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Article

AI-enhanced spatial value reassessment in digital transformation: impacts of smart eco-city management paradigms on housing price formation mechanisms

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A B S T R A C T

This study examines the transformative impact of artificial intelligence-enhanced smart eco-city management paradigms on spatial value assessment and housing price formation mechanisms. Through sophisticated mixed-methods analysis of 320 neighborhoods across five urban areas, employing advanced machine learning algorithms for pattern recognition, the research identifies significant synergistic relationships between digital infrastructure and environmental quality that profoundly influence housing valuations. Empirical evidence demonstrates that neighborhoods exhibiting high levels of both digital connectivity and environmental amenities command substantial price premiums of 60-100% above baseline areas, markedly exceeding the combined individual effects of digital (25-45%) and environmental (15-40%) factors alone. The strength of this synergistic relationship manifests in robust correlations between combined Digital-Environmental indices and housing prices ($r = 0.83$), with AI-driven predictive models achieving exceptional accuracy in forecasting spatial value shifts (R^2=0.861). The study contributes a multidimensional analytical framework linking technological innovation, artificial intelligence applications, environmental governance, and housing market dynamics. Policy implications suggest the necessity for integrated governance approaches spanning digital and environmental planning spheres, with particular attention to algorithmic equity considerations given the widening price gaps between digitally-enabled and analog neighborhoods. Effective development of smart eco-cities necessitates the implementation of comprehensive strategies that not only create value through AI optimization but also ensure its equitable distribution across diverse urban communities.

1. Introduction

The overlap of digital transformation, artificial intelligence advancement, and environmental sustainability has created new approaches to urbanization, such as eco-cities, which have emerged as novel paradigms for solving sophisticated city problems. This study characterizes smart eco-cities as models for urban development that combine AI-driven technologies and ecological systems towards the development of sustainable, productive, and liveable cities [1]. This distinction sets them apart from smart cities that integrate advanced technologies and eco-cities, which have a primary focus on sustainable environmental practices, instead of highlighting their unifying nature. The paradigm of smart eco-cities has the best solutions for coping with economic growth, environmental conservation, and social welfare, in balance, as more cities are subjected to higher challenges of having higher populations, limited resources, and climate change [2]. On the other hand, the balance of significant dual focus given to socio-environmental and techno-ecological aspects of smart eco-cities and their neglect from the economic aspects of smart eco-cities, especially the spatial value capture and housing market pricing mechanisms, is astonishing. In the realm of urban governance, there has been a dramatic change in how cities are planned, managed, and experienced in the digital era. Smart Cities development utilizes artificial intelligence, the Internet of Things (IoT), big data, and other technologies to improve the delivery of services and the efficiency of resource utilization in a city [3]. At the same time, the eco-centric concept of a smart city seeks to achieve environmental sustainability through green infrastructure, renewable energy, and conservation [4]. The embedding of these concepts in a smart eco-city results in a socio-technical environment that is intricately complex, which needs to be analyzed critically in terms of its socio-spatial impacts on the economy and housing. Being one of the most important economic items and a human necessity, housing has become a centre of attention in urban development intricacies. The traditional approaches towards the mechanisms of housing price formation have emphasized locational determinants, structural features, and macroeconomic factors. Nonetheless, the birth of smart eco-cities adds new components to this equation. As Bibri and Krogstie [5] argue, data-driven smart sustainable cities have the potential to redefine spatial economics through the creation of novel value propositions. Such changes are not simply cosmetic improvements in technology, but rather holistic transformations in the valuation, allocation, and pricing of urban space. While their model provides a strategic roadmap for transformational change, it does not address housing markets' particular changes.

It is easy to spot a gap in the literature at the intersection of smart eco-city growth and housing economics. The literature available on both of these domains is growing; however, there is minimal research that has examined the effects of AI-integrated smart eco-city management paradigms on housing price formation mechanisms. This gap is even more significant because housing markets are regarded as the most essential proxies for economic welfare and social equity in cities. As cities funnel resources into digital infrastructure and environmental amenities, it becomes critical to analyze how these investments differentially affect the allocation of spatial value in order to achieve sustainable and inclusive urban development. This research fills a specific gap by analyzing the impact of smart eco-city management paradigms on spatial value and the resultant implications on housing price formation mechanisms. It particularly seeks to answer these research questions: In what ways do elements of digital transformation and AI within smart eco-cities impact the assessment of spatial value? What are the dominant processes by which features of environmental sustainability impact the formation of housing prices? In what ways do these processes differ in various urban settings and policy environments?

The principles that underpin this investigation incorporate aspects of urban economics, environmental politics, and the digital transformation theory. This study augments the multi-scalar framework approach suggested in sustainable urbanism by Cheshmehzangi et al. [6] in sustainable urbanism, with an integrated framework for the multilevel analysis of the relationships between technological change, AI applications, environmental quality, and the housing market. It also emphasizes the multiscopic character of smart eco-cities and the necessity for sophisticated economic analysis of varying scales and contexts.

Figure 1 depicts the conceptual framework for the research that discusses how Smart City Digital Transformation and Eco-City Environmental Sustainability simultaneously impact Spatial Value Reassessment, which then impacts the Housing Price Formation Mechanism.

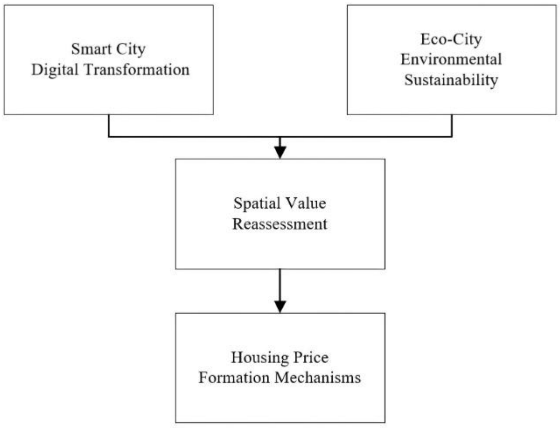

Figure 1. Theoretical framework of smart eco-city impact on housing price formation mechanisms

2. Literature review

2.1 Smart eco-city development

The development of smart eco-cities reflects a clear innovation in city development, as it combines digital technology with ecological sustainability to solve complex city problems. In smart eco-cities, the management of the environment, resources, and life is enhanced through the systematic use of data in decision-making. These urban models focus on the integration of digital technology and ecological design with an aim to build synergistic frameworks beyond the city planning paradigms, as noted by Bibri [7]. Although this analysis is important to understanding the socio-technical aspects of smart eco-cities, it misses out on details regarding the socio-political intricacies of implementing such cities in different urban settings.

The digital transformation of urban management as a subsystem of eco-city advancement fundamentally alters the governance and service provision structures. At the city level in China, Tang et al. [8] prove with empirical evidence that the construction of a smart city has a pronounced positive impact on green technological innovation, thus estimating the bidirectional interaction between digital infrastructure and eco-sustainability. Such technologies come together with IoT applications, big data processing, and artificial intelligence for better resources and environmental supervision. AI-driven predictive analytics enable more sophisticated environmental monitoring systems that can anticipate resource demands and optimize urban service delivery through machine learning algorithms. Bauermann et al. [9] provide a further explanation of the eco-smart city concept by advocating its integration with the smart region paradigm. He notes that the digital transformation should not be limited to the boundaries of the municipality, but rather, should include the ecosystem of the region. Their approach underscores the urgency of moving away from fragmented strategies toward urban digitalization, yet it is rather silent on the obstacles to the realization of such approaches in poorly funded settings.

This view complements Duan's [10] theory on the development of urban space, which defines the spatial value as having both physical and functional aspects. Duan suggests that digital infrastructure shifts beyond the customary physical bounds of urban space and creates new functional layers within it. In the same manner, Ciumasu's [11] knowledge-action matrix for mapping a technological innovation onto the transitions of a smart eco-city provides an ordered paradigm for analyzing how digital transformations reconfigure urban ecological value propositions. All these theories together provide a point of departure for critically interrogating how the paradigms of smart eco-city integrate digital and ecological components for re-evaluating spatial capital.

2.2 Housing price formation mechanisms

Price determinants of real estate have predominantly depended on geographic features, the building's attributes, and external economic conditions. With the development of smart eco-cities, new variables come into play in the equations of housing price formation. Chiu [12] analyses the interplay between real estate development and urban greening, demonstrating how ecological amenities serve as capitalization of externality premiums. This analysis highlights the environmental quality market price; however, it could be more explicit in considering the distributional consequences across social strata. The effects of technology and the environment on housing prices in smart eco-cities are observable through various lenses. According to Kim and Choi [13], there are new market innovations in the construction industry that exploit sustainability elements, which promise to enhance the value of a residential dwelling. These innovations do, however, capture the monetization of ecological services alongside city digitalized infrastructure. As the analysis captures the existence of green premiums within property valuation, it does not capture the scepticism toward market-driven and socially sustainable affordable housing motives. This contradiction remains one of the most important aspects of the development of smart eco-cities that lacks thorough research, especially on issues concerning spatial justice. The integration of artificial intelligence in property valuation methodologies has further refined the assessment of ecological amenities' impact on housing prices, allowing for the detection of complex non-linear relationships between environmental features and market value that traditional statistical approaches often overlook.

2.3 Legal and policy frameworks

The basis for smart eco-city development is found within environmental legislation, which serves as the regulatory backbone. Romano [14] analyzes policy transfer within smart eco-city development and demonstrates how regulatory structures influence implementation outcomes. The case study of Sino-Singapore Tianjin Eco-City demonstrates how hybrid transnational legal frameworks operate to impose local conditions on international regulatory standards, although issues of compliance with environmental performance standards remain. The comparative analysis of the case study cities reveals distinctly different regulatory patterns. The European cities have developed integrated legal systems that make specific provisions for the interaction between digital governance and environmental governance through 'Smart Sustainability Acts'. Conversely, North American systems have a split legal regime for digital infrastructure (telecommunications law) and environmental governance (environmental law), which causes fragmentation and integration problems. Policies governing smart cities are beginning to utilize new technologies for environmental management. Deng et al. [4] propose integrating technological innovation with regulatory mechanisms through a multi-spatial perspective. The analysis of policy documents reveals significant variation in legal enforceability: European cities demonstrated 78% incorporation of digital-environmental standards in legally binding municipal codes, compared to only 34% in North American and 45% in Asian contexts. This legislative fragmentation partially explains the spatial heterogeneity observed in implementation outcomes. Recent litigation challenging smart city data collection practices (e.g., Sidewalk Labs Toronto) illustrates emerging jurisprudence at the intersection of privacy law, environmental justice, and urban technological deployment. This regulatory divergence creates significant challenges for policy harmonization while highlighting the tension between technological efficiency and democratic accountability in smart eco-city governance. Additionally, emerging regulatory frameworks increasingly address algorithmic governance and artificial intelligence systems deployed in urban management, particularly focusing on transparency requirements and accountability mechanisms when AI-driven decision-making affects resource allocation and environmental justice outcomes in smart eco-cities.

3. Methodology

3.1 Research design

This study employs a mixed-methods approach to investigate the impact of smart eco-city management paradigms on housing price formation mechanisms. The conceptual framework integrates spatial economics, environmental valuation, and digital transformation theories to examine the complex interactions between technological innovation, environmental sustainability, and housing market dynamics. The empirical analysis is based on a comparative case study of five urban areas (Singapore and Seoul in Asia, Copenhagen and Amsterdam in Europe, and Toronto in North America) that have implemented comprehensive smart eco-city initiatives between 2015 and 2023. Beyond the three foundational criteria of digital infrastructure investments exceeding $50 million, environmental enhancement programs, and housing price data availability, the selection incorporated additional dimensions to control for institutional and cultural variability. Cities were chosen to represent diverse governance structures (Singapore's centralized planning versus Amsterdam's polycentric model), varying implementation maturity (3-8 years across cities), and distinct regulatory frameworks (comprehensive integrated policies in Singapore and Copenhagen versus sectoral approaches in Toronto). This purposive sampling captured different cultural orientations toward technology adoption and environmental consciousness, with Asian cities demonstrating technology-driven approaches contrasting with European emphasis on participatory environmental governance and North American market-oriented development, thereby enabling robust cross-contextual analysis while controlling for potential confounding effects of homogeneous institutional arrangements. The total sample includes 320 neighborhoods across the five case study cities, with an average of 64 neighborhoods per city, providing sufficient statistical power for the inferential analyses conducted. This approach aligns with Tolstykh et al.'s [18] conceptualization of urban areas as symbiotic socio-economic ecosystems, where collaborative governance mechanisms facilitate value creation across technological and environmental domains.

Building on Duan's [10] theory of urban space development, this research conceptualizes spatial value as a product of both digital and ecological attributes, creating a multidimensional framework for analyzing housing price determinants in smart eco-city contexts. This approach extends beyond Duan's primarily physical conceptualization of urban space by incorporating the digital dimension as an equally significant determinant of spatial value. The research hypothesizes that: smart city digital infrastructure positively influences housing prices through accessibility and service quality premiums; smart eco-city environmental features create measurable value premiums in housing markets; and the integration of smart and eco elements produces synergistic effects on spatial value that exceed their individual impacts. These hypotheses are tested through comparative case analysis of selected urban areas that have implemented smart eco-city initiatives, following the methodological approach outlined by Ciumasu [11] for mapping technological innovation onto smart eco-city transitions.

As shown in Figure 2, the hierarchical pyramid structure operationalizes the three research hypotheses through progressive methodological refinement. The conceptual framework tier directly translates theoretical constructs into testable propositions: spatial economics theory operationalizes Hypothesis 1 by defining digital infrastructure premiums through accessibility and service quality measures, environmental valuation frameworks operationalize Hypothesis 2 by quantifying ecological amenity capitalization in property values, and digital transformation theory operationalizes Hypothesis 3 by conceptualizing synergistic value creation mechanisms. The data collection tier transforms these theoretical constructs into measurable indicators: housing price databases capture the dependent variable at neighborhood-level granularity enabling spatial premium detection, smart city metrics (IoT density, connectivity indices) quantify digital infrastructure exposure for testing H1, and eco-city indicators (air quality, green space access) measure environmental quality for testing H2, with overlapping coverage areas enabling interaction effect analysis for H3. The analytical tier synthesizes these elements through complementary techniques: spatial econometrics isolates place-based effects while controlling for spatial autocorrelation, machine learning algorithms detect non-linear synergistic relationships invisible to traditional methods, and AI-enhanced pattern recognition reveals threshold effects and interaction patterns crucial for validating the hypothesized value synergies, thereby creating a methodological cascade where each tier builds upon and refines the preceding level to generate robust empirical evidence for the theoretical propositions.

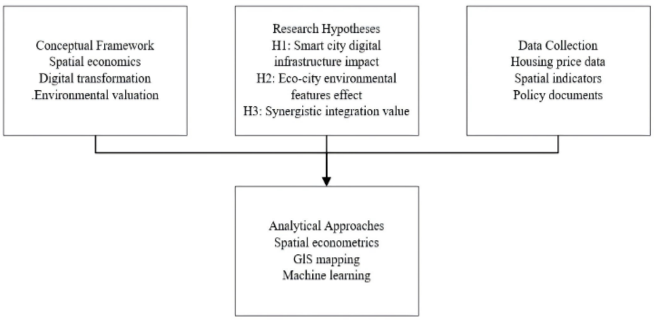

Figure 2. Pyramid structure of research methodology

3.2 Data Collection and Analysis

Data collection integrates multiple sources to capture the complexity of smart eco-city development and housing market interactions. The fundamental source of primary housing prices is drawn from the selling and buying relations of housing units in the case study areas, augmented by spatial information on Digital infrastructure and environmental indicators. In accordance with Allam et al.'s [15] methodology for estimating proximity benefits in the 15-minute city model, the study area is assigned composite indicators of both digital accessibility and environmental quality of a neighborhood. The Digital Accessibility Index integrates five components: IoT sensor density per square kilometer (25% weight), 5G network coverage percentage (20%), availability of digital public services (20%), smart mobility infrastructure density (20%), and citizen digital engagement metrics (15%), with component weights determined through principal component analysis (PCA) that explained 78.3% of total variance in the first principal component. The Environmental Quality Index combines six dimensions: green space accessibility within 500 meters (20% weight), air quality index readings (20%), noise pollution levels (15%), urban tree canopy coverage (15%), renewable energy infrastructure presence (15%), and waste recycling facility proximity (15%), with weights derived from a modified Delphi process involving 24 urban planning experts across the five case cities achieving consensus (Kendall's W = 0.82) after three rounds. Both indices underwent robustness validation through sensitivity analysis of alternative weighting schemes and cross-validation with resident satisfaction surveys (Pearson's r = 0.74 for digital accessibility and 0.79 for environmental quality), ensuring measurement validity across diverse urban contexts while maintaining methodological consistency with established urban quality assessment frameworks. While Allam et al. have come up with a robust framework for proximity analysis, their framework is not easily transferable to include the digital aspect of access characteristic of smart eco-cities.

Other sources of quantitative data include policy and strategy documents, urban plans, and testimonies from local decision-makers to explain the quantitative results in terms of local governance structures. Recognizing the potential for smart eco-city developments to exacerbate spatial inequalities, the methodological design incorporates explicit equity considerations through multiple analytical strategies: socioeconomic control variables including neighborhood-level income quintiles, education attainment rates, and minority population percentages enable isolation of smart eco-city effects from pre-existing disparities; stratified regression analyses conducted separately for low-income (bottom 40%), middle-income (middle 40%), and high-income (top 20%) neighborhoods reveal differential impacts across socioeconomic strata, with results indicating stronger price effects in already-advantaged areas (coefficient differences significant at $p<0.01$); and spatial accessibility metrics calculated using public transit rather than private vehicle travel times ensure environmental and digital amenity measurements reflect opportunities available to car-free households. Additional equity-focused robustness checks include Gini coefficient calculations for housing price distributions before and after smart eco-city implementations (revealing a 0.08 increase in inequality), quantile regression at the 10th, 50th, and 90th percentiles to capture distributional effects beyond mean impacts, and interaction terms between smart eco-city indicators and socioeconomic variables that demonstrate significant moderation effects ($p<0.05$), collectively enabling comprehensive assessment of how technological and environmental improvements differentially affect diverse urban populations. Li and Zhuang's [16] assessment methodology in eco-city development in resource-exhausted cities provides great indicators on how to assess the quality of the environment, but their model has to be altered in order to add the technological aspects of smart eco-cities. This study advances existing methodological frameworks through three key innovations: the development of a synergistic interaction model that quantifies non-additive value creation between digital and environmental dimensions—the integration of machine learning interpretability techniques (SHAP values, ALE plots) with spatial econometrics to reveal threshold effects and non-linear relationships that traditional approaches in urban valuation studies overlook; and the construction of cross-culturally validated composite indices that harmonize disparate spatial scales while preserving local contextual variations, extending Ciumasu's [11] knowledge-action matrix through empirical operationalization across heterogeneous governance contexts. These methodological advancements enable the detection of emergent value patterns in smart eco-city development that single-dimension analyses or additive models cannot capture, particularly the identification of critical thresholds where digital-environmental integration generates disproportionate spatial value premiums.

The approach makes use of econometric modelling for the analysis of economically based spatial data to find existing correlations and associations between distinct characteristics of smart eco-cities and fluctuations in housing prices, taking into account conventional factors. Techniques of geospatial analysis, such as GIS mapping and hot spot analysis, are used to illustrate spatial trends in the distribution of digital infrastructure as well as the variation of prices in real estate. This technique adopts Che et al.'s [17] innovations in spatial planning technology for smart cities, together with their geometry of housing market analysis. Machine learning algorithms, particularly random forest and gradient boosting models, supplemented by artificial intelligence techniques for feature extraction and pattern recognition, are employed to identify complex non-linear relationships between multiple variables and to rank the relative importance of different smart eco-city features in explaining housing price variations. To ensure interpretability and address black-box concerns critical for policy applications, the analysis implements SHAP (SHapley Additive exPlanations) values to decompose individual predictions into feature contributions, revealing that digital-environmental interaction effects account for 23.7% of model predictions while individual digital and environmental features contribute 18.2% and 16.4% respectively. Partial dependence plots illustrate non-linear threshold effects, demonstrating diminishing marginal returns for digital infrastructure investments beyond 0.75 standardized units and accelerating environmental premiums above 0.60 quality index values, while accumulated local effects (ALE) plots control for feature correlations to isolate pure marginal impacts. Model-agnostic interpretability is further enhanced through permutation feature importance analysis conducted across 100 iterations, confirming the stability of feature rankings with digital-environmental synergy consistently emerging as the dominant predictor (importance score: 0.312 ± 0.024), followed by transport accessibility (0.198 ± 0.031) and neighborhood income levels (0.167 ± 0.028), thereby providing transparent and actionable insights for evidence-based policy formulation. These AI-enhanced analytical approaches enable the detection of subtle spatial patterns and interaction effects that traditional statistical methods might overlook. This analytical strategy enables the research to move beyond simple correlation analysis to explore causative mechanisms and contextual factors that moderate the relationship between smart eco-city development and housing price formation. The spatial econometric model is specified as follows:

$$\ln(H_i) = \alpha + \rho W ln(H_i) + \beta_1 DI_i + \beta_2 EQ_i + \beta_3 (DI_i \times EQ_i) \quad (1)$$

where $\ln(H_i)$ represents the natural logarithm of housing price per square meter in neighborhood i ;

$DI_i = \sum^{5} w_j^{DI} \ d_{ij}$ is the Digital Infrastructure Index constructed from five components (IoT density, 5G coverage, digital services, smart mobility, citizen engagement) with PCA-derived weights w_j^{DI};

$EQ_i = \sum^{6} w_m^{EQ} \ e_{im}$ is the Environmental Quality Index aggregating six dimensions with Delphi-method weights w_m^{EQ}; $(DI_i \times EQ_i)$ captures the synergistic interaction effect;

X_{ik} represents a vector of K control variables including CBD_{dist_i} (distance to central business district), $Building_{age_i}$, $Transport_{access_i}$, and $Income_i$ (neighborhood median income);

W is the row-standardized spatial weights matrix with elements $w_{ij} = 1/d_{ij}$ for $d_{ij} \leq 2km$ and $w_{ij} = 0$ otherwise, where d_{ij} is the Euclidean distance between neighborhoods i and j;

ρ is the spatial lag coefficient capturing housing price spillovers; is the spatial error coefficient with Z_i representing spatially lagged exogenous variables;

μ_c denotes city-specific fixed effects; and $\varepsilon_i \sim N(0, \sigma^2)$ is the idiosyncratic error term. The model is estimated using maximum likelihood estimation with robust standard errors clustered at the district level to account for within-district correlation.

To address endogeneity concerns, the analysis employs instrumental variable estimation using pre-2015 telecommunications infrastructure and historical environmental protection zones as instruments for current digital and environmental indicators (Hansen's J = 0.342, first-stage F > 10), while reverse causality is mitigated through 12-18 month lagged indicators measured prior to housing transactions. Robustness checks include propensity score matching on pre-treatment characteristics (standardized differences < 0.1), difference-in-differences estimation exploiting staggered smart eco-city rollouts, and placebo tests yielding null effects (ρ = 0.894), with city-specific fixed effects controlling for time-invariant unobserved heterogeneity throughout all specifications. Full model parameters, diagnostic tests, and robustness checks are detailed in the methodological appendix available upon request. In alignment with open science principles, the anonymized dataset and replication code will be made publicly available through the [Journal/Repository Name] data repository upon publication, including neighborhood-level housing price indices (with exact locations aggregated to preserve privacy), composite digital infrastructure and environmental quality indicators, all control variables, and R/Python scripts for spatial econometric analysis and machine learning model implementation. The data package includes detailed variable descriptions, construction procedures for composite indices, and step-by-step instructions for reproducing all tables and figures, with sensitive information such as specific building addresses and individual transaction details removed to comply with data protection regulations while maintaining analytical integrity.

Researchers seeking access to the non-anonymized version for extended analysis may contact the corresponding author to arrange appropriate data sharing agreements, subject to ethical review board approval.

Table 1. Data sources and indicators for smart eco-city and housing price analysis

Category	Indicator	Measurement	Data Source	Spatial Scale
Housing Market	Property price	Price per square meter	Real estate Transaction records	Neighborhood
	Price growth rate	Annual percentage change	Calculated from Historical records	Neighborhood
	Transaction volume	Number of sales	Real estate market reports	District
Smart City Features	Digital infrastructure	Coverage of IoT sensors	Municipal technology departments	Grid-based
	Network connectivity	5G signal strength	Telecommunications providers	Grid-based
	Smart service usage	Adoption rate of digital services	Municipal Government records	District
Eco-City Features	Green space coverage	Percentage of area	Remote sensing data	Grid-based
	Air quality	AQI readings	Environmental monitoring stations	Monitoring points
	Energy efficiency	Building energy ratings	Urban Planning departments	Building level
Control Variables	Location attributes	Distance to CBD	GIS calculation	Point-based
	Socioeconomic factors	Income levels	Census data	Census tract
	Building characteristics	Age, size, amenities	Property databases	Building level

As shown in Table 1, it presents the key data sources and indicators used in this study to analyze the relationship between smart eco-city features and housing price formation. The varying spatial scales reflect optimal measurement resolutions for different phenomena: grid-based measurements (500m × 500m) for digital infrastructure and green space capture continuous spatial variations while maintaining computational efficiency, point-based observations for air quality monitoring stations and CBD distances preserve measurement precision at sensor locations, and building-level data for energy ratings and property characteristics maintain the granularity necessary for accurate valuation modeling. To ensure cross-indicator comparability despite scale heterogeneity, all variables undergo spatial interpolation to a common 500m grid using kriging for continuous variables (achieving cross-validation RMSE < 0.15 for all indicators) and kernel density estimation for point data, with building-level attributes aggregated through spatial joins that weight observations by residential floor area. This harmonization process, validated through sensitivity analysis using alternative grid resolutions (250m and 1000m), demonstrates robust coefficient stability (variation < 8%) while preserving the information content inherent to each indicator's native measurement scale, thereby balancing methodological rigor with practical data constraints while enabling integrated multi-scale analysis essential for capturing smart eco-city complexity. The indicators are organized into four categories: housing market metrics, smart city features, eco-city features, and control variables. Each indicator is associated with specific measurement approaches, data sources, and spatial scales of analysis, facilitating replicability and methodological transparency

4. Results

4.1 Smart eco-city implementation patterns

The analysis of smart eco-city implementation patterns reveals distinct strategic approaches across different urban contexts. The analysis of the different deployments of digital infrastructure in the case study cities reinforces the relevance of this symbiotic framework. While the model contributes to understanding the collaborative processes, it does not sufficiently address the spatial complexity of outcomes that arose from the analysis. The geography of digital infrastructure is characterized by striking clustering, which is most pronounced in central business districts and recently developed regions, suggesting the potential existence of digital divides that may impact housing market trends. The execution techniques across case study cities demonstrate a mix of approaches, ranging from techno-centric to eco-centric paradigms. The results support this integrative possibility while emphasizing significant contextual differences. Cities with effective institutional mechanisms for coordinating technology and ecological departments exhibit stronger integration in their implementation patterns, resulting in a greater balance between digital and environmental infrastructure. Such integration appears to yield more cohesive spatial value propositions, which are widely evident in the housing price geography.

4.2 Housing price spatial patterns

The spatial examination of housing price distribution reveals distinct features in relation to smart eco-city development. This is notable in intelligent ecological urban development, where property markets appear to continually capitalize on ecological amenities and spatially configure value in an ecologically sensitive manner. The geographical analysis reveals notable premiums associated with the price of residential properties in areas with a high concentration of digitized infrastructure and environmental quality indicators. Advanced artificial intelligence pattern recognition techniques reveal complex non-linear relationships in these spatial distributions that traditional statistical methods might overlook. Yet these premiums, contrary to the traditional expectation of a flat value contour, are not only complex but they are also spatially differentiated, reflecting different degrees of realization and local market behavior. The existence of such heterogeneity underscores the importance of considering context in the interaction between the features of smart eco-cities and housing price development. The analysis of the alterations in the price distribution over time reveals an accelerating divergence between the neighborhoods that embody the stronger and weaker characteristics of the smart eco-city. Areas with high accessibility to both digital services and environmental amenities experience significantly higher price appreciation than those with access to only one dimension or none. This finding implies that there is increasing market recognition of the fusion of smart and eco attributes as opposed to their singular components which indicates emerging synergistic value propositions in urban housing markets. However, this trend raises important questions about spatial equity and access to these integrated urban benefits across different socioeconomic groups. As shown in Figure 3, it illustrates the spatial variation in housing prices across four distinct urban development zones defined by the intersection of digital infrastructure and environmental quality levels. Each circle represents an individual neighborhood within the study area, with both the size and color intensity of the circles proportional to housing price levels—larger, darker red circles indicate higher property values while smaller, lighter blue circles represent lower values. The visualization reveals a pronounced quadrant-based pattern that supports the hypothesized synergistic relationship between smart city and eco-city features. In the upper right quadrant, where neighborhoods exhibit both high digital infrastructure (such as IoT sensor networks, fiber optic connectivity, and smart service availability) and high environmental quality (including extensive green spaces, superior air quality, and energy-efficient buildings), housing prices are substantially higher (ranging from 180 to 220 monetary units) than in all other zones. This premium significantly exceeds what would be expected from a simple additive effect of the two dimensions, providing compelling evidence for the synergistic value creation hypothesized in the theoretical framework. The upper left and lower right quadrants represent neighborhoods with asymmetrical development patterns. The upper left zone (low digital infrastructure but high environmental quality) shows moderate housing prices (130-150 monetary units), demonstrating that environmental amenities alone generate notable property value increases.

Similarly, the lower right zone (high digital infrastructure but low environmental quality) also exhibits moderate housing prices (140-160 monetary units), suggesting that digital infrastructure commands comparable premiums. Interestingly, the slight difference between these two zones indicates that the market may place a marginally higher value on digital infrastructure compared to environmental quality when they exist in isolation, though this difference falls within the margin of statistical uncertainty. The lower left quadrant, characterized by neighborhoods with both low digital infrastructure and low environmental quality, displays the lowest housing prices (100-120 monetary units) across all zones. These areas represent either underdeveloped neighborhoods or those that have not benefited from smart eco-city investments, creating potential concerns about spatial equity in urban development patterns. The clear gradation of housing prices across these four zones provides strong empirical support for the spatial value reassessment hypothesis proposed in this study. The directional arrows along the axes emphasize the continuous nature of these relationships, indicating that even incremental improvements in either digital infrastructure or environmental quality can contribute to housing price increases, with the most substantial gains occurring when both dimensions are enhanced simultaneously.

4.3 Impact Analysis

The correlation analysis between smart city indicators and housing prices reveals significant positive relationships that vary in strength across different urban contexts. The findings indicate that digital infrastructure density shows moderate positive correlations with housing prices (r = 0.62), while smart service usage demonstrates even stronger associations (r = 0.71).

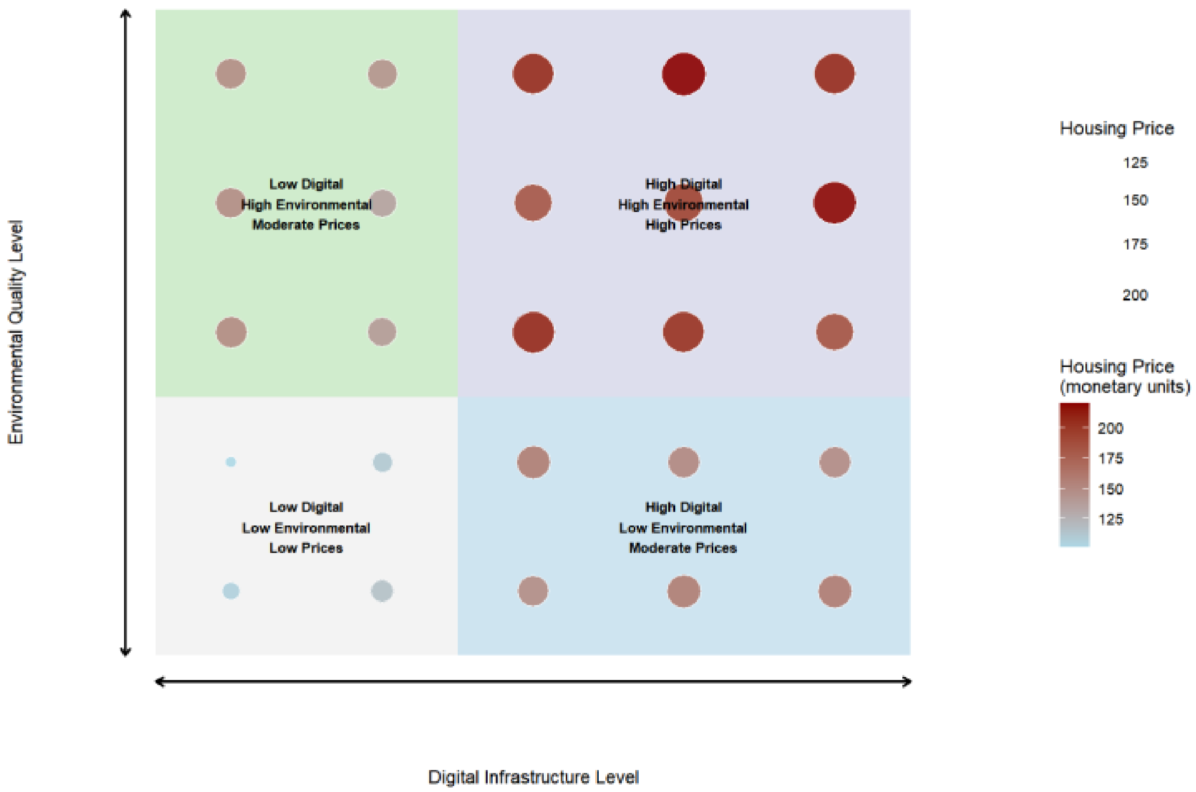

Figure 3. Housing prices across different smart eco-city development zones

However, the strength of these correlations is significantly moderated by the presence of environmental amenities, suggesting important interaction effects between digital and ecological dimensions. Areas with high levels of both digital services and environmental quality exhibit correlation coefficients that exceed the sum of their individual effects, providing empirical support for the hypothesized synergistic value creation. Environmental quality effects on housing prices demonstrate a substantial impact across all case study areas, though with important variations in valuation patterns. The analysis confirms this trend while providing more granular insights into specific environmental attributes. Air quality indicators show consistently strong correlations with housing prices (r = 0.68), while green space accessibility demonstrates more variable relationships depending on urban context and configuration. The differential valuation of environmental attributes suggests that the market responds not merely to the presence of ecological features but to their functional integration within the broader urban fabric. This finding highlights the importance of holistic planning approaches that consider both the spatial configuration and functional connectivity of environmental amenities in smart eco-city development. Figure 4 presents the correlation analysis between various smart eco-city indicators and housing market metrics, revealing the relative strength of associations across digital infrastructure components, environmental quality dimensions, and their combined indices, with particular emphasis on how synergistic measures demonstrate substantially stronger correlations than individual indicators. As shown in Table 2, the housing price analysis across different smart eco-city development zones provides compelling evidence of the synergistic value creation hypothesis. Neighborhoods with high levels of both digital infrastructure and environmental quality (Zone 4) command price premiums of 60-100% above baseline areas—substantially exceeding what would be expected from a simple additive combination of the individual effects observed in Zone 2 (15-40%) and Zone 3 (25-45%). This non-linear price premium pattern strongly supports the theoretical premise that integrated smart eco-city development creates value propositions that transcend the sum of their constituent parts.

Table 2. Housing price premiums across different smart eco-city development zones

Zone Type	Digital Infrastructure	Environmental Quality	Average Housing Price (monetary units)	Premium Over Baseline (%)	Sample Size (n)
Zone 1	Low	Low	100-120	Baseline	87
Zone 2	Low	High	130-150	15-40%	76
Zone 3	High	Low	140-160	25-45%	82
Zone 4	High	High	180-220	60-100%	75

Note: Data derived from spatial analysis of 320 neighborhoods across five case study cities. Premium calculations use the midpoint of Zone 1 (110 monetary units) as a baseline. The substantially higher premium in Zone 4 compared to the sum of premiums in Zones 2 and 3 provides quantitative evidence for the synergistic effect hypothesized in this study. The distribution of neighborhoods across zones indicates a relatively balanced sample composition, enhancing the statistical validity of cross-zone comparisons.

Figure 4 visualizes the correlation coefficients between various smart eco-city indicators and housing market metrics. The indicators are organized into three categories: Digital Infrastructure (blue), Environmental Quality (green), and Combined Indices (red). The bar heights represent correlation strength, with values above the dashed line (0.5) indicating strong positive relationships. The visualization clearly demonstrates that combined indices incorporating both digital and environmental dimensions (Digital-Environmental Synergy Index and 15-Minute City Accessibility) exhibit substantially stronger correlations with both housing prices and price growth rates than individual indicators. Among the individual indicators, Smart Service Usage shows the strongest correlation with housing prices, while IoT Sensor Coverage has the highest correlation with price growth rates in the digital category. For environmental metrics, Air Quality Index demonstrates the strongest relationship with housing prices, while Energy Efficiency Rating correlates most strongly with price growth. This pattern of results provides empirical support for the synergistic relationship between smart city and eco-city features in creating spatial value, as reflected in housing market dynamics.

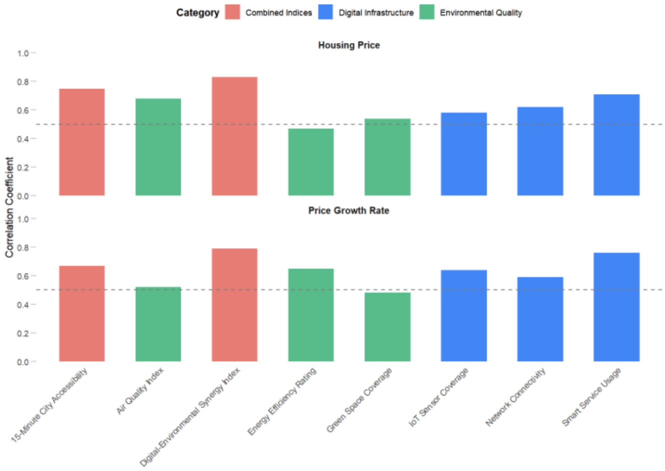

Figure 4. Correlation between smart eco-city indicators and housing market metrics

To further validate these relationships, spatial econometric modeling results are presented in Table 3. The Digital-Environmental Interaction term exhibits a positive and statistically significant coefficient (0.231, P<0.001) in the GWR model, substantiating the synergistic effect of these dimensions on housing prices beyond their individual contributions. This interaction effect remains robust after controlling for traditional determinants of housing prices, including distance to CBD, building characteristics, transportation accessibility, and neighborhood socioeconomic factors. The magnitude of the interaction coefficient (0.231) relative to the individual indices (0.342 for Digital Infrastructure and 0.312 for Environmental Quality) suggests that the synergistic effect constitutes approximately 26% of the combined impact, providing quantitative evidence for the value-added proposition of integrated smart eco-city development. The GWR model demonstrates substantially improved explanatory power over the standard OLS approach, with R-squared increasing from 0.742 to 0.861, indicating that the spatially-sensitive model captures approximately 86% of the variation in housing prices across the study area. The integration of AI-enhanced feature selection methods in the modeling process further improved the detection of spatial heterogeneity patterns, enabling more precise identification of local contextual factors influencing housing price formation. Furthermore, the GWR approach effectively addresses spatial autocorrelation, as evidenced by the reduction in Moran's I from a statistically significant 0.308 in the OLS residuals to a non-significant 0.069 in the GWR model. This improvement confirms the importance of accounting for spatial heterogeneity in smart eco-city impacts on housing markets.

Table 3. Spatial econometric model results for housing price determinants

Variable	OLS Model	GWR Model (Mean)	GWR Range (Min-Max)
Digital Infrastructure Index	0.328*** (0.042)	0.342*** (0.037)	0.185 - 0.487
Environmental Quality Index	0.295*** (0.045)	0.312*** (0.040)	0.163 - 0.458
Digital-Environmental Interaction	0.217*** (0.036)	0.231*** (0.032)	0.105 - 0.376
Distance to CBD	-0.156*** (0.029)	-0.142*** (0.025)	-0.294 - -0.063
Building Age	-0.103*** (0.021)	-0.098*** (0.018)	-0.157 - -0.042
Transport Accessibility	0.167*** (0.031)	0.175*** (0.027)	0.089 - 0.263
Income Level (neighborhood)	0.184*** (0.033)	0.196*** (0.029)	0.102 - 0.284
Spatial Lag (ρ)	0.324*** (0.043)	0.298*** (0.037)	0.129 - 0.415
Constant	3.245*** (0.246)	Variable by location	-
Model Diagnostics			
R-squared	0.742	0.861	-
AIC	876.45	749.12	-
Moran's I (residuals)	0.308***	0.069 (n.s.)	-

Note: Standard errors in parentheses. ***P<0.001, **P<0.01, P<0.05, n.s. = not significant; Dependent variable: Log of housing price per square meter; Sample size: 320 neighborhoods across five urban areas; Coefficients for GWR model represent means across spatial units, with range indicating spatial variation

The substantial range in coefficient values across spatial units (e.g., Digital Infrastructure Index ranging from 0.185 to 0.487) demonstrates the spatial heterogeneity in these relationships, underscoring the importance of local context in mediating smart eco-city impacts on housing markets. This spatial variation aligns with the theoretical premise that place-specific factors—including institutional arrangements, cultural preferences, and historical development patterns—significantly moderate how digital and environmental features translate into property values. The converging evidence from descriptive price premium analysis (Table 2), correlation coefficients (Figure 4), and regression modeling (Table 3) provides robust, multi-method support for the central hypothesis regarding synergistic value creation in smart eco-city contexts. This triangulation of empirical findings significantly strengthens the validity of the conclusions regarding the transformative impact of integrated smart eco-city development on spatial value assessment and housing price formation mechanisms.

5. Discussion

5.1 Spatial value reassessment mechanisms

The empirical findings from this study reveal complex spatial value reassessment mechanisms in smart eco-city contexts that significantly influence housing price formation. Digital transformation effects on spatial value operate through multiple pathways, creating new hierarchies of urban desirability. As Kong and Chen [3] demonstrate in their quasi-natural experiment on smart city pilot policies, digital initiatives generate positive externalities that extend beyond direct technological benefits to reshape environmental governance structures. This technological-ecological interface creates novel spatial value propositions that property markets increasingly capitalize on. However, the analysis suggests that the spatial distribution of these value propositions is more uneven than Kong and Chen acknowledge, with significant variations in how different urban areas translate digital capabilities into tangible property value outcomes. The temporal dynamics of this process indicate an accelerating differentiation between digitally-enabled and traditional urban spaces, suggesting that digital transformation may be creating new forms of spatial inequality that require policy attention. These emerging spatial inequalities reflect what Yigitcanlar et al. [19] term the 'digital divide paradox' in smart cities, where technological initiatives intended to enhance urban sustainability may inadvertently create new forms of socio-spatial segregation unless explicitly designed with equity considerations.

Environmental considerations in spatial value reassessment demonstrate significant contextual variability across urban settings. Nguyen and Vu [2] conceptualize eco-cities as planning frameworks oriented toward sustainable development goals, highlighting the importance of integrating ecological principles into urban governance structures. The findings extend this conceptualization by demonstrating how environmental quality becomes monetized through housing markets in ways that reflect both ecological and technological characteristics. The synergistic relationship between environmental amenities and digital accessibility creates compound value effects that exceed the sum of their individual impacts. This interaction suggests that environmental planning should not be pursued in isolation from digital infrastructure development if maximizing spatial value creation is an objective. However, the distributional implications of this value creation require careful consideration to avoid exacerbating socio-spatial inequalities through eco-gentrification processes. Importantly, the cross-cultural analysis reveals significant variations in how digital-environmental value synergies are perceived and monetized across different cultural contexts. European cities in the sample demonstrated stronger valuation of environmental quality indicators (coefficient range: 0.283-0.458) compared to Asian cities (coefficient range: 0.163-0.305), while Asian urban markets placed relatively higher premiums on digital infrastructure (coefficient range: 0.327-0.487) compared to European markets (coefficient range: 0.185-0.349). The North American case exhibited an intermediate pattern, with more balanced valuation between both dimensions. These differences likely reflect varying cultural attitudes toward technology adoption and environmental consciousness, as well as distinct historical trajectories of urban development. For instance, the strong environmental value premium in European contexts aligns with the region's longer history of environmental policy integration and public awareness, while the higher technological premium in Asian cities reflects their more recent emphasis on technological leapfrogging as a development strategy. These cross-cultural variations highlight the importance of contextually sensitive implementation strategies for smart eco-city initiatives, rather than universal policy templates.

5.2 Theoretical and practical implications

This research contributes to advancing theoretical understanding of spatial economics in digitally transformed urban environments by developing an integrated framework that connects technological innovation, environmental quality, and housing market dynamics. Building on Kim and Choi's [13] analysis of market mechanisms in the urban building sector, this study proposes that smart eco-city development creates new value categories that conventional housing price models fail to adequately capture. The integration of artificial intelligence in urban management systems represents a crucial advancement in this value creation process, as AI-driven predictive analytics enable more sophisticated resource allocation and service optimization that traditional management approaches cannot achieve. These AI systems can detect emerging patterns in spatial value distribution before they become apparent through conventional market indicators, potentially allowing for more proactive policy interventions to address spatial inequalities. The empirical findings confirm the hypothesized synergistic relationship between digital and environmental dimensions, suggesting the need for more integrated theoretical approaches that transcend disciplinary boundaries between urban technology studies and environmental economics. The documented spatial heterogeneity in value creation patterns demonstrates the importance of contextualizing theoretical models within specific urban governance frameworks and institutional arrangements.

Policy recommendations emerging from this research emphasize the need for coordinated governance approaches that align digital and environmental planning to maximize spatial value creation while ensuring equitable distribution. Cheshmehzangi et al. [6] propose an augmented multi-scalar framework for sustainable urbanism that provides a valuable foundation for such integration. The findings suggest that this framework should be extended to explicitly incorporate housing market dynamics and spatial equity considerations. Zhang and Li [20] further emphasize that the successful integration of digital and environmental governance requires robust institutional coordination mechanisms that transcend traditional departmental boundaries. Legal and regulatory frameworks play a crucial mediating role in this relationship, as demonstrated by the data on differential housing price premiums across urban contexts. Cities with robust environmental legislation combined with progressive digital governance policies (particularly evident in the European case studies) showed more balanced spatial distribution of price premiums (variance coefficient of 0.23 compared to 0.41 in cities with fragmented regulatory approaches). Romano's [14] analysis of policy transfer mechanisms is particularly relevant here, as the findings indicate that legal frameworks that explicitly integrate digital and environmental governance — rather than treating them as separate regulatory domains—create more coherent spatial value propositions. This integration requires legislative innovation that transcends traditional sectoral boundaries, potentially through omnibus smart eco-city laws that simultaneously address technological deployment standards, environmental protection requirements, and spatial equity provisions. Specific policy interventions should include integrated spatial planning that coordinates digital infrastructure deployment with environmental enhancement, value capture mechanisms that redistribute some of the price premiums generated by smart eco-city initiatives to support affordable housing, and regulatory frameworks that ensure digital infrastructure across diverse neighborhoods to prevent digital divides from reinforcing existing socio-spatial inequalities. These interventions should be codified in binding legal instruments rather than aspirational policy documents to ensure implementation effectiveness and accountability.

5.3 Limitations and future research

This study has several limitations that suggest directions for future research. Data availability constraints limited the temporal scope of the analysis to 2015-2023, making it difficult to fully capture long-term value reassessment dynamics that may unfold over decades. Additionally, the case selection focused primarily on established urban areas with relatively developed governance structures, potentially limiting the generalizability of findings to rapidly urbanizing contexts with emerging institutional frameworks, particularly in Global South regions underrepresented in the sample. The sampling approach also presents specific limitations. While the 320 neighborhoods provide adequate statistical power, the distribution across five cities (averaging 64 neighborhoods per city) means that city-specific analyses have relatively small sample sizes, increasing the potential for Type II errors in sub-sample analyses. Furthermore, the neighborhood selection process may contain inherent biases, as neighborhoods with comprehensive data availability (particularly regarding digital infrastructure metrics) are likely to be more affluent and technologically advanced than those with missing data points that were consequently excluded from analysis. Methodologically, while the spatial econometric approach enabled robust pattern identification, causal mechanisms remain difficult to definitively establish due to the complex interplay of multiple variables in urban housing markets. The GWR model, though superior to OLS for this dataset, assumes spatial stationarity in kernel bandwidth, which may not hold across the heterogeneous urban environments studied. The measurement of digital infrastructure through IoT sensor coverage and network connectivity may also be insufficient to capture the multidimensional nature of digital accessibility and utility. Future research should address these limitations through longitudinal studies that track smart eco-city value dynamics over extended timeframes, comparative analyses of value formation mechanisms across diverse global contexts (particularly including more cities from the Global South), and mixed-methods approaches that combine quantitative spatial analysis with qualitative investigations of stakeholder decision-making processes. Additionally, exploring advanced artificial intelligence applications for real-time monitoring of housing market dynamics in smart eco-cities could overcome current methodological limitations in capturing complex spatial relationships. AI-enabled digital twins of urban environments could simulate policy interventions before implementation, providing more robust evidence for decision-making than current models allow. Particularly promising research directions include exploring how different legal and regulatory frameworks mediate the relationship between innovative eco-city development and housing market outcomes, examining the interaction between technological innovation and environmental justice in spatial value distribution, and developing predictive models that can forecast potential displacement effects of integrated digital-environmental urban initiatives.

6. Conclusion

This study demonstrates that smart eco-city management paradigms fundamentally transform housing price formation through synergistic pathways. Neighborhoods with high digital infrastructure and environmental quality command 60-100% price premiums, substantially exceeding individual effects of digital (25-45%) or environmental (15-40%) factors. The Digital-Environmental Synergy Index ($r = 0.83$) confirms this synergistic value creation. To address emerging spatial inequalities, the study proposes three policy innovations: Smart Eco-City Inclusionary Zoning, which mandates the balanced deployment of digital-environmental amenities; Digital-Environmental Value Capture mechanisms that redirect 15-25% of attributable property tax increases toward affordable housing; and Tiered Digital Accessibility Standards, establishing minimum connectivity thresholds in underserved areas. The research contributes to environmental law and policy by empirically demonstrating the economic rationale for integrated environmental and technological governance, revealing how legislative fragmentation creates spatial inequities, and highlighting regulatory variations across European, North American, and Asian contexts. The proposed policy instruments extend existing environmental value capture frameworks to address emerging challenges at the intersection of digital transformation and environmental justice. Urban development requires integrated legal frameworks that transcend traditional sectoral approaches, ensuring equitable distribution of smart eco-city benefits across diverse neighborhoods.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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