Artificial Intelligence-Driven Rent Pricing Tools & the Housing Crisis

MCKYNZIE CLARK, AUSTIN NELSON, SANJANA UTIRAMERUR

MCKYNZIE CLARK

Kynzie (she/her) is a researcher and student based in New York City. Eager to understand the growing intersection between technology, law, and networks of care, Kynzie is pursuing a Master of Social Work degree at Columbia University as a Fisher Cummings Fellow. In her studies, she hopes to leverage her experience in advocacy, research, and policy work to advance equity and systems change work. Previously, Kynzie studied political science and Russian language at Yale University. Outside of classes, Kynzie interns at The Bronx Defenders and works with the Center for Intimacy Justice.

AUSTIN NELSON

Austin Nelson (she/her) is a Master of Social Work student at Columbia University with a background in research, community engagement, and data ethics. Her professional experience spans direct service with unhoused populations, trauma-informed youth programming, and nonprofit development. Austin's research interests center on the intersection of technology, equity, and housing justice, drawing from previous work on data ethics in the ICT4D space and gender-based violence interventions. She brings a critical, justice-oriented lens to examining the role of AI in rental markets, with attention to accessibility, bias, and systemic inequality.

SANJANA UTIRAMERUR

Sanjana is an MSW student on the advanced clinical practice track at the School of Social Work. She is passionate about working with diverse populations navigating systemic inequity, particularly in healthcare. In the future, she hopes to attain her LCSW license and provide accessible trauma-informed therapy to marginalized communities.

INSPIRATION

Our interest in the intersection of AI and the housing crisis emerged from my broader focus on social justice and technology. As social work students passionate about policy and ethics, we were struck by how AI tools—often promoted as neutral or innovative—are increasingly shaping access to basic human rights like housing. We were inspired to write this piece after reading about biased tenant screening algorithms and models that reinforce housing discrimination. Researching this topic was both eye-opening and frustrating. There was a wealth of information on AI development, but far less on how these tools impact low-income communities or exacerbate inequality.

ABSTRACT

This policy brief explores the use of artificial intelligence (AI) in rent pricing tools that corporate landlords and property management companies use for rental housing, and its consequences for the housing market. Across the United States, landlords have become increasingly reliant on AI-driven rent pricing tools to raise rents and boost their profits. This technology, which uses both sensitive proprietary data and publicly available information, is reducing housing accessibility, often driving tenants from their homes. As AI becomes increasingly pervasive in our everyday lives, it is essential that we interrogate its uses, especially in those that have as many collateral consequences as housing. We offer an overview of rent regulation history, the underlying AI technology, and existing policy, and make our own policy recommendations.

Keywords: artificial intelligence, housing policy, tenants' rights, data rights, privacy

ARTIFICIAL INTELLIGENCE–DRIVEN RENT PRICING TOOLS AND THE HOUSING CRISIS

Rental housing, like other societal systems, has been increasingly shaped by artificial intelligence (AI) technology in recent years. This shift, however, is not just a technological evolution—it represents a radical departure from traditional rent-setting methods and carries significant implications for privacy and equity. This article argues that artificial intelligence, particularly through rent pricing tools, has adversely affected the already competitive rental housing markets in urban settings by exacerbating discrimination and enabling collusion between landlords. We start by exploring the history of how rental prices have traditionally been set in the United States as well as the evolution of machine learning and AI. Then, we explain how AI-driven rent pricing tools, such as RealPage, affect urban rental housing markets. Finally, we look at policies regulating rental housing, data protection, and AI and offer our own policy recommendations.

I. BACKGROUND

CONTEXT REGARDING RENT IN THE U.S.

Historically, rent-setting in the United States has been shaped by a complex interplay of economic forces, housing regulations, and anti-Black racism. Before the 1930s, homeownership was less common than it is today, with most Americans renting their homes due to high down payments and short loan terms that made buying property difficult (Gordon, 2005). Traditionally, rent-setting was a localized process where individual landlords determined rental prices based on property characteristics and neighborhood demand. The first rent control laws were adopted in the 1920s in response to urbanization, housing shortages, rent increases, and growing tenant advocacy following World War I (Rajasekaran et al., 2019).

During the Great Migration, which spanned most of the twentieth century, millions of African Americans migrated to northern cities in search of economic opportunities and to obtain freedom from oppressive Jim Crow laws in the South. However, these migrants were met with discriminatory housing policies that acted as barriers to wealth accumulation and homeownership. Starting in the 1930s, the Home Owners Loan Corporation created color-coded maps that graded neighborhoods based on their perceived lending risk, which was often directly related to racial demographics (Kaplan & Valls, 2007). Predominantly Black neighborhoods were labeled "hazardous" and outlined in red, and the people living there were systematically denied access to credit, home loans, and mortgage financing. The practice led to the use of the term "redlining," which was institutionalized by the Federal Housing Administration mortgage insurance program. The program made homeownership far more affordable for white families by offering low-down-payment, long-term loans backed by government insurance (Gordon, 2005). As a result of redlining practices, these loans were unavailable to Black families, reinforcing racial segregation and discriminatory housing practices.

Additionally, racially restrictive covenants legally prevented Black families from purchasing or renting homes in white neighborhoods (Coates, 2014). When written into property deeds, these covenants explicitly prohibited sales to nonwhite buyers. Therefore, Black families were forced into overcrowded, deteriorating areas where landlords exploited high demand by charging inflated rent prices.

Redlining and other discriminatory housing policies created the conditions for predatory practices to thrive, further preventing Black homeownership. Contract selling was a deceptive home-buying scheme in which Black families, denied access to traditional mortgages, were forced to purchase homes through high-risk installment contracts. Unlike conventional home loans, these contracts did not grant the buyer equity, and missing even a single payment could result in immediate eviction, allowing the seller to retain the property and all previous payments.

Real estate agents used the tactic of blockbusting—spreading fear that Black families moving into the neighborhood would cause property values to plummet. The tactic drove white homeowners to sell their properties at reduced prices. The agents would then resell these homes to Black buyers at inflated prices, profiting from racial segregation and housing instability (Coates, 2014; Ross, 2008).

Enabled by Federal Housing Administration loans and reinforced by these racist predatory practices, white families conducted "white flight," moving to the suburbs to avoid integration after desegregation mandates. This practice further exacerbated economic and housing disparities. This migration deprived urban centers of crucial tax revenue, leading to deteriorating public services, housing conditions, and schools, all of which primarily impacted Black residents (Dilworth & Gardner, 2019).

The Fair Housing Act (FHA) of 1968, a direct outcome of the Civil Rights Movement, aimed to eliminate discrimination in housing based on race, religion, or national origin. Although this act made redlining illegal, the legacy of redlining continues to shape housing patterns, as Black communities still often face disinvestment, limited access to credit, lower homeownership rates, and high rental costs (Dilworth & Gardner, 2019). Many families of color remain in formerly redlined areas that suffer from underinvestment and gentrification pressures. The current renting population is increasingly diverse, with people of color, young adults, and low-income families making up significant portions (Dilworth & Gardner, 2019).

CONTEXT REGARDING ARTIFICIAL INTELLIGENCE AND DATA

Artificial intelligence refers broadly to inanimate machine operations designed to replicate human cognition. The field of AI is relatively new: The term was only coined in 1956 by Dartmouth College professor John McCarthy, who explored "thinking machines" such as Alan Turing's Enigma (Lawrence Livermore National Laboratory, n.d.). Today, when people refer to AI, they are most often referring to a process known as *machine learning* or a specific type of machine learning called *deep learning*. According to MIT Sloan professor Thomas W. Malone, machine learning has become a critical method that has shaped most AI development for the last ten to fifteen years (Brown, 2021).

The logic behind machine and deep learning is relatively intuitive. Machine learning (ML), simply put, is the process of training a computer program or system to perform tasks without explicit instructions. It uses simplistic structures, such as (but not limited to) decision trees and linear regressions. Deep learning (DL) is more sophisticated and teaches computers to process data in a way that attempts to mimic human neural networks. DL tools require much larger datasets than their ML counterparts and can be used to recognize complex patterns in data across a number of dimensions to make new predictions or insights.

While the complexity DL offers has proved tremendously helpful in a number of applications, it presents problems for others, especially for data containing social factors (such as socioeconomic status, race, gender, or sexuality). All AI algorithms, both ML and DL, are only as good as the data they are trained on, and biased inputs result in biased outputs. The problem of bias has dominated most critiques of AI technology, and fairly so. Examples of "algorithmic bias" that either inadequately represent[1] or even adversely affect people of color[2] are in no short supply. Bias presents an even bigger challenge to DL algorithms. Bias can be deeply embedded within the training data required to make DL algorithms function, and the complexity of DL neural networks makes it extremely difficult to identify, let alone address, instances of bias.

While there are many strategies to try to calibrate algorithms fairly with respect to factors such as race and gender, completely removing bias is not possible (Kleinberg et al., 2017). In his book *The Alignment Problem*, programmer and researcher Brian Christian (2020) has referred to the

1 For example, Google Photos facial recognition has failed to identify Black people as human.

2 For example, the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) algorithm has produced results that disproportionately and negatively affected Black men.

impossibility of achieving perfect fairness as a "brute mathematical fact" for any means of classification, human or machine (p. 70).

HOW DOES AI AFFECT RENTAL HOUSING MARKETS?

So far, we have established two key elements of DL algorithms that will help us explain how AI affects rental markets: 1) They analyze patterns across datasets to make predictions, and 2) they can and will be biased, and that bias is practically impossible to remove.

DL algorithms are mainly used in the rental housing market through AI-driven rent pricing tools. These typically operate by analyzing data from various sources, such as recent rental listings in an area and sales data, to offer market predictions and suggest optimal rent levels to maximize landlord profits. Prima facie, the process mirrors the way that most landlords and property managers determine rental rates *without* AI: They survey the area, consider competitor rates, and calculate other factors that affect what they think is the best rate for them to charge tenants (Vicks, 2024; *Policy Memo: Rent-Setting Software Algorithms*, 2024).

However, upon closer inspection, we find that DL rent pricing tools differ from traditional rent pricing in that:

- They are able to process far higher volumes of data.
- They are accessible to multiple landlords and property managers, leading to pricing collusion.
- They bring an inflated perceived trustworthiness that AI tends to confer.
- They are more prone to hard-to-find bias that disproportionately affects renters of color.

We analyze these issues further using the RealPage/YieldStar rent pricing tool as a case study due to its popularity and impact (Vogell et al., 2022).

REALPAGE AND YIELDSTAR

RealPage is a Texas-based property management software company that provides a technology platform that "enables real estate owners and managers to change how people experience and use rental space" across over 24 million units in North America, Europe, and Asia (RealPage, n.d.). Among the many products RealPage offers is a tool called YieldStar, an "asset optimization system that enables owners and managers to optimize rents to achieve the overall highest yield, or combination of rent and occupancy, at each property" (RealPage, n.d.). YieldStar aggregates both public and proprietary data to set rent prices across entire regions (*Policy Memo: Rent-Setting Software Algorithms,* 2024). This data includes tenants' rent data, credit checks, criminal background information, survey data from landlords and competitors, historical data, and sales transaction data (RealPage, n.d.).

The result has been a sharp and sustained increase in rental costs nationwide, especially in cities like New York, where renters are made to spend upwards of 30% of their total income on rent (Siegel & Bram, 2024). The technology has also emboldened landlords to raise rates higher than they otherwise would. In the words of RealPage executive Andrew Bowen, "I think [AI is] driving [rate increases], quite honestly … As a property manager, very few of us would be willing to actually raise rents double digits within a single month by doing it manually" (Vogell et al., 2022). Without meaningful intervention, these technologies will only deepen existing inequalities, further entrenching a system designed to prioritize profit over people's right to a stable home.

RealPage allows landlords to circumvent price-fixing regulations by enabling them to access data from other landlords and companies without direct cooperation, effectively reducing competition and inflating the housing market. In 2024, the U.S. Department of Justice, in collaboration with eight state attorneys general, filed a civil suit against RealPage for alleged unlawful monopolistic practices that reduce competition among landlords (U.S. Department of Justice, 2024). Moreover, a federal suit in North Carolina accuses the software of violating sections 1 and 2 of the Sherman Anti-Trust Act by monopolizing interstate commerce and restricting competition in the marketplace. This suit is ongoing and has

been amended as of January 7, 2025, to include six apartment landlords as defendants (U.S. Department of Justice, 2025).

II. POLICY LANDSCAPE

RENTAL POLICY

Prior to the introduction of AI pricing tools such as RealPage, landlords determined rent pricing through market analysis and cost considerations, factoring in the economic climate. Traditionally, property managers rely on comparable market analysis, a process that reviews rental prices for similar properties within a given region, to determine competitive rent pricing (Pagourtzi et al., 2003). To ensure profitability, landlords and property managers must consider operational costs such as insurance, mortgage payments, and utilities. These factors, combined with a consideration of current economic conditions such as inflation and employment rates, would be used to set a rental price for each property (Dias & Duarte, 2019).

In the United States, several federal regulations exist to protect against discrimination and monopolistic practices in the housing market. The aforementioned FHA of 1986 prohibits housing discrimination on the basis of sex, race, religion, national origin, disability, or familial status (Fair Housing Act [FHA] 1968/2023). The U.S. Department of Housing and Urban Development (HUD) enforces the FHA and oversees affordability initiatives such as Section 8 vouchers, which assist low-income families seeking affordable housing.

While HUD specifies that AI tools for tenant screening, advertising, and mortgage decisions must comply with the Fair Housing Act, there are no specific federal regulations regarding rent pricing tools. Furthermore, the free housing market is largely protected by the Sherman Anti-Trust Act of 1890, which prohibits price-fixing agreements between competitors, exclusive contracts, and monopolizing a market for products or services (Sherman Anti-Trust Act, 1890). In accordance with this act, landlords and property managers are prohibited from sharing data about their rental units and colluding to inflate rental prices. But as previously mentioned, RealPage has been accused of violating the Sherman Anti-Trust Act by allowing landlords and property managers to access rental data, effectively restricting competition and increasing inflation in rent pricing.

TECH POLICY

Artificial intelligence is relatively new and thus loosely regulated by federal law, leaving the majority of regulations to the state level. Currently, the Federal Trade Commission (FTC) and the National Institute of Standards and Technology (NIST) have issued broad guidelines regarding transparency and consumer protection in AI algorithms (Federal Trade Commission, 2024). Although the NIST provides a suggested framework for transparency and data protection, no comprehensive legislation specifically addresses these concerns (NIST, 2024).

Regarding AI tools in housing, rent pricing tools are loosely regulated through sector-specific policies by HUD and the Federal Housing Finance Agency. However, concerns have risen that AI pricing tools may contribute to discrimination in the housing market by deriving algorithms that rely on historical data and patterns of discrimination against certain ethnic and socioeconomic subgroups. Moreover, the use of artificial intelligence reduces human oversight and creates a lack of transparency on how pricing decisions are made. As consumers across the United States express concern over artificial intelligence, states have begun to introduce legislation around the use of AI tools in housing.

As every state faces unique housing challenges, each state has taken a slightly different approach to regulating AI pricing tools. California is currently facing a housing crisis, as the state has one of the highest median rent and home prices in the nation. As of September 2024, the qualifications for a mortgage on a mid-tier home were more than double the median household income for the previous year (Bentz, 2024). Despite growing concerns, the state has not enacted comprehensive legislation to address AI pricing tools. Currently, the data privacy of California residents is protected by the California Consumer Privacy Act

and the California Privacy Rights Act, both of which restrict data sharing by businesses and grant consumers greater control over personal data collected by AI systems (California Privacy Protection Agency, n.d.). Connecticut and Virginia have enacted similar legislation in an effort to increase transparency and protect consumers' sensitive data.

Although no specific state legislation addresses AI tools in housing, broader civil rights regulations in California prohibit discriminatory practices in housing. For example, both the California Fair Employment and Housing Act and California Government Code Section 12955 prohibit discrimination in housing and employment on the basis of race, color, religion, ancestry, national origin, disability, medical condition, marital status, sexual orientation, sex, or age (Housing discrimination, 1980). While existing legislation is broad, these regulations make it unlawful for AI pricing tools to result in algorithmic discrimination. However, more specific legislation is required to combat price increases that affect the affordability of rent in California.

As of now, Colorado is the only state to enact comprehensive legislation on the development and distribution of artificial intelligence systems: The Colorado Artificial Intelligence Act (CAIA) will become effective February 1, 2026 (Consumer Protections for Artificial Intelligence, 2024). The CAIA targets high-risk artificial intelligence systems in sectors such as education, employment, housing, and healthcare to reinforce standards set by the Fair Housing Act and protect against algorithmic discrimination, defined by unlawful differential treatment that disfavors groups based on protected classifications. The legislation imposes regulations on AI by requiring developers and deployers of high-risk AI systems to use reasonable care in protecting consumers against algorithmic discrimination. For example, developers would be required to provide documentation to deployers on data used to train the system, how it was evaluated, and its intended outputs and use. Furthermore, developers and distributors are required to clearly display the potential risks of algorithmic discrimination on websites for public use. If the AI system presents a risk for algorithmic discrimination, the developer is required to notify the Colorado attorney general within a 90-day period.

These specific limitations on AI systems are designed to combat algorithmic discrimination but do not specifically address antitrust laws or monopolization of the market. AI pricing tools such as RealPage remain in a gray area, where they must adhere to antidiscrimination laws but may still provide enough rental data that landlords and property managers may take advantage of it to manipulate rental prices. This gap in regulation raises concerns over what AI pricing tools may accomplish without stricter oversight.

Furthermore, the current administration has been very vocal about its intentions to continue using and developing AI technologies without “barriers” such as bias prevention or data protections (White House, 2025). The United States also refused to sign the international AI Action Statement at the Paris AI Action Summit earlier this year (Kleinman & McMahon, 2025).

III. POLICY OPTIONS

There are a number of options that U.S. policymakers can and should consider to address issues stemming from AI-driven rent pricing. These options address various regulatory fields involved in the problem, including transparent use of AI, access to personal data, and housing. The three most prominent policy options—strengthening federal oversight of the FHA, introducing AI and data regulation, and adopting rent controls—are outlined in this section.

STRENGTHENING FEDERAL OVERSIGHT OF THE FHA

Instituting a federal mandate stating that landlords and property owners must disclose the use of AI pricing tools and other factors contributing to rent pricing to tenants could ameliorate some of the harmful results of AI-priced housing. With ensured disclosure, renters are presented with enough information to make calculated decisions on whether to utilize AI tools. Additionally, a mandate could create a federal registry of AI systems used in the housing market, requiring developers to submit documentation to demonstrate compliance with antidiscrimination standards set by the FHA (FHA, 1968/2023). Developers and distributors of AI housing tools would be subject to annual audits under the review of HUD. The HUD would then assess potential algorithmic bias, discriminatory outcomes, and data integrity.

One advantage of a federal mandate is that it ensures a consistent national standard for AI tools and alignment with antidiscrimination laws in the housing market. A mandate in addition to a national registry would address gaps in sector-specific federal oversight. However, laws prohibiting algorithmic discrimination and requiring transparency may face lobbying or other pushback from AI developers and stakeholders, and significant federal resources may be needed to implement and enforce the mandate.

AI AND DATA REGULATION

Introducing financial incentives for states to adopt comprehensive legislation similar to CAIA could help address algorithmic discrimination and monopolization of AI pricing tools. In this scheme, federal grants would be provided to states that adopt comprehensive AI legislation. State incentives could encourage tailored solutions to state-specific issues in the housing market. However, without federal oversight, there may be inconsistent regulations and protections across states.

RENT CONTROL

Lastly, the issue of AI rent pricing tools would not exist if not for the state of the U.S. housing and rental market. One possible method for addressing the hypercompetitive nature of rental housing is through rent control and/or antigouging legislation (collectively, “rent regulations”). American cities are more susceptible to AI rent pricing tools because of the lack of policy limitations constraining the range of rent prices landlords can ask for. The U.S. housing market is relatively unregulated as a whole, especially in comparison to many Western European nations. Because AI-driven rent pricing tools encourage landlords to raise rents by higher amounts within shorter time frames, reducing the rate by which a landlord could increase rent would limit the potential impact of the AI recommendations on the rental market.

State interventions in rent controls were quite common in socialist states to maintain the competitiveness of socialist economies on a global scale (Lux et al., 2013). In postsocialist and primarily capitalist economies, state interventions in the rental housing market generally take the form of social housing or private rental-sector regulation. Since World War II, most of these interventions have been to the private rental sector. Some of the strictest systems of state intervention in rental regulations can be found in Sweden and Denmark, where the state regulates rents for all running and newly signed leases (Sardo, 2024, p. 228).

Of course, traditional rent control measures have faced criticism for their inflexibility and for their tendency to disincentivize upkeep and maintenance of units. New York City itself has a long history of rent controls that have been found to be less than successful. Researchers at the Wharton School found that a review of twentieth-century rent control policies revealed they had negative impacts on rental structure quality, especially in smaller prewar-constructed buildings (Gyourko & Linneman, 1990, p. 399). Furthermore, socialized policies often fail to achieve popular support in the U.S., a country whose historic and cultural commitment to the free market is well established.

While rent regulation policies may be difficult to enact at a federal level in the United States, it would be advisable for states or municipalities to adopt a larger role in reviewing lease agreements. Moreover, state governments may consider a liberalization of private rent contracts in combination with rental regulation and tenant protections. This would address the volatility of the rental market, collusion concerns, and ostensibly concerns over abuse of private data. Even requiring landlords to justify changes in rent would increase transparency in the rental

market and could discourage opaque decision-making methods such as those fostered by rent pricing algorithms.

IV. CONCLUSION AND RECOMMENDATIONS

Addressing the impacts of AI-driven rent-setting tools, such as RealPage, requires a strategy that balances ambition with practicality, combining strengthened federal oversight, state-level incentives, and well-designed rent control measures.

Federal oversight would provide a critical foundation, setting consistent nationwide standards in data protection and aligning AI systems with the existing Fair Housing Act. Requiring transparency, establishing a registry of AI tools, and conducting regular HUD audits could create accountability and curb the negative effects of rent pricing tools. For this reason, and a host of other AI-based challenges we continue to face, it is more important than ever to develop a comprehensive policy framework addressing the use of AI and data privacy rights borrowing from the strong precedents set by the EU in the General Data Protection Regulation (GDPR), Digital Services Act (DSA), and AI Act. However, achieving comprehensive federal legislation may face steep political challenges, so it is necessary to supplement these efforts with policies that can be implemented more readily at the state and local levels.

State incentives offer a pragmatic way to drive meaningful change while respecting the unique challenges of local housing markets. By providing grants to states that adopt comprehensive AI legislation, like Colorado's Artificial Intelligence Act, the federal government could empower states to innovate while remaining aligned with broader national goals. This approach allows for regionally tailored solutions that can be implemented without waiting for federal consensus, creating a framework where states lead the way in testing and refining policies to address algorithmic discrimination and monopolistic practices in the housing sector.

Rent control measures round out this strategy by directly addressing the immediate harms of AI-driven rent increases. These policies, which cap excessive rent hikes and require landlords to justify significant increases, protect tenants while remaining adaptable to local conditions. Paired with complementary tools like housing vouchers and incentives for affordable housing development, they provide stability in the rental market and safeguard vulnerable populations.

Together, federal oversight, state-level innovation, and rent regulations form a cohesive and actionable plan to address both the systemic and immediate challenges posed by AI-driven housing systems. These approaches, both individually and collectively, would increase housing equity and decrease exploitative data practices.

Overall, localized rent control measures provide the best first step toward addressing long-standing systemic inequities in the rental housing market *and* preventing AI-driven rent pricing tools from exacerbating these inequities in the market. The recently severely reduced size of the federal government as well as polarized views about the extent to which AI should be regulated (if at all) play heavily into this recommendation. Since rent controls have historically correlated with decreased quality of rental units, they should be introduced alongside stronger landlord accountability measures or increased enforcement of housing court decisions where rental habitability can be disputed.

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