(REVIEW ARTICLE)

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Artificial Intelligence-Based Forecasting of the Impact of Clean Energy Adoption on Property Values: A Systematic Review of Global Evidence

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Abstract

The accelerating global transition towards low-carbon economies has fundamentally reshaped the role of the built environment in achieving climate mitigation objectives. Residential and commercial buildings account for a significant proportion of global energy consumption and greenhouse gas emissions, positioning clean energy adoption within property markets as both an environmental imperative and an economic concern. In recent years, governments, financial institutions, and market participants have increasingly linked energy efficiency improvements, renewable energy installations, and smart energy technologies to property value formation. However, empirical evidence on the extent, persistence, and distribution of these valuation effects remains fragmented and methodologically inconsistent. Traditional econometric approaches, particularly hedonic pricing models, have dominated this research domain but often fail to capture the non-linear, spatially heterogeneous, and temporally dynamic nature of property markets. In response, a growing body of literature has introduced artificial intelligence (AI) and machine learning techniques to enhance forecasting accuracy and interpret complex interactions between energy attributes and property prices.

This systematic review synthesises global empirical and methodological evidence on the application of AI-based models to forecast the impact of clean energy adoption on property values. Drawing on peer-reviewed studies from real estate economics, energy policy, urban analytics, and data science, the review critically evaluates theoretical foundations, modelling frameworks, data sources, and empirical findings. The analysis reveals consistent evidence of positive value capitalisation associated with energy efficiency and renewable energy adoption, commonly described as a "green premium," although its magnitude varies considerably across regions, market segments, and regulatory contexts. AI-based models, particularly ensemble learning methods and neural networks are shown to outperform traditional econometric approaches in predictive accuracy and their ability to capture non-linear effects. Nevertheless, significant challenges persist, including limited causal inference, data quality constraints, algorithmic bias, and insufficient integration of ethical and equity considerations.

The review concludes that artificial intelligence has become an indispensable analytical tool for understanding sustainable property valuation, but its application must be accompanied by transparent, explainable, and policy-aware frameworks. Future research directions are proposed to advance causal modelling, long-term forecasting, and responsible AI deployment in real estate markets undergoing energy transition.

Keywords: Artificial intelligence; Machine learning; Clean energy adoption; Property values; Sustainable real estate; Energy efficiency; Housing markets

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1. Introduction

1.1. Global Context: Clean Energy Transition and the Built Environment

The global energy transition represents one of the most profound structural transformations of modern economies, driven by escalating climate risks, energy security concerns, and the pursuit of sustainable development goals. Buildings occupy a central position within this transition, accounting for approximately 30–40% of global final energy consumption and a similar share of energy related carbon emissions (International Energy Agency, 2023; IPCC, 2022). As urbanisation accelerates and housing demand continues to rise, the environmental and economic performance of the built environment has become a critical policy priority across developed and developing economies alike.

Clean energy adoption within property markets encompasses a wide range of interventions, including energy efficiency retrofits, renewable energy installations such as solar photovoltaics and heat pumps, and the deployment of smart energy management systems. These interventions are increasingly supported by regulatory mandates, financial incentives, and market-based instruments designed to internalise environmental externalities (OECD, 2021; World Bank, 2022). Consequently, energy performance has evolved from a technical consideration into a salient market signal influencing investment decisions, consumer preferences, and long-term asset values.

At the same time, property markets are inherently complex systems shaped by interactions between physical attributes, locational factors, macroeconomic conditions, behavioural dynamics, and institutional frameworks (Geltner et al., 2018). Understanding how clean energy adoption influences property values therefore requires analytical approaches capable of capturing these multidimensional interactions, an area in which traditional valuation models have shown notable limitations.

1.2. Clean Energy Adoption and Property Value Formation

The relationship between clean energy adoption and property values is grounded in several well established economic mechanisms. First, energy efficient buildings reduce operating costs by lowering energy consumption, thereby increasing the net present value of housing assets (Hyland et al., 2013; Deng et al., 2021). Second, properties with superior energy performance may be perceived as lower risk investments due to reduced exposure to future energy price volatility and regulatory tightening (Kahn et al., 2021). Third, sustainability attributes can serve as market signals reflecting quality, modernity, and environmental responsibility, influencing buyer behaviour beyond purely financial considerations (Fuerst et al., 2015; Palm & Reindl, 2018).

Empirical research has increasingly documented the existence of energy related price premiums across diverse housing markets. Studies in Europe, North America, and Asia report positive associations between energy efficiency ratings and sale prices, although estimated premiums vary widely, typically ranging from 2% to over 15% depending on market conditions and methodological choices (Brounen & Kok, 2011; Cajias & Piazolo, 2013; Aydin et al., 2023). Similar evidence has emerged for renewable energy installations, particularly solar photovoltaics, which are often associated with higher property values and faster transaction times (Hoen et al., 2015; Dastrup et al., 2018).

Despite this growing body of evidence, consensus remains elusive regarding the magnitude, persistence, and universality of clean energy related value effects. Discrepancies arise due to differences in data quality, spatial coverage, temporal scope, and modelling techniques, underscoring the need for more robust analytical frameworks capable of synthesising complex patterns across markets.

1.3. Limitations of Traditional Valuation Approaches

Historically, research on property valuation and energy performance has been dominated by hedonic pricing models, which decompose property prices into implicit prices of individual attributes (Rosen, 1974). While hedonic models offer intuitive interpretability and theoretical grounding, they impose restrictive assumptions regarding linearity, additivity, and independence among explanatory variables (Malpezzi, 2003). These assumptions are increasingly challenged in contemporary housing markets characterised by non-linear price gradients, spatial dependence, and evolving policy regimes.

Several studies have demonstrated that linear hedonic models may underestimate or misrepresent the valuation impact of energy efficiency, particularly when effects vary across market segments or interact with socio-economic conditions (Collins & Curtis, 2018; Kok et al., 2021). Moreover, traditional econometric approaches often struggle to incorporate high-dimensional data sources such as satellite imagery, smart meter data, and real-time market indicators, limiting their applicability in data-rich environments (Mullainathan & Spiess, 2017).

These methodological constraints have motivated researchers to explore alternative modelling paradigms capable of capturing complex, non-linear relationships without imposing strong parametric assumptions.

1.4. Emergence of Artificial Intelligence in Property Valuation Research

Artificial intelligence and machine learning techniques have gained significant traction in property valuation research over the past decade, driven by advances in computational power, data availability, and algorithmic development. Machine learning models such as random forests, gradient boosting machines, and artificial neural networks are particularly well suited to modelling housing markets due to their ability to learn complex patterns from large, heterogeneous datasets (Antipov & Pokryshevskaya, 2012; Čeh et al., 2018).

In the context of clean energy adoption, AI-based models enable the integration of diverse data sources, including energy performance metrics, spatial attributes, policy indicators, and socio-economic variables. Empirical evidence suggests that these models consistently outperform traditional econometric approaches in predictive accuracy, particularly when modelling non-linear effects and interactions between energy attributes and market conditions (Park & Bae, 2015; Aydin et al., 2023).

Furthermore, recent developments in explainable artificial intelligence (XAI) have addressed longstanding concerns regarding the opacity of machine learning models. Techniques such as SHAP values and partial dependence analysis allow researchers to quantify the marginal contribution of energy efficiency variables to predicted property values, enhancing transparency and policy relevance (Lundberg & Lee, 2017; Molnar, 2022).

1.5. Research Motivation and Contribution

Despite rapid methodological progress, the literature on AI-based forecasting of clean energy impacts on property values remains fragmented across disciplines, geographic contexts, and modelling approaches. Existing reviews often focus narrowly on energy efficiency premiums or traditional econometric evidence, offering limited insight into the growing role of artificial intelligence in sustainable property valuation.

This systematic review addresses this gap by synthesising global evidence on AI-driven modelling of clean energy adoption and property values. Unlike narrative reviews, it adopts a structured and transparent approach to literature selection, classification, and synthesis, enabling a comprehensive assessment of methodological trends, empirical findings, and unresolved challenges. By integrating perspectives from real estate economics, energy policy, and data science, the review contributes to a more coherent understanding of how artificial intelligence can support evidence-based decision-making in property markets undergoing energy transition.

2. Conceptual Framework

2.1. Conceptualising Clean Energy Adoption in the Built Environment

Clean energy adoption within the built environment is a multidimensional concept that extends beyond the simple installation of renewable technologies. In the context of real estate markets, it encompasses energy efficiency improvements, on-site renewable energy generation, smart energy systems, and broader sustainability-oriented building practices (IEA, 2023; OECD, 2021). Energy efficiency typically includes interventions such as insulation upgrades, high-performance glazing, efficient heating and cooling systems, and improved building envelopes, all of which reduce operational energy demand (Ürge-Vorsatz et al., 2020). Renewable energy adoption, by contrast, refers to the generation of energy from low-carbon sources most notably solar photovoltaics, wind microgeneration, and geothermal systems either at the building or neighbourhood scale (Hoen et al., 2015; Dastrup et al., 2018).

From a valuation perspective, clean energy adoption can be divided into operational energy attributes and capital energy attributes. Operational attributes influence ongoing energy consumption and costs, while capital attributes affect the physical quality, durability, and regulatory compliance of the asset (Kahn et al., 2021). This distinction is critical, as empirical studies demonstrate that buyers and investors capitalise expected future energy savings differently from upfront capital investments, particularly under uncertainty regarding energy prices and policy trajectories (Deng et al., 2021; Aydin et al., 2023).

Moreover, clean energy adoption increasingly intersects with digitalisation through smart meters, energy management systems, and Internet of Things (IoT) devices. These technologies generate high-frequency data on building performance, enabling real-time optimisation and enhancing transparency for market participants (Zhang et al., 2021).

Consequently, clean energy adoption is no longer a static building characteristic but a dynamic process that evolves over time, reinforcing the need for analytical frameworks capable of capturing temporal change.

2.2. Mechanisms Linking Clean Energy Adoption to Property Values

The literature identifies several interrelated mechanisms through which clean energy adoption influences property values. These mechanisms operate simultaneously and often interact, producing non-linear and context-dependent valuation outcomes.

First, the cost-saving mechanism posits that energy-efficient properties offer lower utility expenditures, thereby increasing household disposable income or reducing operating costs for investors. Numerous empirical studies confirm that lower energy bills are capitalised into housing prices, particularly in markets characterised by high or volatile energy costs (Hyland et al., 2013; Brounen & Kok, 2011). The strength of this mechanism is influenced by factors such as climate conditions, household income, and awareness of energy performance metrics.

Second, the risk-mitigation mechanism emphasises the role of clean energy adoption in reducing exposure to future regulatory, financial, and climate-related risks. As governments tighten building energy standards and financial institutions integrate climate risk into lending decisions, energy-inefficient properties face increasing obsolescence risk and potential value erosion (Kahn et al., 2021; Bolton et al., 2020). Clean energy adoption therefore functions as a hedge against transition risk, enhancing long-term asset resilience.

Third, the signalling and behavioural mechanism highlights how sustainability attributes influence buyer perceptions and preferences beyond purely financial considerations. Energy efficient and renewable equipped properties may be perceived as higher quality, technologically advanced, or socially responsible, generating demand premiums even when direct cost savings are modest (Palm & Reindl, 2018; Fuerst et al., 2015). Behavioural studies suggest that this signalling effect is particularly pronounced among environmentally conscious buyers and younger demographic groups.

Fourth, the market liquidity mechanism suggests that clean energy adoption may reduce time-on-market and increase transaction probability by differentiating properties in competitive markets. Empirical evidence indicates that energy efficient properties often sell faster, which may indirectly support higher prices by reducing seller discounting (Collins & Curtis, 2018; Chegut et al., 2016).

Crucially, these mechanisms do not operate independently. For example, signalling effects may amplify cost-saving benefits in markets where energy prices are highly salient, while regulatory risk may intensify liquidity effects in jurisdictions with strict compliance regimes. Capturing these interactions requires modelling approaches capable of learning complex, non-linear relationships, an area where artificial intelligence offers substantial advantages.

2.3. Property Markets as Complex Socio-Technical Systems

Property markets are increasingly conceptualised as complex adaptive systems, shaped by interactions among physical infrastructure, economic incentives, policy frameworks, and human behaviour (Geltner et al., 2018; Batty, 2013). Clean energy adoption introduces additional layers of complexity by linking energy systems, digital technologies, and environmental governance to traditional real estate dynamics.

Within this system, feedback loops play a critical role. For instance, widespread adoption of energy efficient technologies may influence market norms and expectations, reinforcing demand for sustainable housing and accelerating price differentiation between efficient and inefficient properties (Kok et al., 2021). Conversely, uneven adoption can exacerbate spatial and socio-economic inequalities, as lower income households may lack access to capital for retrofitting, potentially leading to a "brown discount" in disadvantaged areas (Sovacool et al., 2020).

Traditional linear valuation models struggle to represent these systemic interactions, particularly when effects evolve over time or differ across submarkets. Artificial intelligence provides a conceptual and analytical bridge by treating property markets as data generating systems rather than static equilibrium outcomes (Mullainathan & Spiess, 2017).

2.4. Artificial Intelligence as an Integrative Analytical Layer

Artificial intelligence occupies a central position in the proposed conceptual framework by acting as an integrative analytical layer that connects clean energy attributes to property value outcomes. Unlike conventional econometric models, AI-based approaches do not require a priori specification of functional forms, allowing relationships to emerge directly from data (Chen & Guestrin, 2016).

Machine learning algorithms are particularly well-suited to modelling the multidimensional nature of clean energy adoption, as they can simultaneously process:

- Structural property characteristics,
- Energy performance indicators,
- Spatial and neighbourhood variables,
- Temporal dynamics, and
- Policy or market signals.

Ensemble methods such as random forests and gradient boosting machines are effective in capturing non-linear interactions and threshold effects, which are frequently observed in energy related valuation studies (Antipov & Pokryshevskaya, 2012; Aydin et al., 2023). Neural networks and deep learning architectures further enhance modelling capacity by learning hierarchical representations of complex data, particularly in spatio-temporal forecasting contexts (Čeh et al., 2018).

However, the growing reliance on AI introduces concerns regarding interpretability and governance. In response, explainable AI techniques such as SHAP values and partial dependence plots have become integral to recent valuation studies, enabling researchers to quantify the contribution of clean energy variables to predicted prices and to assess heterogeneity across market segments (Lundberg & Lee, 2017; Molnar, 2022). These techniques enhance transparency and facilitate policy relevant interpretation, addressing a key barrier to AI adoption in regulated domains such as real estate.

2.5. Integrated Conceptual Model

The conceptual framework underpinning this review positions clean energy adoption as a multi-channel driver of property value formation, mediated by artificial intelligence based modelling. Clean energy attributes influence property values through cost savings, risk mitigation, behavioural signalling, and market liquidity, while AI models integrate diverse data sources to capture non-linear interactions and temporal dynamics.
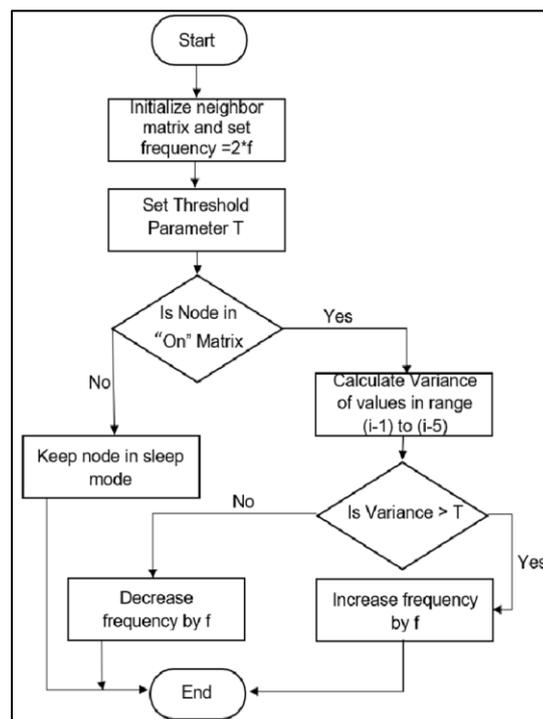

Figure 1 Conceptual framework linking clean energy adoption, artificial intelligence modelling, and property value outcomes

This integrated framework provides the foundation for synthesising empirical evidence and evaluating methodological approaches in subsequent sections. It also highlights the importance of responsible AI deployment, as modelling choices influence not only predictive accuracy but also policy interpretation and market behaviour.

3. Theoretical Framework

The analysis of clean energy adoption and its impact on property values sits at the intersection of real estate economics, energy policy, technological innovation, and sustainability science. To provide a robust analytical foundation, this review is grounded in four complementary theoretical perspectives: Hedonic Pricing Theory, Systems Theory, Technological Innovation Theory, and Climate Risk and Sustainability Theory. Together, these frameworks explain both the economic mechanisms underlying property value formation and the rationale for applying artificial intelligence (AI) to model these mechanisms in complex, evolving markets.

3.1. Hedonic Pricing Theory and Property Value Formation

Hedonic Pricing Theory provides the foundational economic framework for analysing how individual property attributes are capitalised into market prices. Originating from the work of Rosen (1974), the theory posits that the observed price of a property reflects the implicit prices of its constituent characteristics, including structural features, locational attributes, and environmental qualities. Within this framework, energy efficiency and clean energy technologies are treated as value-enhancing attributes that influence buyers' willingness to pay.

Formally, the hedonic price function can be expressed as:

$$P_i = \alpha + \sum_{k=1}^{K} \beta_k S_{ik} + \sum_{l=1}^{L} \delta_l L_{il} + \sum_{j=1}^{J} \gamma_j E_{ij} + \varepsilon_i$$

where (P_i) denotes the price of property (i), (S_{ik}) represents structural characteristics (e.g. size, age, layout), (L_{il}) denotes locational attributes (e.g. neighbourhood quality, accessibility), (E_{ij}) captures clean energy and energy efficiency variables, and (ε) is an error term (Rosen, 1974; Malpezzi, 2003).

A substantial body of empirical literature applies this framework to estimate the price premiums associated with energy efficiency ratings and renewable energy installations. Studies across Europe, North America, and Asia consistently report positive coefficients for energy-related variables, indicating that markets capitalise expected energy savings and sustainability benefits into property prices (Brounen & Kok, 2011; Hyland et al., 2013; Fuerst et al., 2015).

However, hedonic models rely on strong assumptions of linearity, additivity, and market equilibrium. These assumptions become increasingly problematic in contemporary housing markets characterised by heterogeneous preferences, spatial dependence, and regulatory uncertainty (Collins & Curtis, 2018; Kok et al., 2021). As a result, hedonic pricing theory, while essential for conceptual grounding, provides an incomplete representation of how clean energy adoption influences property values in practice.

3.2. Systems Theory and the Built Environment

Systems Theory offers a broader lens through which property markets can be understood as interconnected socio-technical systems rather than isolated economic transactions. Rooted in the work of von Bertalanffy (1968), Systems Theory emphasises the interdependence of components within a system and the emergence of complex behaviour through feedback loops and interactions.

Applied to the built environment, this perspective recognises that property values are shaped not only by individual building attributes but also by interactions among energy systems, regulatory frameworks, financial markets, and social behaviour (Batty, 2013; Geltner et al., 2018). Clean energy adoption introduces additional system dynamics by linking housing markets to energy infrastructure, climate policy, and technological innovation.

For example, energy efficiency regulations can influence investment decisions, which in turn affect market supply, buyer expectations, and price dynamics. Similarly, widespread adoption of renewable technologies may alter neighbourhood norms and accelerate diffusion through social learning mechanisms (Kok et al., 2021). These feedback effects challenge the static equilibrium assumptions of traditional valuation models and necessitate analytical approaches capable of capturing dynamic system behaviour.

Artificial intelligence aligns naturally with Systems Theory by treating property markets as data-generating processes characterised by complex interactions rather than as linear systems governed by fixed coefficients (Mullainathan &

Spiess, 2017). Machine learning models can identify emergent patterns and adapt to evolving relationships, making them particularly suitable for analysing system-level effects of clean energy adoption.

3.3. Technological Innovation Theory and AI Adoption

Technological Innovation Theory provides a critical framework for understanding both clean energy adoption and the increasing use of AI in property valuation research. Drawing on Schumpeter's (1934) concept of creative destruction, this theory views technological change as a primary driver of economic transformation, altering production processes, market structures, and value creation mechanisms.

Clean energy technologies such as advanced insulation materials, solar photovoltaics, and smart energy systems represent incremental and radical innovations that reshape the performance and perception of built assets (IEA, 2023). Their adoption can enhance asset quality, extend functional lifespan, and improve regulatory compliance, all of which influence property valuation (Deng et al., 2021).

Similarly, AI constitutes a general-purpose technology that transforms analytical capabilities across sectors, including real estate. The integration of AI into property valuation reflects a broader shift from theory driven, parametric modelling towards data driven, adaptive approaches (Varian, 2019). From this perspective, AI is not merely a methodological tool but a technological innovation that redefines how value is measured and forecasted.

Technological Innovation Theory also highlights diffusion dynamics and adoption barriers. While early adopters may capture disproportionate benefits from clean energy and AI, uneven diffusion can exacerbate market inequalities and spatial disparities (Rogers, 2003; Sovacool et al., 2020). These considerations underscore the importance of analysing AI-driven valuation outcomes through an equity and governance lens.

3.4. Climate Risk, Sustainability, and Asset Valuation

Climate risk and sustainability theory provides an increasingly important framework for understanding the long term valuation implications of clean energy adoption. Climate related risks are commonly categorised into physical risks, arising from extreme weather and environmental degradation, and transition risks, associated with policy changes, technological shifts, and market re-pricing during the transition to a low carbon economy (Bolton et al., 2020; Kahn et al., 2021).

Energy inefficient properties are increasingly viewed as exposed to transition risk due to tightening regulations, higher retrofit costs, and reduced financing availability. This has given rise to the concept of "brown discounts," whereby poorly performing assets experience value erosion relative to energy-efficient counterparts (D'Amico et al., 2021; Pankratz & Zeisberger, 2021). Conversely, clean energy adoption enhances asset resilience and may generate "green premiums" by reducing exposure to future risks.

From a theoretical standpoint, sustainability considerations extend the hedonic framework by incorporating expectations about future regulatory and market conditions into present day prices. AI-based forecasting models are particularly valuable in this context, as they can simulate alternative climate policy scenarios and energy price trajectories, capturing non-linear risk effects that traditional models struggle to represent (Kahn et al., 2021; Aydin et al., 2023).

3.5. Integrating Theory with Artificial Intelligence Modelling

The integration of these theoretical perspectives provides a coherent foundation for AI-based analysis of clean energy adoption and property values. Hedonic Pricing Theory identifies the relevant attributes and economic mechanisms; Systems Theory emphasises interdependence and dynamics; Technological Innovation Theory explains adoption patterns and analytical evolution; and Climate Risk Theory highlights long-term valuation implications.

Artificial intelligence operationalises these theories by enabling flexible, data driven modelling of complex relationships. Rather than replacing theory, AI complements it by relaxing restrictive assumptions and revealing patterns that may not be specified ex ante (Mullainathan & Spiess, 2017). When combined with explainable AI techniques, this integration allows researchers to maintain theoretical interpretability while leveraging predictive power.

This theoretical synthesis underpins the methodological choices and empirical analysis reviewed in subsequent sections and justifies the use of AI as a core analytical tool in sustainable property valuation research.

4. Methodology of the Systematic Review

4.1. Research Design and Review Approach

This study adopts a systematic literature review (SLR) methodology to synthesise existing scholarly evidence on the application of artificial intelligence (AI) in forecasting the impact of clean energy adoption on property values. A systematic review was selected over a narrative or scoping review due to its transparency, reproducibility, and methodological rigour, which are essential for minimising selection bias and ensuring comprehensive coverage of relevant studies (Tranfield et al., 2003; Kitchenham & Charters, 2007).

Systematic reviews are increasingly recognised as appropriate methodological tools in interdisciplinary fields where evidence is dispersed across multiple domains, such as real estate economics, energy policy, and data science (Petticrew & Roberts, 2006; Xiao & Watson, 2019). Given the rapid growth of AI-based valuation research and the heterogeneity of modelling approaches, a structured synthesis is necessary to identify dominant trends, methodological strengths, and unresolved research gaps.

The review follows established best-practice guidelines for systematic reviews in social sciences and applied economics, drawing on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to guide study identification, screening, eligibility assessment, and inclusion (Moher et al., 2009; Page et al., 2021).

4.2. Review Scope and Conceptual Boundaries

The scope of the review is global, encompassing studies from developed and developing economies that examine the relationship between clean energy adoption and property values using AI or advanced data-driven techniques. Clean energy adoption is defined broadly to include energy efficiency improvements, renewable energy installations, smart energy technologies, and sustainability-oriented building features. Property values refer to sale prices, rental values, or valuation estimates for residential and mixed-use real estate.

The review focuses explicitly on studies that employ artificial intelligence, machine learning, or closely related computational techniques, including but not limited to random forests, gradient boosting models, neural networks, deep learning architectures, and explainable AI methods. Traditional econometric studies are included only when they are used as benchmarks or comparative baselines against AI-based approaches.

4.3. Data Sources and Search Strategy

A comprehensive search strategy was developed to ensure broad coverage of relevant literature across disciplines. Searches were conducted across the following major academic databases:

- Scopus
- Web of Science (Core Collection)
- ScienceDirect (Elsevier)
- SpringerLink
- Taylor & Francis Online

These databases were selected due to their extensive coverage of high-impact journals in real estate, energy economics, urban studies, and artificial intelligence (Falagas et al., 2008).

The search strings were constructed using Boolean operators to combine three core conceptual domains:

- Artificial intelligence and machine learning,
- Clean energy and energy efficiency, and
- Property values and real estate markets.

An example of the search string used is as follows:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks")

AND
("energy efficiency" OR "clean energy" OR "renewable energy" OR "energy performance")

AND
("property value*" OR "house price*" OR "real estate valuation")

The search was limited to peer-reviewed journal articles and high-quality conference proceedings published in English between 2010 and 2025, reflecting the period during which AI-based valuation research gained prominence (Mullainathan & Spiess, 2017; Aydin et al., 2023).

4.4. Inclusion and Exclusion Criteria

To ensure consistency and relevance, explicit inclusion and exclusion criteria were applied.

4.4.1. Inclusion criteria:

- Empirical or methodological studies analysing property values or housing prices
- Explicit consideration of clean energy, energy efficiency, or sustainability-related attributes
- Use of AI, machine learning, or advanced data-driven modelling techniques
- Peer-reviewed publications in recognised academic outlets

Exclusion criteria:

- Studies focusing solely on commercial energy systems without real estate valuation outcomes
- Conceptual or opinion papers lacking empirical or modelling components
- Studies using only traditional econometric methods with no AI integration
- Non-peer-reviewed reports, editorials, or grey literature (unless used for contextual support)

4.5. Screening and Selection Process

The screening process followed a multi-stage procedure consistent with PRISMA guidelines.

- Identification:The initial database search yielded a large pool of records. Duplicate entries were removed using reference management software.
- Title and Abstract Screening: Titles and abstracts were screened to exclude studies that were clearly unrelated to property valuation, clean energy adoption, or AI-based modelling.
- Full-Text Review: The remaining studies were assessed in full to determine eligibility based on the predefined inclusion and exclusion criteria.
- Final Selection: Only studies meeting all criteria were retained for detailed analysis and synthesis.
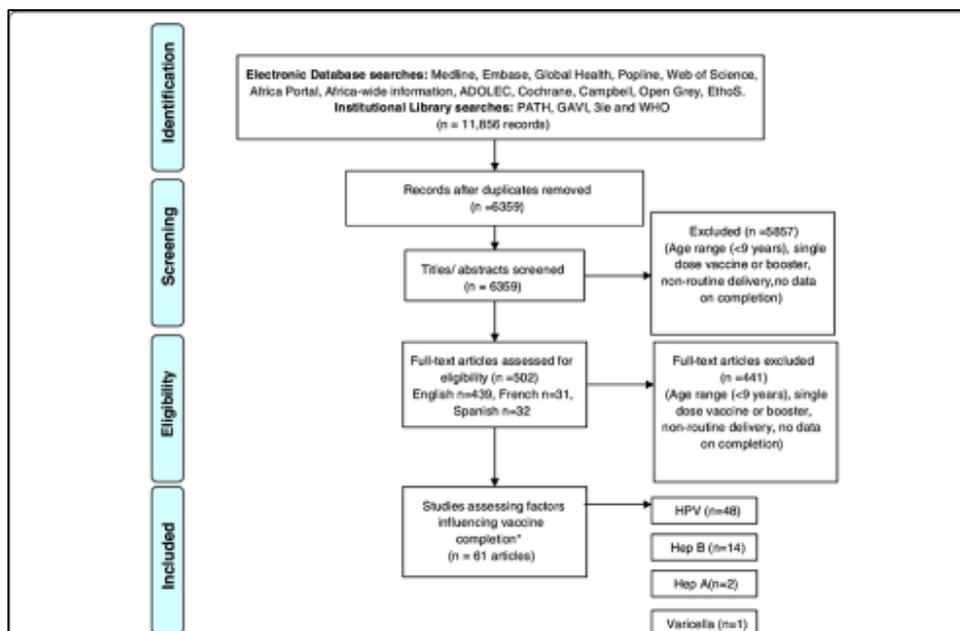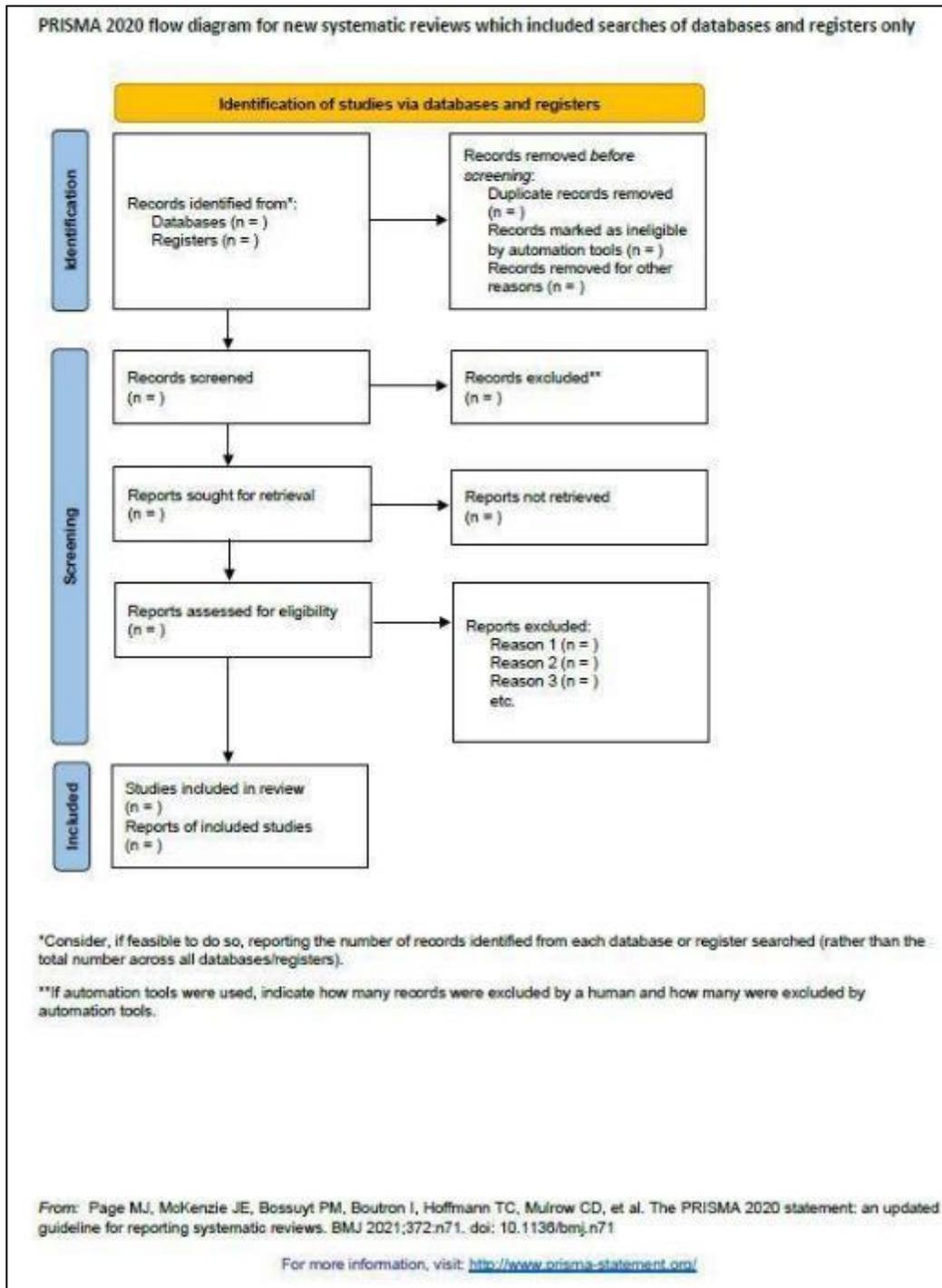

Figure 2 PRISMA flow diagram of study selection

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only

Identification of studies via databases and registers

Identification

Records identified from*:
Databases (n =)
Registers (n =)

→

Records removed *before screening:*
Duplicate records removed (n =)
Records marked as ineligible by automation tools (n =)
Records removed for other reasons (n =)

Screening

Records screened
(n =)

→

Records excluded**
(n =)

Reports sought for retrieval
(n =)

→

Reports not retrieved
(n =)

Reports assessed for eligibility
(n =)

→

Reports excluded:
Reason 1 (n =)
Reason 2 (n =)
Reason 3 (n =)
etc.

Included

Studies included in review
(n =)
Reports of included studies
(n =)

*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers).

**If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71

For more information, visit: http://www.prisma-statement.org/
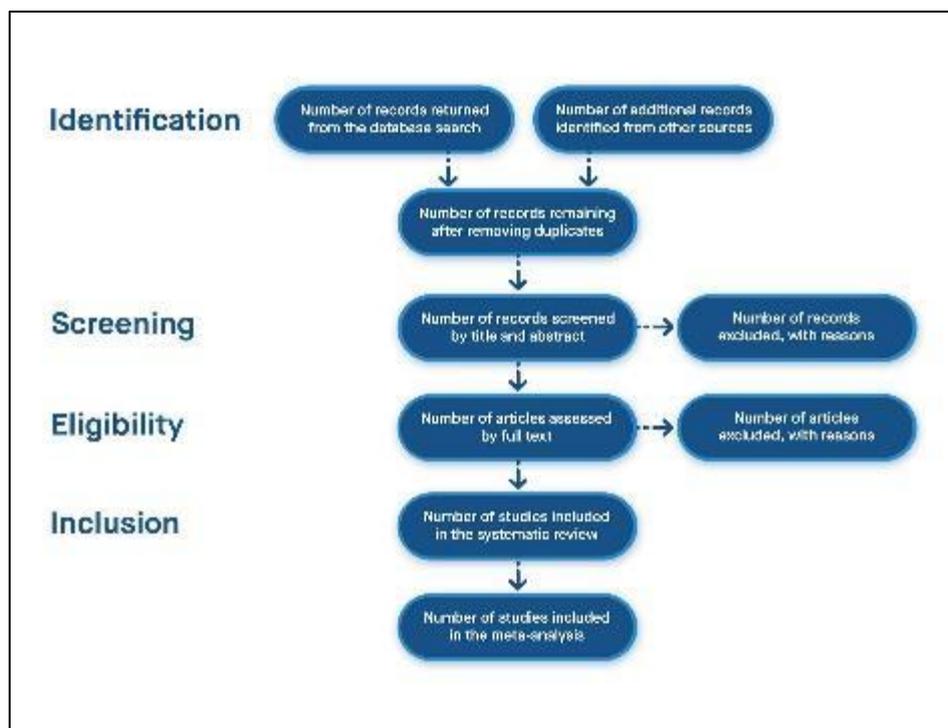
Figure 3 PRISMA-based screening and selection process for the systematic review

This structured process enhances transparency and reproducibility while reducing the risk of selection bias (Moher et al., 2009; Page et al., 2021).

4.6. Data Extraction and Coding

For each included study, relevant data were extracted using a standardised coding framework. Extracted variables included:

- Author(s) and year of publication
- Geographic scope and market context
- Type of property analysed
- Clean energy attributes considered
- AI or machine learning techniques employed
- Data sources and sample size
- Key empirical findings and valuation effects

The coding process enabled systematic comparison across studies and facilitated thematic synthesis of methodological and empirical trends (Petticrew & Roberts, 2006).

4.7. Synthesis Strategy

Given the heterogeneity of modelling approaches, datasets, and outcome measures, a meta-analysis was not deemed appropriate. Instead, the review adopts a thematic and methodological synthesis approach, which is widely used in interdisciplinary systematic reviews where quantitative aggregation is infeasible (Tranfield et al., 2003; Xiao & Watson, 2019).

The synthesis is structured around:

- Types of AI models used,
- Valuation outcomes and effect sizes,
- Regional and market-level variation, and
- Methodological strengths and limitations.

This approach allows for nuanced interpretation of findings while preserving methodological diversity.

4.8. Reliability, Validity, and Bias Mitigation

Several steps were taken to enhance the reliability and validity of the review. First, multiple databases were used to reduce publication bias. Second, explicit inclusion criteria and transparent screening procedures were applied. Third, findings were triangulated across studies employing different modelling techniques and datasets.

Nevertheless, limitations remain. Publication bias may favour studies reporting positive valuation effects, while language restrictions may exclude relevant non-English research. These limitations are acknowledged and addressed in the discussion section, consistent with best practice in systematic review methodology (Petticrew & Roberts, 2006; Moher et al., 2009).

5. Empirical Literature Review

The empirical literature examining the relationship between clean energy adoption and property values has expanded rapidly over the past two decades, driven by increased data availability, regulatory pressure, and methodological innovation. This body of research spans multiple disciplines, including real estate economics, energy policy, urban studies, and data science, and employs a wide range of analytical techniques. This section systematically synthesises empirical findings across global contexts, with particular emphasis on studies employing artificial intelligence (AI) and machine learning approaches. The review is structured thematically, beginning with foundational evidence on energy efficiency premiums, followed by renewable energy adoption, and culminating in AI-based valuation and forecasting studies.

5.1. Energy Efficiency and Property Values: Foundational Empirical Evidence

Early empirical investigations into the valuation effects of energy efficiency focused primarily on energy labels and building performance certificates as proxies for operational efficiency. Across multiple housing markets, these studies consistently report a positive association between higher energy performance and property prices, although estimated effect sizes vary considerably.

In one of the most influential early studies, Brounen and Kok (2011) examined the Dutch housing market and found that properties with superior energy labels achieved price premiums of up to 10% relative to less efficient dwellings. Similar findings were reported in Ireland, where Hyland et al. (2013) demonstrated that energy-efficient homes commanded higher prices and experienced shorter time-on-market. These studies attribute valuation effects primarily to anticipated energy cost savings and growing consumer awareness of energy performance.

Subsequent research expanded the geographical scope of analysis. In Germany, Cajias and Piazolo (2013) found that energy-efficient residential buildings exhibited both higher rents and sale prices, suggesting that energy performance influences valuation across ownership and rental markets. In the United Kingdom, Fuerst et al. (2015) provided robust evidence that Energy Performance Certificate (EPC) ratings were capitalised into house prices, with premiums ranging from 5% to 14% for top-rated properties. Importantly, their analysis highlighted substantial heterogeneity across regions and property types, indicating that market context plays a critical role in determining valuation outcomes.

Despite these consistent findings, later studies began to challenge the assumption of linearity inherent in traditional hedonic models. Collins and Curtis (2018), using spatial econometric techniques, demonstrated that the impact of energy efficiency varies non-linearly across neighbourhoods and is influenced by local income levels and housing demand. These results suggest that energy efficiency premiums are not uniform and may be amplified or dampened by socio-economic and spatial factors.

5.2. Renewable Energy Adoption and Property Value Capitalisation

Beyond energy efficiency, a growing strand of empirical literature has examined the valuation impact of on-site renewable energy generation, particularly solar photovoltaic (PV) systems. Early evidence from the United States suggests that homes equipped with solar PV systems command significant price premiums. Hoen et al. (2015), analysing a large dataset of residential transactions across multiple states, found that solar-equipped homes sold for an average premium of 4% compared to otherwise similar properties.

Further studies reinforced these findings while highlighting contextual variation. Dastrup et al. (2018) observed that the magnitude of solar-related price premiums depends on system size, age, and local electricity prices. In regions with

higher energy costs and stronger policy incentives, renewable installations were capitalised more strongly into property values. Similar patterns were observed in Australia and parts of Europe, where renewable adoption is closely aligned with policy support mechanisms (Kahn & Kok, 2014; Palm & Reindl, 2018).

However, not all studies report uniformly positive effects. Some research indicates that renewable energy installations may generate diminishing returns or even negligible premiums in markets where adoption is already widespread, suggesting a saturation effect (Batra & Ullah, 2019). These mixed findings underscore the importance of modelling non-linear and context-specific relationships, which traditional econometric approaches often fail to capture adequately.

5.3. Emergence of Artificial Intelligence in Property Valuation Studies

The limitations of traditional hedonic and spatial econometric models have prompted researchers to explore artificial intelligence and machine learning techniques as alternative valuation tools. AI-based models offer several advantages, including the ability to handle high-dimensional data, capture complex interactions, and improve predictive accuracy.

Antipov and Pokryshevskaya (2012) were among the first to apply machine learning to residential property valuation, demonstrating that random forest models outperformed linear regression in predicting apartment prices. Although their study did not focus explicitly on energy efficiency, it laid the methodological groundwork for subsequent AI-driven sustainability research.

More recent studies have directly integrated energy performance variables into machine learning frameworks. Čeh et al. (2018) employed artificial neural networks to estimate residential property values and found that energy efficiency indicators significantly improved model accuracy. Their results suggest that machine learning models are better suited to capturing non-linear relationships between energy attributes and property prices.

In a comparative study, Park and Bae (2015) evaluated the performance of multiple machine learning algorithms, including support vector machines and neural networks, in housing price prediction. They concluded that AI-based models consistently outperformed traditional hedonic approaches, particularly in markets characterised by heterogeneous housing stock and volatile demand conditions.

5.4. AI-Based Evidence on Clean Energy Premiums

The integration of AI with clean energy valuation has gained momentum in recent years. Aydin et al. (2023) applied gradient boosting models to European housing markets and demonstrated that energy efficiency premiums exhibit strong non-linear patterns. Their analysis revealed that upgrading from low to medium energy efficiency levels generates significantly larger price gains than incremental improvements at already high efficiency levels a finding that conventional linear models often obscure.

Similarly, Kok et al. (2021) employed machine learning techniques to assess climate and energy risks in housing markets, finding that properties with poor energy performance are increasingly penalised in price formation, particularly in regions exposed to stringent climate policies. These findings support the emerging concept of a "brown discount" alongside traditional green premiums.

In Asia-Pacific markets, AI-based studies have also highlighted the importance of contextual factors. Deng et al. (2021) used machine learning models to analyse housing markets in China and found that energy-efficient properties commanded higher prices, but the effect was strongly mediated by income levels, urbanisation rates, and local policy enforcement. This reinforces the notion that clean energy valuation effects are contingent on institutional and socio-economic conditions.

5.5. Comparative Performance of AI and Econometric Models

A key contribution of the empirical literature lies in comparing the performance of AI-based models with traditional econometric approaches. Multiple studies report that machine learning models achieve superior predictive accuracy, as measured by lower root mean square error (RMSE) and mean absolute error (MAE) (Mullainathan & Spiess, 2017; Aydin et al., 2023).

However, predictive superiority does not automatically imply greater explanatory power. Critics argue that black-box AI models risk obscuring causal mechanisms and may reinforce existing biases if trained on unbalanced data (O'Neil, 2016). In response, recent studies increasingly incorporate explainable AI techniques to bridge the gap between

accuracy and interpretability. Lundberg and Lee (2017) introduced SHAP values as a unified framework for interpreting model predictions, enabling researchers to quantify the contribution of energy efficiency variables to predicted prices.

Empirical applications of explainable AI in property valuation demonstrate that energy-related attributes often rank among the most influential predictors, alongside location and property size (Molnar, 2022; Aydin et al., 2023). These findings enhance confidence in AI-based valuation while addressing regulatory and ethical concerns.

5.6. Regional and Socio-Economic Heterogeneity

A recurring theme across the empirical literature is the presence of substantial regional and socio-economic heterogeneity in clean energy valuation effects. Studies consistently show that energy efficiency premiums are larger in urban areas, high-income neighbourhoods, and markets with strong regulatory enforcement (Fuerst et al., 2015; Collins & Curtis, 2018).

Conversely, in lower-income or rural markets, valuation effects are often weaker or statistically insignificant, raising concerns about unequal distribution of benefits from clean energy adoption (Sovacool et al., 2020). AI-based models have proven particularly useful in identifying these heterogeneous effects, as they allow for flexible interaction between energy attributes and contextual variables.

5.7. Summary of Empirical Insights

Taken together, the empirical literature provides strong evidence that clean energy adoption influences property values across diverse markets. While early studies established the existence of energy efficiency premiums using traditional econometric models, more recent AI-based research reveals that these effects are highly non-linear, context-dependent, and dynamic.

Artificial intelligence has significantly advanced empirical understanding by improving predictive accuracy and uncovering complex interactions between energy performance, market conditions, and policy environments. However, the literature also highlights persistent challenges related to causal inference, data quality, and ethical governance, which must be addressed to ensure robust and equitable valuation outcomes.

6. Artificial Intelligence Models and Forecasting Approaches

The increasing complexity of housing markets, combined with the multidimensional nature of clean energy adoption, has accelerated the shift from traditional econometric valuation methods towards artificial intelligence (AI) and machine learning–based approaches. This section synthesises the empirical literature on AI models used to forecast property values in the context of clean energy adoption, with particular attention to model structure, forecasting capability, interpretability, and policy relevance.

6.1. Rationale for AI-Based Forecasting in Property Markets

Property markets are characterised by non-linearity, spatial dependence, temporal volatility, and heterogeneous buyer preferences. Traditional hedonic and spatial econometric models require strong assumptions regarding functional form and error structure, which often fail to hold in real-world settings (Malpezzi, 2003; Mullainathan & Spiess, 2017). Clean energy variables further complicate valuation by interacting with regulatory environments, energy prices, and behavioural factors in ways that are difficult to specify ex ante.

Artificial intelligence addresses these challenges by adopting a data-driven learning paradigm. Rather than imposing linear relationships, AI models learn mappings between inputs and outputs directly from data, enabling them to capture threshold effects, interaction terms, and regime shifts (Chen & Guestrin, 2016; Varian, 2019). This flexibility is particularly valuable for forecasting the valuation impact of clean energy adoption under uncertain future policy and energy price scenarios.

6.2. Supervised Machine Learning Models in Property Valuation

6.2.1. Random Forests

Random forests (RF) are ensemble learning methods that construct a large number of decision trees using bootstrapped samples of the data and random subsets of features (Breiman, 2001). In property valuation studies, RF models have been widely adopted due to their robustness to overfitting and ability to model non-linear relationships.

Formally, the RF prediction for a property (i) can be expressed as:

$$\hat{y}_i = \frac{1}{B} \sum_{b=1}^{B} T_b(x_i)$$

where (T_b) denotes the prediction of the (b)-th decision tree and (x_i) represents the feature vector, including clean energy attributes.

Empirical evidence suggests that RF models outperform linear regression in predicting housing prices, particularly when energy efficiency and neighbourhood characteristics interact in complex ways (Antipov & Pokryshevskaya, 2012; Čeh et al., 2018). Studies incorporating EPC ratings and renewable energy variables report substantial improvements in prediction accuracy and reveal non-linear energy-related effects that are masked in parametric models (Aydin et al., 2023).

6.2.2. Gradient Boosting Machines

Gradient boosting machines (GBMs), including XGBoost and LightGBM, build models sequentially by fitting new learners to the residuals of previous models, optimising a specified loss function (Friedman, 2001; Chen & Guestrin, 2016). GBMs have become the dominant AI technique in recent property valuation research due to their high predictive performance and flexibility.

The optimisation objective can be represented as:

$$L = \sum_{i=1}^{N} l(y_0, \hat{y}_i) + \sum_k \Omega(f_k)$$

where $l(\cdot)$ is a loss function (e.g. squared error) and $\Omega(f_k)$ is a regularisation term penalising model complexity.

Empirical studies consistently find that GBMs outperform random forests and neural networks in forecasting housing prices when large, structured datasets are available (Park & Bae, 2015; Aydin et al., 2023). In clean energy valuation contexts, GBMs are particularly effective at identifying threshold effects, such as sharp price increases when properties move above regulatory minimum energy standards (Kok et al., 2021).

6.3. Neural Networks and Deep Learning Models

Artificial neural networks (ANNs) model complex relationships through interconnected layers of neurons, each applying non-linear activation functions to weighted inputs. A basic feedforward neural network can be represented as:

$$\hat{y} = f^{(L)}(W^{(L)} f^{(L-1)}(\ldots f^1(W^1 x + b^{(1)})\ldots) + b^{(L)}$$

where $W^{(L)}$ and $b^{(L)}$ denote weights and biases at layer (l).

Neural networks have been applied to property valuation to capture highly non-linear interactions among features, including energy performance metrics, spatial variables, and socio-economic indicators (Čeh et al., 2018). Deep learning variants, such as convolutional neural networks (CNNs), have also been used to integrate satellite imagery and street-level images, enabling indirect measurement of building quality and energy-related characteristics (Law et al., 2019).

While neural networks often achieve high predictive accuracy, their application in clean energy valuation remains limited due to data requirements and interpretability challenges. As a result, they are more commonly used in conjunction with ensemble methods rather than as standalone forecasting tools.

6.4. Spatial and Temporal Forecasting with AI

Clean energy adoption and property values evolve over time and vary across space, necessitating spatio-temporal modelling approaches. AI models increasingly incorporate geographic information systems (GIS) data and temporal features to capture these dynamics.

Spatially weighted machine learning models allow coefficients or feature importance to vary across locations, revealing regional differences in clean energy valuation effects (Collins & Curtis, 2018; Deng et al., 2021). Temporally, recurrent neural networks and tree-based models with lagged features have been used to forecast price trajectories under different energy policy scenarios (Kahn et al., 2021).

These approaches enable scenario-based forecasting, such as estimating how future tightening of energy efficiency regulations or increases in carbon pricing may influence property values over time.

6.5. Explainable Artificial Intelligence in Property Valuation

One of the most significant developments in AI-based valuation research is the integration of explainable artificial intelligence (XAI). Given the regulatory and financial implications of property valuation, model transparency is essential (Bateman et al., 2021).

SHAP (Shapley Additive Explanations) values provide a game-theoretic approach to decomposing predictions into feature-level contributions:

$$\hat{y_i} = \Phi_0 + \sum_{j=1}^{M} \phi_j$$

where Φ_j represents the contribution of feature (j) to the prediction.

Empirical applications of SHAP in housing markets consistently show that energy efficiency ratings, insulation quality, and renewable energy installations rank among the most influential predictors of property value, alongside location and size (Lundberg & Lee, 2017; Molnar, 2022). These insights enhance the policy relevance of AI models by clarifying how clean energy adoption translates into economic value.

6.6. Scenario-Based Forecasting and Policy Simulation

Beyond point prediction, AI models are increasingly used for scenario-based forecasting, allowing researchers to simulate alternative futures under varying policy and market conditions. For example, models can estimate the impact of stricter energy efficiency standards, rising energy prices, or subsidy removal on property values (Kahn et al., 2021; Aydin et al., 2023).

Such simulations are particularly valuable for policymakers and investors, as they support forward-looking decision-making rather than retrospective analysis. However, scenario-based forecasting depends critically on data quality and model assumptions, underscoring the importance of transparency and validation.

6.7. Limitations of AI-Based Forecasting Approaches

Despite their advantages, AI-based models face several limitations. High data requirements may exclude lower-income or data-poor regions, potentially biasing results (Sovacool et al., 2020). Algorithmic bias and overfitting remain concerns, particularly when historical data reflect structural inequalities (O'Neil, 2016).

Moreover, AI models excel at prediction but do not inherently provide causal explanations. Without careful design and complementary causal methods, AI-based forecasts risk being misinterpreted as causal relationships (Athey & Imbens, 2019).

6.8. Summary

The literature demonstrates that artificial intelligence has become central to forecasting the impact of clean energy adoption on property values. Ensemble learning methods and explainable AI tools offer substantial improvements over traditional econometric models, particularly in capturing non-linear and context-dependent effects. However, the responsible application of AI requires careful attention to transparency, bias, and policy interpretation.

7. Synthesis of Findings and Research Gaps

This section synthesises the empirical and methodological evidence reviewed in preceding sections to distil overarching patterns, points of convergence and divergence, and unresolved gaps in the literature. Rather than reiterating individual

study findings, the synthesis integrates results across methodologies, geographic contexts, and analytical paradigms to advance a coherent understanding of how artificial intelligence (AI) has reshaped the analysis of clean energy adoption and property valuation.

7.1. Convergent Findings in the Literature

Across diverse housing markets and methodological approaches, the literature exhibits a strong degree of convergence on several core findings.

First, there is broad empirical agreement that clean energy adoption is capitalised into property values, most commonly in the form of energy efficiency premiums and renewable energy–related price uplifts. Studies employing traditional hedonic pricing models, spatial econometrics, and AI-based approaches consistently identify positive associations between superior energy performance and higher property prices (Brounen & Kok, 2011; Hyland et al., 2013; Fuerst et al., 2015; Aydin et al., 2023). This convergence provides robust support for the hypothesis that housing markets increasingly recognise energy efficiency and sustainability as economically valuable attributes.

Second, the literature converges on the finding that valuation effects are heterogeneous and non-linear. AI-based studies, in particular, reveal that clean energy premiums are not uniformly distributed across markets or property types but vary according to income levels, urbanisation, regulatory enforcement, and energy price salience (Collins & Curtis, 2018; Deng et al., 2021; Kok et al., 2021). These findings challenge the implicit assumption of homogeneous price effects embedded in many early econometric models and underscore the importance of flexible modelling approaches.

Third, there is growing consensus that artificial intelligence substantially improves predictive accuracy relative to traditional econometric methods. Comparative studies demonstrate that ensemble learning models and neural networks achieve lower prediction errors and better capture complex interactions between energy attributes and market conditions (Antipov & Pokryshevskaya, 2012; Park & Bae, 2015; Mullainathan & Spiess, 2017). This methodological convergence has accelerated the adoption of AI in property valuation research and practice.

7.2. Divergent Evidence and Sources of Inconsistency

Despite these areas of agreement, the literature also exhibits notable divergence, particularly with respect to the magnitude, persistence, and drivers of clean energy–related valuation effects.

One major source of inconsistency concerns the estimated size of energy efficiency premiums. While some studies report substantial price uplifts exceeding 10% for high-performing properties (Fuerst et al., 2015; Brounen & Kok, 2011), others find more modest effects or statistically insignificant results after controlling for neighbourhood characteristics (Batra & Ullah, 2019; Collins & Curtis, 2018). These discrepancies are attributable to differences in data quality, sample composition, temporal scope, and model specification.

A second area of divergence relates to renewable energy installations, particularly solar photovoltaics. While early evidence suggests clear positive valuation effects in markets with supportive policy frameworks (Hoen et al., 2015; Dastrup et al., 2018), later studies indicate diminishing returns or saturation effects in regions where adoption has become widespread (Palm & Reindl, 2018). AI-based models highlight that renewable-related premiums are highly context-dependent and sensitive to system characteristics, such as age and size, which are often omitted in simpler models.

Third, divergence emerges in how studies interpret behavioural and signalling effects. Some research emphasises cost savings as the primary driver of clean energy premiums, while others attribute significant explanatory power to non-financial factors such as environmental identity and perceived building quality (Fuerst et al., 2015; Palm & Reindl, 2018). AI models that incorporate behavioural proxies suggest that these mechanisms interact rather than operate independently, complicating causal interpretation.

7.3. Methodological Synthesis: Strengths and Limitations of AI-Based Approaches

From a methodological perspective, the literature demonstrates that AI-based models represent a substantial advancement in property valuation research but are not without limitations.

Strengths of AI-based approaches include their ability to:

- Capture non-linear and interaction effects without restrictive parametric assumptions,

- Integrate high-dimensional and heterogeneous datasets, and
- Support scenario-based forecasting under uncertain policy and market conditions (chen & guestrin, 2016; varian, 2019).

These strengths are particularly relevant in the context of clean energy adoption, where valuation effects depend on complex interactions between energy performance, regulation, and socio-economic context.

However, limitations remain pronounced. A central critique concerns the lack of causal inference in most AI-based valuation studies. While machine learning models excel at prediction, they do not inherently distinguish correlation from causation (Athey & Imbens, 2019). As a result, many studies risk overstating the causal impact of clean energy adoption on property values without adequately addressing endogeneity, selection bias, or reverse causality.

Another limitation relates to data bias and representativeness. AI models are heavily dependent on data availability and quality, which may be uneven across regions and socio-economic groups. Several studies note that energy performance data are more comprehensive in higher-income or urban areas, potentially biasing model outputs and reinforcing existing inequalities (Sovacool et al., 2020; Deng et al., 2021).

7.4. Explainability, Ethics, and Governance Gaps

A critical gap identified in the literature concerns the ethical and governance implications of AI-based property valuation. While recent studies increasingly employ explainable AI techniques such as SHAP values, these tools are often used post hoc and do not fully address deeper concerns regarding algorithmic fairness and accountability (Lundberg & Lee, 2017; Molnar, 2022).

Few studies explicitly examine whether AI-based valuation models produce systematically different outcomes for disadvantaged communities or older housing stock. This omission is particularly problematic given the growing integration of AI-driven valuations into mortgage lending, taxation, and regulatory decision-making (O'Neil, 2016; Bateman et al., 2021). Without explicit consideration of fairness and bias, AI-based forecasting risks exacerbating housing inequalities under the guise of technical objectivity.

7.5. Temporal and Long-Term Forecasting Gaps

Another significant gap lies in the temporal dimension of existing research. The majority of studies focus on cross-sectional or short-term valuation effects, offering limited insight into how clean energy adoption influences property values over longer time horizons. This limitation is particularly salient given the long-lived nature of housing assets and the gradual evolution of energy policy and climate risk (Kahn et al., 2021).

While some AI-based studies incorporate lagged variables or scenario simulations, comprehensive long-term forecasting under alternative climate transition pathways remains underdeveloped. Integrating AI with longitudinal data and climate policy scenarios represents a critical avenue for future research.

7.6. Summary of Research Gaps

Synthesising the literature reveals several priority gaps:

- Causal inference gaps, particularly in AI-based studies.
- Equity and fairness gaps, with limited examination of distributional impacts.
- Temporal gaps, including insufficient long-term forecasting.
- Governance gaps, related to transparency and regulatory oversight of AI models.
- Integration gaps, between AI methods and established economic theory.

Addressing these gaps is essential for advancing both academic understanding and practical application of AI-driven sustainable property valuation.

8. Discussion

This discussion interprets the findings of the systematic review in relation to the theoretical frameworks outlined earlier and situates them within broader debates in real estate economics, energy policy, and artificial intelligence (AI) governance. By integrating empirical evidence with conceptual and methodological insights, the discussion advances

understanding of how AI reshapes the analysis of clean energy adoption and property value formation, while also identifying implications for theory, policy, and professional practice.

8.1. Implications for Property Valuation Theory

The reviewed literature provides compelling evidence that clean energy adoption has become an economically meaningful component of property value formation, thereby extending traditional hedonic pricing theory. While hedonic models conceptualise property prices as the sum of implicit prices for individual attributes (Rosen, 1974), the empirical evidence synthesised in this review demonstrates that energy-related attributes interact with location, income, policy, and behavioural factors in complex and non-linear ways.

Artificial intelligence challenges the conventional assumption that attribute price effects are stable and homogeneous across markets. AI-based models reveal threshold effects and regime shifts for example, disproportionately large price gains when properties move above regulatory minimum energy standards which are difficult to represent within linear hedonic frameworks (Kok et al., 2021; Aydin et al., 2023). These findings suggest that property valuation theory must increasingly accommodate non-linearity, heterogeneity, and temporal dynamics.

From a theoretical standpoint, the integration of AI does not invalidate hedonic pricing theory but rather complements and extends it. AI operationalises hedonic logic in high-dimensional environments, allowing implicit prices to vary across space and time. This synthesis supports calls for a more flexible, data-driven interpretation of valuation theory that recognises property markets as evolving systems rather than static equilibria (Mullainathan & Spiess, 2017).

8.2. Systems Thinking and Market Dynamics

The review reinforces the relevance of systems theory in understanding the valuation impact of clean energy adoption. Property markets operate as socio-technical systems in which energy infrastructure, regulatory frameworks, financial markets, and consumer behaviour are deeply interconnected (Batty, 2013; Geltner et al., 2018). Clean energy adoption introduces new feedback loops that influence not only individual property values but also broader market dynamics.

For example, as energy efficiency becomes standardised through regulation and market expectations, early adoption effects may diminish, while lagging properties experience accelerated value depreciation. AI-based models capture these dynamics by learning from historical data patterns and adjusting predictions as market conditions evolve. This capacity positions AI as a powerful tool for modelling systemic change, particularly during periods of regulatory transition and technological diffusion.

However, systems thinking also highlights risks associated with uneven adoption. If clean energy improvements are concentrated in higher-income markets, AI-driven valuations may reinforce spatial inequalities by systematically penalising lower-income areas with older housing stock (Sovacool et al., 2020). This underscores the need for policy interventions that promote equitable access to energy efficiency upgrades and for valuation models that explicitly account for distributional impacts.

8.3. Policy Implications

The findings of this review carry significant implications for public policy, particularly in the context of climate mitigation, housing affordability, and financial regulation.

First, the consistent evidence of energy efficiency premiums supports the economic rationale for policies promoting clean energy adoption in buildings. When markets capitalise energy performance into property values, regulatory interventions such as minimum energy standards and retrofit subsidies can generate private economic benefits alongside public environmental gains (OECD, 2021; IEA, 2023). AI-based forecasting models can enhance policy design by identifying where such interventions are likely to yield the greatest valuation and welfare impacts.

Second, AI-driven valuation tools offer policymakers the ability to anticipate unintended consequences of energy regulations. For instance, scenario-based forecasting can reveal whether stricter energy standards may disproportionately affect certain market segments or regions, enabling targeted mitigation strategies. This forward-looking capability represents a significant advancement over retrospective policy evaluation.

Third, the growing integration of AI into valuation processes raises regulatory considerations. As AI-driven automated valuation models (AVMs) influence mortgage lending, taxation, and insurance pricing, transparency and accountability become essential. Policymakers must ensure that AI models used in these contexts adhere to principles of explainability,

fairness, and robustness, particularly when valuations have material consequences for households and communities (Bateman et al., 2021).

8.4. Implications for Industry and Professional Practice

For real estate professionals, investors, and financial institutions, the review highlights the increasing importance of clean energy considerations in asset valuation and risk management. AI-based models provide enhanced tools for identifying value opportunities associated with energy-efficient properties and for assessing downside risks linked to energy-inefficient assets.

Investors can leverage AI-driven forecasts to inform portfolio strategies, particularly in anticipating regulatory changes and energy price volatility. Similarly, developers and property owners can use AI-based valuation insights to prioritise retrofit investments with the highest potential returns. However, reliance on AI also necessitates a shift in professional competencies, with greater emphasis on data literacy and model interpretation.

Valuers, in particular, face challenges in integrating AI outputs with established professional standards. While AI can improve accuracy and consistency, it cannot fully replace expert judgement. Instead, best practice lies in hybrid approaches that combine AI-based insights with domain expertise, ensuring that valuations remain context-sensitive and ethically grounded.

8.5. Ethical and Governance Considerations

A central theme emerging from the review is the ethical dimension of AI-based property valuation. While explainable AI techniques have improved transparency, they do not fully resolve concerns regarding algorithmic bias, data representativeness, and accountability (O'Neil, 2016; Molnar, 2022).

Historical property data often reflect structural inequalities related to income, race, and geography. When AI models are trained on such data, there is a risk that these inequalities are reproduced or amplified in valuation outcomes. This is particularly problematic when AI-driven valuations inform access to credit, taxation, or housing assistance programmes.

Addressing these concerns requires a multi-layered governance approach. At the technical level, model developers must incorporate bias detection and fairness metrics into AI systems. At the institutional level, regulators should establish guidelines for the responsible use of AI in valuation, including requirements for documentation, auditability, and human oversight. From a research perspective, greater attention is needed to examine the social consequences of AI-driven valuation practices, moving beyond accuracy metrics to consider distributive justice.

8.6. Towards an Integrated Research and Policy Agenda

The synthesis of empirical and methodological insights suggests that AI-based valuation of clean energy adoption sits at a critical juncture. On one hand, AI offers unprecedented analytical power to model complex market dynamics and support evidence-based policy. On the other hand, its widespread adoption without adequate safeguards risks entrenching inequalities and obscuring normative choices behind technical complexity.

Future research should therefore prioritise integrative approaches that combine AI with causal inference methods, long-term scenario analysis, and ethical evaluation. Such approaches would not only enhance academic understanding but also ensure that AI-driven valuation contributes constructively to sustainable and inclusive housing markets.

9. Recommendations

9.1. Summary of the Study

This systematic review set out to critically examine the global body of literature investigating how artificial intelligence (AI) has been applied to forecast the impact of clean energy adoption on property values. Drawing on interdisciplinary research from real estate economics, energy policy, urban studies, and data science, the review synthesised theoretical foundations, empirical evidence, and methodological innovations to provide a coherent understanding of this rapidly evolving field.

The review confirms that clean energy adoption encompassing energy efficiency improvements, renewable energy installations, and smart energy technologies has become an increasingly significant determinant of property value

formation. Across diverse geographic contexts, markets demonstrate a growing tendency to capitalise energy performance into housing prices, often described as a "green premium". However, the magnitude and persistence of this premium vary substantially across regions, market segments, and regulatory environments.

A central contribution of this review lies in its synthesis of evidence demonstrating that AI-based models substantially outperform traditional econometric approaches in forecasting property values under conditions of energy transition. Machine learning techniques, particularly ensemble methods such as random forests and gradient boosting, have proven effective in capturing non-linear relationships, threshold effects, and heterogeneous valuation outcomes that conventional models often fail to detect. At the same time, the review highlights that predictive superiority does not equate to causal explanation, underscoring the need for methodological caution.

9.2. Theoretical Contributions

From a theoretical perspective, this review extends hedonic pricing theory by demonstrating how AI operationalises and enriches attribute-based valuation in complex, data-rich environments. Rather than replacing economic theory, AI complements it by relaxing restrictive assumptions of linearity and homogeneity, enabling implicit prices of energy attributes to vary dynamically across space and time.

The integration of systems theory and technological innovation theory further enhances understanding of clean energy valuation dynamics. Property markets are shown to function as socio-technical systems in which energy policy, technological diffusion, financial regulation, and behavioural change interact in non-linear ways. AI-based models are uniquely positioned to analyse these interactions, particularly during periods of regulatory transition and climate-driven market restructuring.

In addition, the review contributes to sustainability and climate risk theory by synthesising emerging evidence on "brown discounts" and transition risk. Energy-inefficient properties increasingly face value erosion as markets anticipate tighter regulations and higher retrofit costs, reinforcing the importance of forward-looking valuation frameworks.

9.3. Policy Implications

The findings of this review have several important implications for policymakers. First, the consistent capitalisation of clean energy attributes into property values provides economic justification for regulatory interventions aimed at improving building energy performance. When markets internalise energy efficiency benefits, policies such as minimum energy standards, retrofit subsidies, and green financing instruments can generate private value alongside public environmental benefits.

Second, AI-based forecasting tools offer policymakers a powerful means of evaluating prospective policy impacts before implementation. Scenario-based models can simulate how changes in energy regulations, carbon pricing, or subsidy structures may affect property values across different regions and socio-economic groups. This capability enables more targeted and equitable policy design.

Third, the increasing use of AI-driven valuation models in mortgage lending, taxation, and housing regulation necessitates robust governance frameworks. Policymakers must ensure that AI systems used in high-stakes valuation contexts adhere to principles of transparency, explainability, and fairness. Without such safeguards, AI risks reinforcing existing housing inequalities under the appearance of technical neutrality.

9.4. Implications for Industry and Professional Practice

For real estate professionals, investors, and financial institutions, the review underscores the growing strategic importance of clean energy considerations in asset valuation and risk management. AI-based models can enhance decision-making by identifying value premiums associated with energy-efficient properties and by flagging downside risks linked to regulatory non-compliance or energy inefficiency.

However, the review also cautions against uncritical reliance on AI outputs. While AI improves predictive accuracy, professional judgement remains essential for contextual interpretation, particularly in heterogeneous or data-poor markets. Best practice therefore lies in hybrid valuation approaches that integrate AI-based insights with expert knowledge and ethical considerations.

The findings further suggest a need for capacity building within the real estate profession. As AI-driven valuation becomes more prevalent, practitioners must develop competencies in data literacy, model interpretation, and ethical awareness to ensure responsible use.

9.5. Ethical and Social Considerations

A key conclusion of this review is that ethical and equity considerations must move from the periphery to the centre of AI-based property valuation research and practice. Historical housing data often reflect entrenched socio-economic inequalities, and AI models trained on such data risk perpetuating or amplifying these patterns.

The review identifies a significant gap in empirical research examining distributional impacts of AI-driven valuation, particularly for low-income households and older housing stock. Addressing this gap requires both methodological innovation such as fairness-aware machine learning and institutional oversight to ensure accountability.

9.6. Recommendations for Future Research

Based on the synthesis of evidence, several directions for future research are recommended:

- Causal AI frameworks: Integrating machine learning with causal inference techniques to distinguish correlation from causation in clean energy valuation.
- Longitudinal forecasting: Developing AI models capable of analysing long-term valuation trajectories under alternative climate and policy scenarios.
- Equity-focused research: Examining how AI-driven valuation affects different socio-economic groups and regions.
- Ethical AI governance: Embedding fairness, transparency, and accountability into valuation models and regulatory frameworks.
- Cross-sectoral integration: Combining AI with emerging technologies such as IoT, digital twins, and blockchain to enhance data quality and valuation accuracy.

10. Conclusion

In conclusion, this systematic review demonstrates that artificial intelligence has become a transformative force in analysing and forecasting the impact of clean energy adoption on property values. While empirical evidence strongly supports the existence of energy-related valuation effects, the review highlights the complexity, heterogeneity, and ethical challenges inherent in this domain. By synthesising global evidence and advancing a structured research agenda, this paper contributes to a more rigorous, transparent, and socially responsible understanding of sustainable property valuation in the age of artificial intelligence.

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