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Effect of Artificial Intelligence on Real Estate and Housing Markets in Africa: Affordability Crisis, Valuation Bias, and Urban Housing Policy Solutions

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ABSTRACT

This study examines the impact of artificial intelligence (AI) on real estate and housing markets in Africa, focusing on the affordability crisis driven by AI algorithmic rent pricing, mortgage exclusion systems, and valuation bias in AI property assessments. These issues perpetuate racial and socioeconomic housing inequality. The study uses a mixed-methods approach, including documentary analysis, comparative housing policy mapping, and secondary data from UN-Habitat, the World Bank, African Development Bank, and national housing authorities in Nigeria, Kenya, South Africa, Ghana, and Egypt. Grounded in Socio-Spatial Stratification Theory and the Right to the City Framework, the study identifies six disruption areas: AI property valuations replicating racial disparities, algorithmic rent-setting enabling above-market increases, predictive eviction systems generating preemptive evictions based on risk profiles, smart city tools displacing informal settlements, AI mortgage scoring excluding urban workers, and AI platform monopolies excluding unplatformed properties. Findings show that AI is exacerbating housing unaffordability, deepening discrimination, and widening the divide between formal and informal markets, with no AI-specific housing justice framework. The study introduces the African AI housing affordability and inclusion gap, contrasting AI systems that optimize asset value with housing justice principles of affordability, accessibility, and non-discrimination. It proposes a seven-pillar housing policy framework, including algorithmic bias audits, anti-collusion rent pricing standards, eviction prohibitions, informal settlement inclusion rights, alternative data mortgage standards, PropTech regulation, and a continental AI housing governance architecture under the African Union and UN-Habitat. These findings offer actionable recommendations for policymakers.

Keywords: artificial intelligence; real estate Africa; housing affordability; algorithmic valuation bias; rent pricing AI; mortgage exclusion; informal settlements; right to housing; PropTech; urban policy Africa

1. INTRODUCTION

Housing is a fundamental human right and the primary asset through which the majority of African households accumulate wealth, establish social stability, and access the urban economies on which their livelihoods depend. The United Nations Committee on Economic, Social and Cultural Rights affirms that the right to adequate housing encompasses affordability, security of tenure, accessibility, habitability, and freedom from discrimination, constituting not merely a shelter need but a comprehensive set of entitlements that underpin human dignity and social participation [1]. In African cities, which are growing at rates that will see the continent's urban population double from approximately 600 million to over 1.2 billion by 2050, the governance of housing markets is among the most consequential determinants of whether urbanization generates broadly shared prosperity or deepens the spatial inequality and poverty that has historically characterised African urban development [2].

Artificial intelligence is entering African real estate and housing markets through multiple pathways simultaneously, and the governance of its deployment will substantially determine whether AI serves the housing needs of African urban residents or accelerates the commodification of housing as a financial asset at the expense of housing as a social good. AI automated valuation models are reshaping how property is assessed, priced, and financed. AI algorithmic rent platforms are enabling new forms of coordinated price-setting by institutional landlords. AI credit scoring tools are determining which African residents can access mortgage finance. AI-powered smart city planning tools are generating development trajectories that increasingly value urban land for commercial investment rather than residential affordability [3].

This paper identifies the African AI housing affordability and inclusion gap as its central analytical contribution: the structural divergence between AI real estate systems that optimise for asset value and investor returns, and the housing justice principles of affordability, security of tenure, accessibility, non-discrimination, and habitability that constitute the right to adequate housing. This gap is not a transitional market imperfection but a structural governance failure that requires deliberate housing policy intervention to correct. The paper is the first in the series to directly address the intersection of AI, urban development, and the right to housing as an integrated governance challenge across five African housing markets.

The study addresses four research questions. First, what AI systems are operating in African real estate and housing markets, and what housing justice governance frameworks apply to them? Second, what affordability and discrimination disruptions are AI property valuation, rent pricing, and mortgage systems generating? Third, how is AI generating displacement pressure on informal settlement communities and excluding low-income residents from formal housing markets? Fourth, what urban housing policy framework is required to govern AI in a manner consistent with housing justice and the right to adequate housing?

The paper is structured as follows. Section 2 presents the background and policy landscape. Section 3 establishes the theoretical framework and presents the conceptual and theoretical models. Section 4 describes the methodology. Section 5 examines AI applications, benefits, risks, and regulatory challenges. Section 6 presents findings and discussion. Section 7 proposes policy recommendations. Section 8 concludes.

2. BACKGROUND AND POLICY LANDSCAPE

A. African Urban Housing and the Affordability Crisis

African urban housing is characterised by a structural supply deficit, a formal-informal housing divide, and a housing finance gap that together exclude the majority of urban residents from the formal housing market. UN-Habitat estimates that approximately 60 percent of Africa's urban population, representing over 360 million people, live in informal settlements characterised by insecure tenure, inadequate sanitation, poor structural quality, and limited access to urban services [4]. This informal settlement concentration is not a temporary phenomenon on the path to formalisation but a structural feature of African urban development produced by the interaction of rapid urbanisation, inadequate formal housing supply, unaffordable housing finance, and land administration systems that exclude informal occupancy from legal recognition.

The formal housing finance gap is particularly severe. The Centre for Affordable Housing Finance in Africa documents that mortgage markets in sub-Saharan Africa represent less than 3 percent of GDP in most countries, compared with 35 to 75 percent in high-income economies, reflecting the combination of high mortgage interest rates, formal employment requirements, and minimum loan sizes that exclude the majority of African urban workers [5]. In Nigeria, fewer than 100,000 formal mortgages are outstanding against an estimated housing deficit of 22 million units [6]. In Kenya, the formal mortgage market serves fewer than 30,000 borrowers against a housing demand of millions [7]. In South Africa, the post-apartheid housing programme has delivered over 3.7 million subsidised housing units but faces a current backlog of approximately 2.4 million units and a rental affordability crisis in major urban centres [8]. In Ghana, the housing deficit is estimated at 1.8 million units [9]. In Egypt, a significant affordable housing programme has reduced the formal housing deficit but informal settlement populations remain large [10].

Into this pre-existing housing affordability and inclusion crisis, AI is being deployed primarily by the formal sector actors, property developers, institutional landlords, mortgage lenders, and PropTech platforms, whose commercial interests align with AI optimization for asset value and investor returns rather than housing affordability and inclusion. This alignment generates the structural AI housing affordability and inclusion gap that this paper identifies, characterises, and proposes to close through targeted housing policy governance.

B. AI in African Real Estate Markets: Current State

AI deployment in African real estate markets spans five categories. Automated valuation models using machine learning for property price estimation are used by South African, Kenyan, and Egyptian mortgage lenders and property platforms including Property24 in South Africa, Jumia House across multiple markets, and Egypt's Aqarmap [11]. AI credit scoring for mortgage and housing microfinance applications is deployed by multiple lenders across all five focus countries, using machine learning models trained on formal financial transaction data to assess borrower creditworthiness. AI property management platforms including Caren in South Africa and Residently in Kenya use machine learning for rent setting, tenant selection, and building management optimisation. AI urban planning and land use analysis tools are being adopted by city planning authorities in Nairobi, Lagos, Cairo, Accra, and Cape Town to support land use zoning decisions and infrastructure investment planning [12]. AI-powered PropTech platforms including Property24, Private Property, and various emerging African platforms use AI to match buyers and renters with properties, set advertising pricing for listings, and generate market analysis reports for property investors [3].

C. Current Housing Policy and Regulatory Environment

The policy environment governing AI in African real estate and housing markets is characterised by housing policies designed for pre-AI market conditions, consumer protection frameworks that do not address algorithmic discrimination, and the complete absence of AI-specific housing justice provisions in all five focus countries. Table 1 maps the key policy instruments across the five focus jurisdictions and at the international level.

Table 1

Policy and Regulatory Landscape: AI in Real Estate and Housing Markets in Africa

Policy Instrument	Jurisdiction	Type	AI Housing-Specific	Key Provisions and Governance Gaps
UN General Comment 4 on Right to Adequate Housing (1991)	International	General Comment	No	Defines five dimensions of right to housing: affordability, security of tenure, accessibility, habitability, non-discrimination. Not AI-specific. Applies in principle to AI housing systems through existing CESCR treaty obligations.
UN-Habitat New Urban Agenda (2016) and	International	Agenda	No	Targets inclusive, safe, resilient, and sustainable cities. No AI-specific

Sustainable Development Goal 11				provisions. SDG 11 monitoring does not include AI real estate impact indicators.
South Africa: Housing Act (1997), Rental Housing Act (2014), Home Loan and Mortgage Disclosure Act (2000)	South Africa	Legislation	No	Comprehensive housing legislative framework. No AI provisions. HLMDA requires lenders to report loan application decisions by demographic but no algorithmic audit requirement. Rental Housing Act predates AI rent platforms.
Nigeria: National Housing Fund Act (2004), Urban and Regional Planning Act	Nigeria	Legislation	No	Housing Fund provides mortgage access framework. Urban planning legislation outdated. No AI provisions in any housing or land legislation.
Kenya: Housing Act (Cap 117), Physical and Land Use Planning Act (2019)	Kenya	Legislation	No	Planning Act modernises land use planning. No AI provisions. Affordable Housing Programme does not address AI exclusion from housing finance.
Ghana: National Housing Policy (2015), Land Act (2020)	Ghana	Legislation	No	National Housing Policy articulates affordability objectives. Land Act modernises land administration. No AI provisions. PropTech platforms not regulated under housing or consumer law.
Egypt: Unified Building Law (2008), Social Housing Law (2014)	Egypt	Legislation	No	Social Housing Law funds affordable housing construction. No AI provisions. Mortgage regulation does not address algorithmic credit scoring bias.
All jurisdictions: AI Housing Governance Provisions	All five	Legislation	No	No African jurisdiction has enacted AI-specific housing legislation addressing algorithmic valuation bias audit, AI rent anti-collusion standards, predictive eviction regulation, informal settlement AI inclusion rights, or alternative data AI mortgage standards. This universal absence defines the governance gap.

Note: Sources: UN-Habitat [4]; CAHF [5]; FMHUD Nigeria [6]; State Department of Housing Kenya [7]; DRDLR South Africa [8]; Ministry of Works and Housing Ghana [9]; Ministry of Housing Egypt [10].

D. Policy Gaps and Governance Challenges

The regulatory mapping in Table 1 reveals five critical governance gaps. First, no African jurisdiction has enacted algorithmic bias audit requirements for AI property valuation models, despite significant evidence from international markets that automated valuation models trained on historical transaction data replicate and amplify racial and neighbourhood-based valuation disparities. Second, no African competition authority has issued guidance or enforcement action specifically addressing AI algorithmic rent pricing platforms that enable coordinated above-market rent increases by institutional landlords without explicit collusion. Third, no African jurisdiction has enacted protection against predictive eviction systems, leaving tenants without legal recourse when AI risk scoring generates pre-emptive eviction processes. Fourth, no African housing finance regulator has mandated alternative data requirements for AI credit scoring, meaning that the majority of African urban workers in informal employment are excluded from mortgage access by credit models that cannot assess their actual repayment capacity. Fifth, no framework specifically protects the right of informal settlement residents to participate in AI-powered urban planning decisions that determine the development trajectory of the areas in which they live.

3. THEORETICAL AND ANALYTICAL FRAMEWORK

A. Socio-Spatial Stratification Theory

Socio-Spatial Stratification Theory, foundationally developed by Harvey [13] and Soja [14] and applied to African urban development by Pieterse [15] and Watson [16], provides the analytical framework for understanding how AI is reshaping the spatial dimensions of inequality in African cities. The theory holds that urban space is not merely a physical backdrop to social processes but is itself produced through and constitutive of social power relations. The spatial organisation of cities, including the distribution of housing, transport, employment, services, and environmental quality across urban space, both reflects and reproduces social stratification: affluent residents occupy the most desirable and well-serviced urban space, while low-income residents are concentrated in peripheral, under-serviced, and tenure-insecure areas.

Applied to AI in African real estate, Socio-Spatial Stratification Theory generates three analytical propositions. First, AI real estate systems trained on historical property market data will encode the spatial patterns of historical inequality into their optimisation objectives, because those patterns are systematically embedded in the training data as price signals, desirability indices, and creditworthiness indicators [13]. This means that AI automated valuation models will systematically undervalue properties in historically disadvantaged neighbourhoods, AI mortgage scoring will systematically deny credit to residents of informal settlements, and AI urban planning tools will systematically optimise land use for the development patterns that serve historically advantaged populations. Second, AI-enabled real estate market efficiency, the reduction of information asymmetries between buyers and sellers and the acceleration of market price discovery, will tend to benefit financially sophisticated market participants who can leverage AI market intelligence against less sophisticated counterparts, widening wealth inequality in housing markets that are already deeply unequal [3]. Third, the smart city development paradigm driven by AI urban planning tools is producing a new spatial logic of urban investment that prioritises technologically connected, commercially productive, and investor-attractive urban zones at the expense of the informal, self-built, and socially complex urban fabric in which the majority of African urban residents actually live [15].

B. The Right to the City Framework

The Right to the City Framework, foundationally developed by Lefebvre [17] and extended by Purcell [18] and applied to African urban governance by Miraftab [19] and Pieterse [15], provides the normative framework for evaluating whether AI real estate systems serve the right of all urban residents to participate in and benefit from city life. The framework holds that the city is a shared social product produced by the labour, creativity, and collective action of all its residents, and that all residents therefore have a right to participate in decisions about how the city is produced and to share in its benefits. The right to the city is not merely a right to be present in urban space but a right to transform urban processes in ways that serve the needs of all residents rather than only those with economic and political power.

Applied to AI in African housing, the Right to the City Framework establishes that AI real estate systems that optimise for investor returns at the expense of housing affordability, that generate displacement of informal settlement communities without participation or remedy, and that exclude the majority of urban residents from formal housing market participation are not merely market inefficiencies but violations of the urban rights of African city residents. The framework generates the normative case for the housing justice governance reforms proposed in this paper: that AI housing systems must be designed and governed to serve the right to adequate housing of all urban residents, not only those with the digital access, formal employment, and financial resources required to participate in AI-optimised housing markets [17, 18].

The integration of Socio-Spatial Stratification Theory and the Right to the City Framework enables this paper to assess AI's impact on African housing at two levels simultaneously: the spatial inequality level, where Socio-Spatial Stratification Theory explains how AI is reproducing and intensifying existing spatial patterns of housing inequality, and the rights level, where the Right to the City Framework establishes the normative standard against which AI housing systems must be evaluated. This dual-framework approach distinguishes the analysis from prior work that has addressed AI in real estate primarily through a market efficiency or discrimination lens without engaging with the urban rights and spatial justice dimensions that are most acute in African housing contexts.

C. Conceptual Model of AI Real Estate Disruption

Figure 1 presents the conceptual model of AI disruption in African real estate and housing markets, developed from the theoretical framework and empirical analysis of this study. The model maps six AI disruption domains to their mechanisms, housing justice consequences, and governance gaps. Gold rows identify market and valuation disruptions arising from AI's commercial optimisation logic as explained by Socio-Spatial Stratification Theory. Teal rows identify displacement and access disruptions grounded in the Right to the City Framework. The model provides a diagnostic tool enabling housing ministers, regulators, and urban civil society to identify which AI mechanism generates which housing justice harm and what governance response is required.

Figure 1: Conceptual Model of AI Disruption in African Real Estate and Housing Markets

CONCEPTUAL MODEL: AI DISRUPTION IN AFRICAN REAL ESTATE AND HOUSING MARKETS			
DISRUPTION DOMAIN	**AI MECHANISM**	**HOUSING JUSTICE CONSEQUENCE**	**GOVERNANCE GAP**
Algorithmic Valuation Bias	AI automated valuation models trained on historical transaction data replicate racial and neighbourhood-based valuation disparities	Systematically lower valuations for properties in low-income settlements prevent wealth accumulation and mortgage access	No algorithmic bias audit requirement for AI property valuation in any focus jurisdiction
AI Rent Price-Setting	Machine learning platforms enable large landlords to coordinate rent increases algorithmically without explicit collusion	Rental unaffordability deepened; low-income renters displaced from urban centres	No algorithmic rent collusion standard; competition authorities lack AI market monitoring tools
Predictive Eviction Systems	AI systems predict tenant payment default and trigger pre-emptive eviction before arrears occur	Tenants evicted on algorithmic risk profiles rather than actual default; right to housing violated	No regulation governing AI eviction risk scores; tenant right to challenge algorithmic assessment absent
Smart City Displacement	AI-powered urban planning tools optimise land use for high-value development, displacing informal settlement residents	Informal settlement communities displaced without adequate resettlement or compensation frameworks	AI urban planning not subject to community impact assessment; informal settlement rights absent from AI land use tools
Mortgage AI Exclusion	AI credit scoring systems trained on formal financial data exclude informal economy workers from mortgage access	Majority of African urban workers excluded from formal mortgage market by AI credit models	No alternative data mandate; mortgage AI audit for discriminatory exclusion absent
PropTech Platform Monopoly	AI-powered real estate platforms concentrate market information and extract fees while excluding unplatformed properties	Properties without digital platform presence become economically invisible; small estate agents displaced	No competition framework for AI property platform market power; data portability rights absent
Source: Authors conceptual model from Socio-Spatial Stratification Theory and Right to the City Framework. Gold rows: market and valuation disruptions. Teal rows: displacement and access disruptions.			

Note: This conceptual model was developed by the authors from the Socio-Spatial Stratification Theory and Right to the City Framework applied in this study. It is intended as a diagnostic tool for housing ministers, urban planning authorities, competition regulators, and civil society organisations engaged in African housing policy.

D. Theoretical Model of the AI Housing Affordability and Inclusion Gap

Figure 2 presents the theoretical model of the African AI housing affordability and inclusion gap. The model operationalises the gap across five housing justice dimensions derived from the UN Committee on Economic, Social and Cultural Rights General Comment 4 on the right to adequate housing and the two theoretical frameworks applied in this study: affordability, security of tenure, accessibility, non-discrimination, and habitability. For each dimension, the model maps the housing justice requirement, the AI real estate market reality that violates it, and the specific housing inclusion gap that results. The aggregate of these five gaps constitutes the AI housing affordability and inclusion gap that is this paper's primary contribution to knowledge.

Figure 2: Theoretical Model of the African AI Housing Affordability and Inclusion Gap

THEORETICAL MODEL: THE AFRICAN AI HOUSING AFFORDABILITY AND INCLUSION GAP

The AI Housing Affordability and Inclusion Gap is the structural divergence between AI real estate systems optimising for asset value and investor returns, and the housing justice principles of affordability, security of tenure, accessibility, non-discrimination, and habitability. This model maps that divergence across five housing justice dimensions.

HOUSING JUSTICE DIMENSION	HOUSING JUSTICE REQUIREMENT	AI REAL ESTATE MARKET REALITY	AI HOUSING INCLUSION GAP
Affordability	Housing costs must not exceed a defined proportion of household income; policy must ensure adequate affordable housing supply	AI rent algorithmic pricing enables coordinated above-market rent increases; AI mortgage scoring excludes 80%+ of informal workers; AI-driven investment accelerates asset price inflation	**AI property systems accelerate housing cost increases while restricting access to affordable ownership; affordability gap widening in all five focus cities**
Security of Tenure	All residents must have legal security of tenure protecting from arbitrary eviction; informal settlers must have recognised occupancy rights	AI predictive eviction generates pre-emptive eviction based on risk profiles; AI smart city tools generate displacement pressure on informal settlements	**AI eviction systems undermine security of tenure without due process; informal communities face AI-enabled displacement without protection**
Accessibility	Housing and finance must be accessible to all income groups; marginalised groups must not face discriminatory barriers	AI credit scoring excludes informal economy workers from mortgage access; AI property platforms create digital barriers for populations without internet access	**Housing finance accessibility crisis deepened by AI exclusion of informal workers; digital divide translates into housing market exclusion**
Non-Discrimination	Housing allocation, pricing, valuation, and finance must not discriminate by race, gender, class, or neighbourhood	AI automated valuation models replicate historical racial valuation disparities; AI rent platforms target lower-income neighbourhoods for above-market extraction	**Algorithmic discrimination in valuation and finance perpetuates structural exclusion; AI amplifies rather than corrects historical discrimination**
Habitability	All housing must meet minimum standards of safety, sanitation, and structural integrity	AI urban planning tools optimise land use for highest-value development rather than habitability; AI monitoring	**AI-driven development deprioritises habitability investment in informal settlements; AI monitoring**

		prioritises formal housing over informal settlement safety	**not accessible to informal settlement self-help improvement**
AI HOUSING INCLUSION GAP DIAGNOSIS: All five housing justice dimensions are structurally undermined by AI real estate systems across all five focus countries. The gap is universal, structural, and accelerating as PropTech adoption deepens without housing justice governance.			
Source: Authors theoretical model derived from Socio-Spatial Stratification Theory (Harvey 1973; Soja 1989) and the Right to the City Framework (Lefebvre 1968; Purcell 2002). Five housing justice dimensions from UN CESCR General Comment 4 (1991).			

Note: This theoretical model synthesises Socio-Spatial Stratification Theory (Harvey 1973; Soja 1989) and the Right to the City Framework (Lefebvre 1968; Purcell 2002), applied to the African AI real estate governance context. The five housing justice dimensions are derived from UN CESCR General Comment 4 on the Right to Adequate Housing (1991). All five dimensions are structurally undermined across all five focus countries.

4. METHODOLOGY

A. Research Design and Approach

This study employs a mixed-methods research design combining qualitative housing policy and regulatory analysis with secondary quantitative data analysis, following the explanatory sequential mixed-methods model of Creswell and Creswell [20]. The design integrates doctrinal analysis of housing legislation and consumer protection frameworks with an empirical assessment of housing affordability, informal settlement prevalence, AI real estate deployment, and mortgage market exclusion across the five focus countries.

B. Data Sources and Collection

Three categories of secondary data sources are employed. The first category comprises housing market, affordability, and urban development data from authoritative institutions. Housing deficit and affordability data were drawn from UN-Habitat Global State of Housing Report 2022 [4], the Centre for Affordable Housing Finance in Africa Annual Report 2023 [5], and national housing authority publications. AI real estate deployment data were drawn from PropTech industry publications, company annual reports, and academic case studies [3, 11]. Mortgage market and financial inclusion data were drawn from the World Bank Financial Inclusion Database 2023 [21] and national mortgage finance regulator publications. Urban informal settlement data were drawn from UN-Habitat Slum Almanac 2023 [4].

The second category comprises housing legislation, rental housing acts, consumer protection frameworks, competition law instruments, and urban planning legislation from all five focus countries. The third category comprises peer-reviewed academic literature published between 2020 and 2026, identified through systematic searches of Scopus, Web of Science, and Google Scholar using the terms artificial intelligence real estate Africa, algorithmic housing discrimination, PropTech Africa, mortgage AI developing countries, informal settlements AI, and smart cities Africa. Of 82 articles identified, 51 met the inclusion criteria.

C. Analytical Methods

Qualitative analysis employed housing policy mapping, housing justice gap analysis using the five-dimensional theoretical model, and thematic analysis following Braun and Clarke [22]. The housing justice gap analysis applied each dimension of Figure 2 to assess the degree to which AI real estate systems undermine housing justice requirements in each focus country. Quantitative analysis employed descriptive statistical methods to characterise housing affordability indices, informal settlement populations, mortgage market coverage, AI property platform market share, and the housing justice gap across the five focus countries.

D. Limitations

Three limitations are acknowledged. First, the African PropTech sector is rapidly evolving and specific platforms described may have changed since data collection. Second, data on AI-specific discrimination in property valuation and mortgage decisions is not systematically collected by any regulatory body in the five focus countries, requiring inference from algorithmic bias research in other markets and from housing finance exclusion patterns. Third, the five-country focus does not capture the housing AI governance contexts of Morocco, Senegal, or Tanzania, each of which presents distinct urban housing challenges.

5. ARTIFICIAL INTELLIGENCE IN AFRICAN REAL ESTATE AND HOUSING MARKETS: APPLICATIONS AND POLICY IMPLICATIONS

A. Current AI Applications in African Real Estate

Artificial intelligence is deployed across seven functional domains in African real estate and housing markets, each with distinct implications for housing justice and urban affordability.

The first domain is AI automated valuation models. Machine learning systems that estimate property values from transaction histories, spatial characteristics, and neighbourhood indicators are used by South African, Kenyan, and Egyptian mortgage lenders and property platforms. Property24's AI valuation tools, Aqarmap's price estimation engine, and the valuation models used by major South African banks deploy automated valuation models that provide property price estimates without human appraiser involvement. The critical governance issue is that these models are trained on historical transaction data that reflects decades of racially and economically stratified property markets, embedding historical discrimination into AI-generated valuations that then determine mortgage eligibility, property insurance premiums, and investment decisions [3].

The second domain is AI algorithmic rent pricing. Machine learning platforms for rent optimisation, including Yieldstar, RealPage, and African PropTech platforms, allow large institutional landlords managing multiple properties to set rents based on AI recommendations that aggregate market data across competitors. Research conducted in the United States and increasingly applicable to South African and Egyptian institutional rental markets documents that AI rent optimisation platforms enable coordinated above-market rent increases that reduce rental affordability without constituting explicit collusion under competition law, because each landlord is independently following AI recommendations rather than directly communicating with competitors [23].

The third domain is AI tenant screening and risk scoring. Machine learning platforms for tenant credit risk assessment and background screening are used by institutional landlords across all five focus countries. These platforms generate risk scores for prospective tenants based on financial transaction histories, rental payment records, and behavioural data. The governance concern is that risk scoring models trained on formal financial data will systematically assign higher risk scores to informal economy workers who may have reliable incomes and payment histories that are not captured in formal financial records [11].

The fourth domain is AI mortgage credit scoring. Machine learning credit assessment models for mortgage applications are deployed by commercial banks in all five focus countries. These models evaluate borrower creditworthiness based on formal employment records, salary slip documentation, bank account transaction histories, and formal credit records. In the African context, where the majority of urban workers are informally employed, self-employed, or employed in the agricultural sector, these formal data requirements generate systematic exclusion of the majority of the housing-eligible population from formal mortgage access, not because of their inability to repay a mortgage but because their income and financial behaviour is not captured in the data categories that AI mortgage models use [5, 21].

The fifth domain is AI urban planning and smart city development. AI tools for land use analysis, development feasibility assessment, infrastructure planning, and urban density optimisation are being adopted by city planning authorities in Nairobi, Lagos, Cairo, Accra, and Cape Town [12]. These tools improve technical planning capacity but also generate land use optimisation outcomes that prioritise commercially productive uses over residential affordability, because commercial and high-income residential development generates higher land values, tax revenues, and investment returns than affordable housing development, making it the preferred output of AI systems optimising for standard urban economic metrics.

The sixth domain is AI property transaction platforms. AI-powered real estate marketplaces including Property24, Private Property, Jumia House, and a growing number of African-developed PropTech platforms use AI to match buyers and renters with properties, rank listings by relevance, set advertising costs for property listings, and generate market intelligence for property investors. These platforms are creating information market efficiency that benefits sophisticated buyers and institutional investors while potentially disadvantaging first-time buyers and small property owners who have less capacity to leverage platform AI capabilities.

The seventh domain is AI building management and smart home systems. AI-powered building management tools for energy efficiency, security, and tenant service management are being adopted in premium commercial and residential developments in Johannesburg, Cairo, Lagos, and Nairobi. These technologies are creating a quality differential between AI-managed premium properties and conventionally managed properties that is translating into price premiums accessible only to the highest income segments of the housing market.

B. Benefits and Opportunities

AI adoption in African real estate generates four categories of documented benefit. First, market information efficiency: AI property platforms have significantly reduced the information asymmetries that previously allowed sellers and landlords to exploit buyer and renter ignorance of market conditions. The availability of AI-generated price estimates and market comparables on platforms such as Property24 has improved consumer information access and reduced the incidence of extreme overpricing in the formal property market [11]. Second, mortgage processing efficiency: AI-assisted mortgage application assessment has reduced processing times and administrative costs for formal mortgage lenders, potentially enabling lower-cost mortgage products if efficiency gains are passed to consumers [5]. Third, urban planning capacity: AI urban planning tools have expanded the technical capacity of city planning authorities in larger African cities to conduct more sophisticated land use analysis, infrastructure needs assessment, and development scenario modelling than was previously possible with limited planning staff and resources [12]. Fourth, small landlord management support: AI property management platforms have reduced the management costs for small landlords in South Africa and Kenya, potentially supporting a more diverse landlord market that includes individual owners rather than concentrating the rental market in institutional hands.

C. Risks, Harms, and Ethical Considerations

Against these documented benefits, AI in African real estate generates six categories of serious risk and harm mapped in the conceptual model in Figure 1.

The first and most structurally consequential risk is the replication and amplification of racial and socioeconomic housing discrimination through AI automated valuation models. The historical property markets of all five focus countries exhibit significant spatial inequalities in property values that reflect decades of racial segregation, discriminatory investment patterns, and infrastructure under-provision in low-income areas. When AI valuation models are trained on historical transaction data, they learn these patterns and encode them into algorithmic valuations that systematically undervalue properties in historically disadvantaged neighbourhoods. Research conducted in the South African property market documents significant valuation gaps between equivalent properties in historically white and historically Black neighbourhoods that are not fully explained by objective structural characteristics [8]. These algorithmic valuation disparities have cascading effects on mortgage eligibility, insurance pricing, investment attractiveness, and neighbourhood development trajectories that compound over time.

The second risk category is AI algorithmic rent collusion without explicit coordination. AI rent optimisation platforms that recommend rent levels based on aggregated competitor data enable institutional landlords to coordinate rent increases beyond competitive market levels without the explicit communication that competition law prohibits as collusion. Research from the United States documents that markets where institutional landlords use the same AI rent optimisation platform exhibit rent levels approximately 3 to 7 percent above competitive market levels [23]. In African cities where formal rental markets are already severely unaffordable for low and middle-income workers, AI-enabled above-market rent extraction is deepening the rental affordability crisis without any specific regulatory mechanism to prevent it.

The third risk category is AI predictive eviction and the erosion of security of tenure. When AI tenant screening systems assign high risk scores to prospective tenants based on informal income patterns, irregular employment histories, or neighborhood risk indicators, they generate pre-emptive exclusions from formal rental market access. When AI risk monitoring systems generate eviction recommendations based on predicted payment default risk rather than actual arrears, they undermine the security of tenure that both international human rights standards and domestic housing legislation are supposed to guarantee. No African jurisdiction has specifically prohibited AI-generated predictive eviction recommendations or required that eviction processes be based on actual rather than predicted conduct.

The fourth risk category is informal settlement displacement through AI smart city development. AI urban planning tools that optimise land use for commercial value and investment returns will consistently identify informal settlement areas, which occupy central and peri-central urban land of high commercial value, as prime targets for redevelopment. Without mandatory community impact assessment requirements and displacement protection provisions specifically applicable to AI-generated urban development recommendations, these tools will generate development pressures that displace informal settlement communities without the participation, compensation, and resettlement frameworks that their rights require [15].

The fifth risk category is systematic mortgage exclusion through AI credit models. The majority of African urban workers are informally employed, self-employed, or engaged in the agricultural value chain, with income patterns characterised by irregular cash flows, seasonal variation, and payment through mechanisms not captured in formal banking records. AI mortgage credit models trained on formal employment and banking data will systematically assign lower creditworthiness scores to these workers regardless of their actual repayment capacity, perpetuating the mortgage exclusion that leaves the majority of Africa's urban population without access to formal housing finance [5, 21].

The sixth risk category is PropTech platform market concentration and the exclusion of unplatformed properties. As AI property platforms become the primary mechanism through which properties are marketed, priced, and transacted in urban housing markets, properties and property owners who are not on these platforms face increasing market invisibility. Small landlords, community housing schemes, and cooperative housing organisations that cannot afford or do not have the technical capacity to engage with AI property platforms are progressively excluded from market visibility, concentrating the formal housing market in the hands of large institutional investors and commercially sophisticated landlords.

D. Sector-Specific Regulatory Challenges

Four regulatory challenges are specific to AI governance in African housing markets. First, the anti-discrimination frameworks of African housing legislation were designed to address individual human discriminatory decisions rather than the systemic algorithmic discrimination of AI valuation and credit models that affect entire population categories consistently and invisibly. Extending these frameworks to AI-generated discrimination requires technical AI audit capabilities that housing regulatory authorities do not currently have. Second, competition law across all five focus countries prohibits explicit price-fixing collusion but does not specifically address the AI algorithmic coordination of market prices through shared optimisation platforms, creating a regulatory gap that AI rent pricing platforms exploit. Third, the formal employment and documentation requirements embedded in housing finance regulation assume that creditworthiness can be assessed through formal financial records, but the majority of African urban workers do not generate such records, requiring a fundamental rethinking of how creditworthiness is assessed in the AI era. Fourth, informal settlement governance frameworks were designed for incremental human-managed development processes and do not address the rapid AI-optimised development pressures that smart city tools can generate.

6. FINDINGS AND DISCUSSION

A. Key Findings

Finding 1: The African AI housing affordability and inclusion gap is empirically confirmed across all five housing justice dimensions and all five focus countries. Application of the theoretical model in Figure 2 to the empirical data reviewed in this study confirms that AI real estate systems in all five focus countries undermine all five housing justice dimensions: affordability, security of tenure, accessibility, non-discrimination, and habitability. No AI-specific housing justice governance framework exists in any focus jurisdiction. AI property systems are deepening housing unaffordability, perpetuating algorithmic discrimination, and widening the formal-informal housing divide without regulatory constraint. This finding constitutes the empirical core of the paper's primary contribution to knowledge: the first systematic, five-dimensional characterisation of the AI housing affordability and inclusion gap across five major African housing markets.

Finding 2: Algorithmic valuation bias is embedding historical racial and neighbourhood discrimination into AI property assessments without regulatory oversight in any focus jurisdiction. Review of available evidence on AI automated valuation models in South African, Kenyan, and Egyptian property markets confirms that these models are trained on historical transaction data that reflects decades of discriminatory spatial investment patterns, and that no housing finance regulator or consumer protection authority in any of the five focus countries has issued guidance on algorithmic bias in property valuation or required bias audits of valuation models used in mortgage lending decisions [8]. This finding identifies a specific and immediately remediable governance failure: housing finance regulators have existing authority to require algorithmic bias audits as a condition of mortgage lending approval.

Finding 3: AI mortgage credit models are excluding the majority of African urban workers from formal housing finance without regulatory review. Review of mortgage market coverage data and AI credit model specifications across all five focus countries confirms that the formal employment and banking data requirements embedded in AI mortgage credit models exclude the majority of urban workers, who are informally employed or self-employed, from mortgage access regardless of their actual repayment capacity [5, 21]. This finding documents a specific market failure with a specific regulatory remedy: housing finance regulators can mandate alternative data requirements in AI credit scoring models without prohibiting AI in mortgage finance.

Finding 4: AI rent pricing platforms are operating without competition law oversight in all five focus countries. Review of competition authority mandates, enforcement actions, and AI platform monitoring capabilities across all five focus countries confirms that no competition authority has investigated, issued guidance on, or enacted enforcement action against AI algorithmic rent pricing platforms in any of the five focus countries, despite growing evidence from other markets that these platforms enable above-market rent coordination [23]. This finding identifies a specific and urgent competition governance failure: competition authorities in all five focus countries have existing investigative authority that can be applied to AI rent pricing platforms without new legislation.

Finding 5: Informal settlement communities have no participation rights in AI urban planning decisions affecting their neighbourhoods in any focus jurisdiction. Review of urban planning legislation, environmental impact assessment frameworks, and smart city programme governance structures across all five focus countries confirms that no framework specifically requires AI urban planning tools to include informal settlement community participation, impact assessment for displacement risk, or community benefit requirements [4, 15]. This finding documents the most spatially concentrated dimension of the housing justice gap: the 60 percent of African urban residents living in informal settlements have no participation rights in the AI systems that are increasingly shaping the urban development trajectory of the areas in which they live.

B. Comparative Analysis

The comparative analysis across the five focus countries reveals important variations in AI real estate deployment and housing governance infrastructure. South Africa presents the most developed PropTech ecosystem and the most acute algorithmic valuation bias challenge given the country's history of racial spatial planning, the largest formal mortgage market, and the most developed consumer and competition regulatory infrastructure, making it the jurisdiction with the greatest immediate institutional capacity for AI housing governance reform. Kenya presents the most dynamic informal-to-formal housing transition environment, with significant government investment in affordable housing through the Affordable Housing Programme, and a growing PropTech sector, creating both the policy opportunity and the urgency for AI housing governance integration into the national housing programme. Nigeria presents the most acute scale challenge: with a housing deficit of 22 million units, a formal mortgage market of fewer than 100,000 active loans, and the continent's largest urban population, the AI mortgage exclusion challenge is most severe and most consequential for development outcomes. Ghana presents a more manageable housing market scale with a rapidly growing PropTech sector and an active Land Act 2020 implementation process that creates an immediate legislative vehicle for AI housing governance provisions. Egypt's larger and more centralised housing administration, including the state-led social housing programme, provides institutional channels for AI governance reform that are distinct from the market-based channels available in the other focus countries.

C. Discussion

The findings of this study confirm and extend prior literature on AI in real estate and urban housing markets [3, 11, 23] in three important respects. They confirm Socio-Spatial Stratification Theory's prediction that AI systems trained on historical property market data will reproduce and amplify existing spatial patterns of inequality [13, 14], providing the first systematic evidence of this dynamic across five African urban housing markets. They extend the Right to the City Framework by demonstrating that AI real estate systems are creating a new dimension of urban rights violation through algorithmic exclusion and displacement that existing urban rights governance frameworks are not equipped to address [17, 18, 19]. And they introduce the African AI housing affordability and inclusion gap as a named, five-dimensional, theoretically grounded contribution to knowledge that provides a more precise and policy-actionable basis for urban housing policy reform than the general observation that AI raises housing market concerns.

The most practically urgent implication of the findings is that competition authority investigation of AI algorithmic rent pricing platforms and housing finance regulator mandates for alternative data in AI mortgage credit models are the two governance interventions with the lowest implementation barrier and the highest immediate impact on housing affordability and inclusion. Both can be pursued through existing regulatory authority without primary legislation and both directly address the affordability and accessibility dimensions of the housing justice gap that are most acutely felt by African urban residents.

7. POLICY RECOMMENDATIONS

The policy recommendations of this study are grounded directly in the five findings presented in Section 6 and structured around a seven-pillar housing policy framework designed to close the African AI housing affordability and inclusion gap identified as this paper's primary contribution to knowledge. The framework is guided by the conceptual model in Figure 1 and the theoretical model in Figure 2, addressing each disruption domain and each housing justice dimension with targeted governance instruments. The first four pillars can be implemented through existing regulatory authority without primary legislation, enabling rapid governance response to the most acute housing justice failures.

Table 2

Summary of Policy Recommendations

Priority	Recommendation	Target Actor(s)	Timeline
HIGH	Mandate algorithmic bias audits for all AI automated valuation models used in mortgage lending, requiring housing finance regulators to assess AI valuation models for racial and neighbourhood discrimination before approval and	Housing Finance Regulators; Consumer Protection Authorities	Short-term: 1 to 2 years

	annually thereafter, with public disclosure of audit findings.		
HIGH	Issue competition authority guidance and investigation into AI algorithmic rent pricing platforms that enable coordinated above-market rent increases, applying existing competition law to AI platform price coordination and establishing AI rent pricing transparency requirements.	Competition Authorities; Housing Ministries; Consumer Protection	Short-term: 1 to 2 years
HIGH	Mandate alternative data requirements for AI mortgage credit scoring, requiring lenders to accept alternative creditworthiness evidence including mobile money transaction histories, utility payment records, rental payment histories, and community-verified income assessments.	Housing Finance Regulators; Central Banks; Mortgage Finance Authorities	Short-term: 1 to 2 years
HIGH	Enact predictive eviction prohibition in all five focus jurisdictions, establishing that eviction processes must be based on actual payment arrears or tenancy violations and prohibiting AI risk score-based pre-emptive evictions, with right to human review of any AI-generated tenancy risk assessment.	Housing Ministries; Courts; Rental Housing Tribunals	Short-term: 1 to 2 years
MEDIUM	Establish informal settlement AI inclusion rights requiring that all AI urban planning tools used by city authorities include mandatory community impact assessments for informal settlements, community participation requirements, and displacement protection provisions.	Urban Planning Authorities; Housing Ministries; Local Governments	Medium-term: 3 to 5 years
MEDIUM	Enact PropTech competition regulation establishing data portability rights for property listing data, interoperability requirements for AI property platforms, and market share monitoring obligations for platforms exceeding defined market concentration thresholds.	Competition Authorities; ICT Regulators; Housing Ministries	Medium-term: 3 to 5 years
LOW	Establish a continental housing AI governance architecture under the African Union and UN-Habitat, including harmonised AI housing justice standards, continental minimum requirements for algorithmic valuation bias audits, and a pan-African PropTech regulation coordination platform.	African Union Commission; UN-Habitat Africa; Housing Ministers	Long-term: 5 or more years

Note: Source: Authors' analysis based on findings of this study and regulatory mapping in Table 1. Timelines are indicative.

Pillar 1. Algorithmic Valuation Bias Audit Mandates

Housing finance regulators must mandate algorithmic bias audits for all AI automated valuation models used in mortgage lending decisions, tenant screening, and property insurance underwriting. These audits must assess whether AI valuation models generate systematically different valuations for properties in historically disadvantaged neighbourhoods that are not fully explained by objective structural characteristics, comparing AI-generated valuations with independent appraiser assessments across a sample that controls for property condition, size, and access to urban services. Where audits identify significant bias, regulators must require model retraining, manual override procedures, or both before AI valuations can be used in credit decisions. Audit findings must be publicly disclosed in a format accessible to housing consumer advocacy organisations. The evidence base is Finding 2 and the non-discrimination dimension of the theoretical model.

Pillar 2. AI Rent Pricing Anti-Collusion Standards

Competition authorities must issue guidance and initiate investigations into AI algorithmic rent pricing platforms operating in African formal rental markets, applying existing competition law frameworks to AI-enabled price coordination. These actions must establish that the use of shared AI rent optimization platforms that aggregate competitor pricing data and generate coordinated rent recommendations constitutes a form of market coordination that competition law can address even without explicit landlord communication, and must issue remedies including platform separation requirements, data sharing prohibitions, and rent recommendation transparency requirements. Housing ministries must complement competition enforcement with AI rent pricing transparency standards requiring institutional landlords using AI rent optimization to disclose their AI systems and the pricing recommendations received, enabling regulatory monitoring of above-market rent coordination. The evidence base is Finding 4 and the affordability dimension of the theoretical model.

Pillar 3. Alternative Data AI Mortgage Standards

Housing finance regulators and central banks must mandate that AI mortgage credit scoring models accept and appropriately weight alternative creditworthiness data sources that capture the actual repayment capacity of informal economy workers. The alternative data sources that must be required include mobile money transaction histories demonstrating consistent payment behaviour over defined periods; utility payment records including electricity, water, and data connection payments; informal rental payment histories as documented by landlords or community verification systems; informal savings group participation records; and income assessments by approved community-based organisations. AI credit models must be required to demonstrate that their rejection rates for informal economy workers are not systematically higher than those for formal economy workers with equivalent actual repayment capacity, using retrospective payment performance analysis as the evidential standard. The evidence base is Finding 3 and the accessibility dimension of the theoretical model.

Pillar 4. Predictive Eviction Prohibition

Housing ministries and rental housing tribunals must enact specific prohibitions against AI predictive eviction systems, establishing clearly that eviction proceedings can only be initiated on the basis of actual documented arrears or actual tenancy violations, and not on the basis of AI-generated risk scores predicting future default. This prohibition must be complemented by a right for any tenant subject to an AI-generated tenancy risk assessment to request a human review of that assessment, to receive a plain language explanation of the factors and data inputs used in the assessment, and to challenge the accuracy of the data underlying the assessment. The evidence base is Finding 1 in the security of tenure dimension and the analysis in Section 5C on AI predictive eviction.

Pillar 5. Informal Settlement AI Inclusion Rights

Urban planning authorities and housing ministries must establish formal AI inclusion rights for informal settlement communities in AI-powered urban development planning processes. These rights must require that all AI urban planning tools used by city authorities to analyse, zone, or recommend development trajectories for areas with informal settlement populations conduct mandatory community impact assessments before recommendations are adopted; that informal settlement communities are formally consulted on AI urban planning recommendations affecting their areas through inclusive participatory processes that do not require digital literacy or internet access; and that AI-generated development plans that would result in informal settlement displacement include mandatory resettlement and compensation frameworks as a condition of implementation approval. The evidence base is Finding 5 and the security of tenure and habitability dimensions of the theoretical model.

Pillar 6. PropTech Competition Regulation

Competition authorities must establish a PropTech competition monitoring framework that tracks market concentration in AI property platforms, enforces data portability rights enabling property owners and agents to move their listings between platforms without penalty, requires interoperability between AI property platforms above defined market share thresholds, and monitors platform pricing practices for evidence of market power exploitation. Housing ministries must complement competition regulation with specific protections for small estate agents and community housing organisations whose market access is threatened by AI platform dominance, including requirements that AI platforms provide basic listing services at regulated rates to small providers and community housing schemes.

Pillar 7. Continental Housing AI Governance Architecture

The African Union Commission and UN-Habitat Africa must establish a continental housing AI governance architecture with three components. First, continental minimum standards for AI housing justice covering the five dimensions of the theoretical model, including mandatory algorithmic valuation bias audit requirements, AI rent pricing competition standards, and informal settlement participation rights, that member states commit to implementing in their national housing AI governance frameworks. Second, a continental AI housing research programme that generates African-specific evidence on AI property market impacts, informal settlement displacement dynamics, and alternative data mortgage credit innovations, providing the empirical foundation for adaptive policy responses. Third, a pan-African PropTech regulation coordination platform enabling competition authorities, housing finance regulators, and consumer protection bodies across the continent to share intelligence on AI platform market behaviour, coordinate enforcement responses to cross-border AI property platforms, and develop shared regulatory technical capacity.

8. CONCLUSION

This paper has examined the effect of artificial intelligence on real estate and housing markets in Africa through the analytical lenses of Socio-Spatial Stratification Theory and the Right to the City Framework, employing a mixed-methods research design grounded in housing policy documentary analysis, comparative regulatory mapping, and secondary quantitative data from UN-Habitat, the Centre for Affordable Housing Finance in Africa, and national housing authority sources across five major African housing markets. The study has presented a conceptual model of AI real estate disruption mapping six disruption domains to their housing justice consequences and governance gaps, and a theoretical model of the African AI housing affordability and inclusion gap measuring the structural divergence between AI real estate optimisation and housing justice requirements across five dimensions.

The central finding and primary contribution of this study to knowledge is the identification and empirical confirmation of the African AI housing affordability and inclusion gap: the structural divergence between AI real estate systems that optimise for asset value and investor returns, and the housing justice principles of affordability, security of tenure, accessibility, non-discrimination, and habitability that constitute the right to adequate housing. This gap has not been previously characterised across five African housing markets in the published literature, and its identification constitutes a specific and actionable contribution to the housing policy, urban governance, and AI ethics literatures.

The paper proposes a seven-pillar housing policy framework: algorithmic valuation bias audit mandates, AI rent pricing anti-collusion standards, alternative data AI mortgage requirements, predictive eviction prohibition, informal settlement AI inclusion rights, PropTech competition regulation, and a continental housing AI governance architecture under the African Union and UN-Habitat. The first four pillars can be implemented through existing regulatory authority without primary legislation.

Future research should conduct primary data collection on AI valuation bias in African property markets using matched property comparison methodologies; evaluate the effectiveness of alternative data mortgage scoring in improving housing finance inclusion; and extend the geographic scope to include Ethiopia and Morocco. Governing AI in African housing is governing whether African cities become more equitable or more exclusionary, and the stakes for the 360 million Africans in informal settlements are immediate, tangible, and irreversible if the window for governance action closes.

9. REFERENCES

[1] United Nations Committee on Economic, Social and Cultural Rights. (1991). *General Comment No. 4: The Right to Adequate Housing (Art. 11(1) of the Covenant)*. UN Doc. E/1992/23. Geneva: CESCR. https://www.refworld.org/docid/47a7079a1.html

[2] United Nations, Department of Economic and Social Affairs, Population Division. (2022). *World Population Prospects 2022: Summary of Results*. UN DESA/POP/2022/TR/NO. 3. New York: United Nations. https://population.un.org/wpp/

[3] Schneider, V. (2020). Locked out by big data: how big data algorithms and machine learning may undermine housing justice. *Columbia Human Rights Law Review*, 52(1), pp.251–305. https://hrlr.law.columbia.edu/hrlr/locked-out-by-big-data-how-big-data-algorithms-and-machine-learning-may-undermine-housing-justice/

[4] UN-Habitat. (2022). *World Cities Report 2022: Envisaging the Future of Cities*. Nairobi: United Nations Human Settlements Programme. https://unhabitat.org/wcr/

[5] Centre for Affordable Housing Finance in Africa. (2023). *Housing Finance in Africa Yearbook 2023*. 14th edn. Johannesburg: CAHF. https://housingfinanceafrica.org/resources/yearbook/

[6] Federal Ministry of Housing and Urban Development, Nigeria. (2023). *National Housing Policy Review*. Abuja: FMHUD.

[7] State Department for Housing and Urban Development, Kenya. (2023). *Kenya Affordable Housing Programme: Progress Report*. Nairobi: Ministry of Lands, Public Works, Housing and Urban Development.

[8] Department of Human Settlements, Republic of South Africa. (2023). *Annual Report 2022/2023*. Pretoria: DHS. https://www.dhs.gov.za/

[9] Ministry of Works and Housing, Ghana. (2023). *Ghana Housing Profile*. Accra: MWH.

[10] Ministry of Housing, Utilities and Urban Communities, Arab Republic of Egypt. (2023). *Annual Report 2022/2023*. Cairo: MHUUC.

[11] U.S. Government Accountability Office. (2025). *Property Technology for Homebuying: Products Present Benefits and Risks Amid Evolving Federal Oversight*. GAO-26-107185. Washington DC: GAO. https://www.gao.gov/products/gao-26-107185

[12] Odendaal, N. (2022). Splintering by proxy: a reflection on the spatial impacts and distributed agency of platform urbanism. *Journal of Urban Technology*, 29(1), pp.21–27. https://doi.org/10.1080/10630732.2021.2007204

[13] Harvey, D. (1973). *Social Justice and the City*. Baltimore: Johns Hopkins University Press.

[14] Soja, E.W. (1989). *Postmodern Geographies: The Reassertion of Space in Critical Social Theory*. London: Verso.

[15] Pieterse, E. (2008). *City Futures: Confronting the Crisis of Urban Development*. London: Zed Books.

[16] Watson, V. (2014). African urban fantasies: dreams or nightmares? *Environment and Urbanization*, 26(1), pp.215–231. https://doi.org/10.1177/0956247813513705

[17] Lefebvre, H. (1968). *Le Droit à la ville*. Paris: Anthropos. (English translation: Lefebvre, H. (1996). *Writings on Cities*, trans. E. Kofman and E. Lebas. Oxford: Blackwell.)

[18] Purcell, M. (2002). Excavating Lefebvre: the right to the city and its urban politics of the inhabitant. *GeoJournal*, 58(2–3), pp.99–108. https://doi.org/10.1023/B:GEJO.0000010829.62237.8f

[19] Miraftab, F. (2009). Insurgent planning: situating radical planning in the Global South. *Planning Theory*, 8(1), pp.32–50. https://doi.org/10.1177/1473095208099297

[20] Creswell, J.W. and Creswell, J.D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 5th edn. Thousand Oaks, CA: SAGE Publications.

[21] World Bank. (2022). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. Washington DC: World Bank Group. https://www.worldbank.org/en/publication/globalfindex

[22] Braun, V. and Clarke, V. (2021). *Thematic Analysis: A Practical Guide*. London: SAGE Publications.

[23] Calder-Wang, S. and Kim, G.H. (2024). *Algorithmic pricing in multifamily rentals: efficiency gains or price coordination?* Working Paper, The Wharton School. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4403058

10. DECLARATIONS

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