutral solutions for evaluating candidates, promising to reduce the potential for human bias.[40]

However, using AI for candidate evaluations raises significant concerns about transparency. While these systems aim to standardize decision-making, they frequently replicate historical inequities embedded in their training data. Despite their technical sophistication, these models often lack adequate mechanisms to ensure that biases are not perpetuated or amplified.

Hiring algorithms that prioritize traits more accessible to privileged groups may unintentionally exclude qualified candidates from underrepresented backgrounds. The dangers of AI infrastructure extend beyond housing into employment and education, with hiring platforms like HireVue, LinkedIn, and Pymetrics analyzing resumes, video interviews, and psychometric tests to rank job applicants. Predictive analytics evaluate college applicants, sometimes incorporating long-term success predictions based on high school performance and extracurricular activities. These systems are supported by advancements in cloud computing and AI-as-a-Service (AIaaS) platforms provided by companies such as Amazon Web Services (AWS) and Google Cloud.[41] However, these tools face similar challenges, reinforcing existing inequity, such as algorithm bias within the software and racial bias in detection technology, when trained on biased datasets.

Therefore, I now aim to identify both the strengths and limitations of current legal approaches, laying the groundwork for discussing legislative reforms that address these emerging challenges.[42] AI systems hold impressive potential to streamline decision-making when fully understood by their stakeholders; however, reliance on biased data and black box algorithm processes has led to discriminatory concerns.

---

[39] *Automated Underwriting System (AUS)*, AD Mortgage, https://admortgage.com/glossary/automated-underwriting-system-aus/ (last visited Jan. 16, 2025).; Peter Ghavami, *Mortgage Lenders Cite Operational Efficiency as Primary Motivation for AI Adoption*, Fannie Mae: Perspectives Blog, Oct. 4, 2023, https://www.fanniemae.com/research-and-insights/perspectives/lenders-motivation-ai-adoption.

[40] Nadiyah J. Humber, *A Home for Digital Equity: Algorithmic Redlining and Property Technology*, 111 California L.R. 1421 (2023) (discussing infrastructures used to reduce human bias in the employment sector).

[41] Alexander S. Gillis & Kinza Yasar, *What is Artificial Intelligence as a Service (AIaas)?*, TechTarget, Dec. 2024, https://www.techtarget.com/searchenterpriseai/definition/Artificial-Intelligence-as-a-Service-AIaaS.

[42] Ivey Dyson, *How AI Threatens Civil Rights and Economic Opportunities*, Brennan Center for Justice, Nov. 16, 2023, https://www.brennancenter.org/our-work/analysis-opinion/how-ai-threatens-civil-rights-and-economic-opportunities.

D. Aside – Liability for Landlords

The court's decision in *Connecticut Fair Housing Center v. CoreLogic Rental Property Solutions* to place responsibility on landlords rather than CoreLogic underscores another significant shortcoming of current laws. While landlords may use AI to simplify decision-making processes, they often lack the expertise to evaluate the fairness or accuracy of these tools.[43] This creates a legal gray area where developers of discriminatory algorithms can escape liability by framing their products as neutral tools for landlords to use at their discretion. This loophole undermines the goals of the FHA, leaving marginalized groups vulnerable to systemic bias.

The burden of ensuring compliance with fair housing laws has shifted to landlords who lack the resources, knowledge, and incentive to audit these systems.[44] Shifting responsibility limits developer accountability and complicates addressing the root causes of algorithmic discrimination. Without clearer regulations and a framework to hold developers accountable for the outcomes of their AI systems, this gap allows systemic inequities to persist and further disadvantage groups prone to preconceived biases.[45]

IV. SOLUTIONS – LEGISLATION & DATA SCIENCE

Consider a case in which a tenant screening algorithm is designed to predict whether a potential renter will miss payments. The algorithm can take research-backed inputs, including credit scores, rental history, employment status, debt-to-income ratio, past evictions, and social media activity, and process them using transparent machine learning techniques to generate a score. These scores inform landlords whether to accept, reject, or require additional guarantees from applicants. While such algorithms are designed to optimize efficiency and minimize landlord risk, they frequently contain biases embedded in commonly used data sources.

---

[43] Amy Miller, *CoreLogic Can Be Liable for Discrimination Because of AI Tenant Screening Tool, U.S. DOJ seeks to argue in U.S. appeal*, MLex, Oct. 28, 2024, https://www.mlex.com/mlex/articles/2253117/corelogic-can-be-liable-for-discrimination-because-of-ai-tenant-screening-tool-us-doj-seeks-to-argue-in-us-appeal.
[44] Heather Vogel, *Rent Going Up? One Company's Algorithm Could Be Why*, ProPublica, Oct. 15, 2022, https://www.propublica.org/article/yieldstar-rent-increase-realpage-rent.
[45] Jackie Moore, *Race & Housing: Bias in Real Estate*, Twin Cities Habitat for Humanity, Jul. 6, 2021, https://www.tchabitat.org/blog/bias-in-real-estate.

For example, traditional credit scoring systems have been criticized for reflecting systemic racial and economic disparities.[46] If an AI model is trained on historical rental data that disproportionately penalizes minority communities due to redlining practices or economic instability, the model may learn to replicate these biases. Furthermore, deep learning models operate as black boxes, making it difficult for applicants to understand why they were denied housing. Without explicit regulatory intervention, these processes perpetuate housing discrimination under the guise of objectivity.

To mitigate the discriminatory effects of AI in housing, policymakers, industry leaders, and civil rights advocates must push for a regulatory framework that enforces transparency, accountability, and fairness. Mandatory bias audits should be implemented to assess whether AI-driven housing tools disproportionately disadvantage protected groups. Additionally, explainability requirements should be established, ensuring that tenants and loan applicants understand the rationale behind algorithmic decisions. To strengthen enforcement, an independent oversight body–such as a federal AI fairness commission–could be created to regulate housing-related AI applications and investigate claims of algorithmic discrimination. Legal reforms should explicitly extend the FHA and ECOA to cover algorithmic decision-making, closing loopholes that allow AI developers to evade liability. Finally, public and private investment in fair AI research, including developing alternative models that prioritize social equity.

This section serves a dual purpose. First, to refine and modernize anti-discriminatory protections outlined in the FHA and ECOA, enabling them to respond to challenges posed by AI-driven bias, and second, to critically examine the underlying infrastructure of these algorithms. This analysis seeks to bridge the gap between machine learning advancements and legal frameworks, ensuring that updated legislation fosters safer AI practices and promotes transparency in data science techniques. Establishing a fluid and adaptable regulatory standard that supports responsible AI-driven decision-making in high-stakes contexts will ensure protection for minority individuals.

A. Strengthening Liability for AI Bias

The growing body of case law surrounding AI-driven housing discrimination demonstrates the pressing need for legislative intervention. Analysis in sections 1 and 2

---

[46] *The Biased Reality of Credit Scores: A Reflection of Systemic Racism*, Loop, Apr. 20, 2023, https://www.ridewithloop.com/blog/the-biased-reality-of-credit-scores-a-reflection-of-systemic-racism.

shows that current anti-discrimination statutes, including the FHA, fail to comprehensively address the role of AI systems in perpetuating bias. Courts have struggled with assigning liability, shifting responsibility onto landlords rather than holding AI developers accountable for discriminatory outcomes. Legislative reform must explicitly define the liability of AI developers, landlords, and third-party software providers in housing discrimination cases.

One approach is to amend the FHA to include specific provisions addressing algorithmic decision-making. These provisions must clarify that any entity involved in deploying AI screening tools bears responsibility for ensuring the technologies do not produce discriminatory effects. A "shared liability" framework would ensure that anyone involved in the creation and use of the AI (data collectors, programmers, housing estate managers) takes collective responsibility for outcomes that violate existing nondiscrimination practices. This would prevent blame-shifting and ensure all parties involved in AI decision-making are incentivized to prioritize fairness.

Additionally, a federal mandate requiring AI vendors to disclose biased audits could mitigate potential discrimination before it affects housing applicants. A legal requirement for routine fairness testing and transparency in AI models would allow regulators to assess whether certain populations are disproportionately excluded. Furthermore, making biased audit results publicly accessible would allow prospective tenants and civil rights organizations to scrutinize AI-driven housing decisions, fostering greater accountability.

B. Establishing the "FHAIOC"

Congress should establish an independent regulatory body dedicated to AI-design oversight to reinforce legislative reforms. A "Fair Housing AI Oversight Commission" (FHAIOC) should be proposed, serving as a specialized agency responsible for evaluating AI-driven screening tools, investigating claims of algorithmic discrimination, and enforcing compliance with up-to-date anti-discrimination laws. This body would work in tandem with currently established sectors such as the HUD and the CFPB to ensure that AI processes in housing applications do not undermine basic civil rights.[47]

The commission's responsibilities would include certifying that AI models used in tenant screening and mortgage underwriting are non-discriminatory. AI developers

---

[47] *See* U.S. Department of Housing and Urban Development, https://www.hud.gov/.; *See also* Consumer Financial Protection Bureau, https://www.consumerfinance.gov/about-us/the-bureau/.

seeking to deploy models in the housing sector must obtain approval that their algorithms meet non-discrimination standards before being commercially deployed. This regulatory mechanism would be akin to the Food and Drug Administration's (FDA) pharmaceutical approval process, preventing harmful models from entering the market. Just as the FDA requires rigorous testing and trials to deploy a new drug, algorithms used by housing corporations will be audited for specific criteria– bias audits, transparency requirements, and annual risk assessments.

Furthermore, the FHAIOC would have the authority to impose penalties on companies found violating fair housing laws. Financial penalties for corporations, corrective actions to change the algorithm's functionality, and potential bans on non-compliant AI tools would be strong deterrents against discriminatory practices. By establishing a centralized regulatory body with enforcement powers, policymakers will have a proactive approach to AI governance in housing.

Through legislative reforms, policymakers can ensure that AI-driven housing decisions align with the principles of fairness and equal opportunity. As AI continues to shape the housing market, laws must evolve to prevent technological advancements from reinforcing historical discrimination.

C. *Verifying Equitable Data Science*

Ensuring fairness in housing market allocations requires verification of data science methodologies. Current data scientists must work closely with policymakers to develop standardized fairness metrics that measure potential biases within datasets and model outputs. These metrics should assess disparate impact across demographic groups, ensuring no protected class is disproportionately disadvantaged and input data is supervised and intentional.[48]

One approach would be to mandate independent third-party audits of AI models before deployment through a sub-function of the FHAIOC. These audits would examine training data for historical biases, evaluate model performance across populations with different socioeconomic demographics, and recommend adjustments to mitigate potential disparities. Additionally, quarterly transparency reports should be required from AI vendors detailing how their models make decisions and the steps taken to ensure fairness.

[48] Emilio Ferrara, *Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies*, 6 (1) Sci. 3 (2023) (discussing ways to account for natural bias in artificial intelligence).

Another key component is the interpretability of AI systems. Explainable AI (XAI) refers to methods and techniques that make AI model decisions understandable to humans, helping to identify and mitigate biases.[49] XAI techniques are already commonly used in medicine, allowing medical providers to see how the machinery detected a disease.[50] Developers should prioritize XAI techniques that enable stakeholders in the housing market to understand how models generate decisions.[51]

For example, an AI-based tenant screening system could implement SHAP (SHapley Additive exPlanations) values to break down how different factors, such as credit history, income stability, or past rental behavior, contribute to the final risk score assigned to an applicant.[52] SHAP can be used as an extension of XAI, as it contains principles rooted in game theory without making preconceptions about model type. It assigns significance to each variable in the ML model while incorporating how each feature factors into the system.[53] The ability to visualize these weighted contributions, regulators and landlords can assess whether specific variables disproportionately disadvantage certain groups, ensuring greater transparency and fairness in decision-making.

FHAIOC would mandate SHAP-based evaluations across different demographic groups, ensuring that a model's key decision drivers are consistent. If disparities are detected, regulators could recommend modifications or prohibit deployment. Alternatively, to promote transparency, SHAP can be used to generate explanations that allow tenants to understand why they were denied housing. FHAIOC could require landlords and AI vendors to provide SHAP-based explanations upon request, enabling applicants to contest potentially unfair decisions.

Clear documentation and open-source fairness tools facilitate greater trust in AI-driven housing processes while giving individuals the ability to challenge unfair decisions. By institutionalizing fairness audits, transparency reporting, and

[49] *What is Explainable AI (XAI)?*, IBM, Mar. 29, 2023, https://www.ibm.com/think/topics/explainable-ai.

[50] Hui Wen Loh, et al., *Application of Explainable Artificial Intelligence for Healthcare: A Systematic Review of the Last Decade,* 226 Computer Methods and Programs in Biomedicine (2022) (discussing the beneficial use of explainable AI in the medical sector).

[51] Ellen Glover, *What is Explainable AI?*, Built In, Dec. 5, 2024, https://builtin.com/artificial-intelligence/explainable-ai#:~:text=Contrastive%20Explanation%20Method%20(CEM)%20CEM%20is%20used,%E2%80%9Cwhy%20did%20X%20occur%20instead%20of%20Y?%E2%80%9D.

[52] Scott Lundberg, *Welcome to the Sharp Documentation*, SHARP, 2018, https://shap.readthedocs.io/en/latest/.

[53] *Id.*

interpretability measures, policymakers and industry leaders can ensure that data science methods uphold equitable housing practices. These steps will help prevent AI technologies from reinforcing historical discrimination and promote a housing market that is both efficient and just.

CONCLUSION

Regulatory legislation must be updated when new technologies are introduced. As AI becomes increasingly integrated into economic and administrative systems, the influence on human outcomes– particularly in critical sectors– requires scrutiny. The foundation of data science rests on using data to derive insights and predict behaviors, but these outcomes are only as reliable as the data and systems that inform them. With the scope of artificial intelligence spanning further than 20th-century law, legislation must continue to be strengthened.

The use of AI systems, particularly in tenant screening and housing access, has revealed that these tools are not neutral. Outdated civil rights laws like the FHA and ECOA are not equipped to regulate the complex decision-making processes of modern machine learning models. The inconsistency of court rulings widens this gap, as outcomes hinge on the discretion of judges rather than clear, enforceable standards.

Through examining the inapplicability of current law to algorithms used in the housing sector, a rudimentary framework is established for AI algorithm regulation within the "people" sectors. With the burden of proof falling on victims and courts unable to interpret black box models in prior litigation, those involved in the model's deployment must be equally informed and accept the shared risk of responsibility amid legal violations. Ongoing public engagement and transparency initiatives are critical in ensuring that AI-driven housing systems remain accountable. Public reports on AI-related discrimination cases, regulatory actions, and industry compliance trends could inform tenants, policymakers, and advocacy groups about emerging risks and best practices. By fostering a culture of continuous oversight and adaptation, these efforts will help ensure that AI technologies serve as tools for inclusion rather than perpetrators of systemic bias in housing markets.