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Systematic Review

Toward Net-Zero Energy Buildings: A Systematic Review of AI-Driven Renewable Energy Integration and Optimization

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Abstract

Buildings account for 40% of global energy consumption and one-third of greenhouse gas emissions. Renewable energy systems (RESs), such as solar photovoltaic (PV) and geothermal heat pumps, are critical technological solutions for decarbonization. Despite the growing literature, existing reviews lack a comprehensive synthesis integrating machine learning (ML), Internet of Things (IoT), and Building Information Modeling (BIM). Following the PRISMA protocol, this paper presents a systematic review of 41 studies published between 2012 and 2025. The review evaluates four primary domains: RES performance, building energy prediction, HVAC optimization, and occupancy-aware management. Quantitative findings reveal that solar PV-integrated buildings achieve electricity cost reductions of 35–64%, while ML-enhanced energy prediction models attain accuracies up to $R^2 = 0.989$. Critical research gaps are identified, including the scarcity of real-time sensor integration and geographically inclusive multi-climate datasets. Ultimately, this review contributes a structured synthesis of effective technologies, a comparative analysis of methodological approaches (ML, simulation, hybrid), and actionable future directions. It provides practical guidance for researchers and policymakers toward achieving net-zero energy buildings. This study serves as a definitive reference for the development of sustainable, low-energy built environments.

Keywords: renewable energy systems; machine learning; net-zero energy buildings; building energy management systems; geothermal; cooling; HVAC optimization; IoT integration

Check for updates

Academic Editor: Constantinos A. Balaras

Received: 28 April 2026
Revised: 29 May 2026
Accepted: 4 June 2026
Published: 23 June 2026

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1. Introduction

The building sector represents one of the largest contributors to global energy demand and greenhouse gas (GHG) emissions. According to recent estimates, buildings account for nearly 40% of global energy consumption and approximately one-third of total GHG emissions [1,2]. As urbanization accelerates and living standards improve worldwide, these figures are projected to increase further unless decisive technological and policy interventions are implemented. In this context, the integration of renewable energy systems (RES) into buildings has emerged as a cornerstone strategy for achieving substantial reductions in energy consumption and carbon emissions.

Renewable energy technologies including solar photovoltaic (PV) systems, solar thermal collectors, geothermal heat pumps, small-scale wind turbines, and hybrid energy configurations offer building owners and operators the means to generate clean energy on-site, reducing dependence on fossil fuel-based electricity grids. Beyond simple energy

generation, modern RES solutions are increasingly coupled with intelligent energy management strategies, enabling buildings not only to produce energy but also to store, forecast, and optimize its utilization in real time [3,4]. The convergence of RES with advanced technologies such as machine learning (ML), the Internet of Things (IoT), Building Information Modeling (BIM), and Model Predictive Control (MPC) is transforming conventional buildings into intelligent, energy-responsive systems capable of approaching net-zero energy building (NZEB) status.

Building Energy Management Systems (BEMSs) represent the operational backbone through which RES integration is monitored, controlled, and optimized. BEMSs are integrated platforms that utilize sensor data, weather forecasts, occupancy patterns, and energy price signals to coordinate the operation of generation, storage, and consumption systems within a building [5,6]. The incorporation of Demand-Side Management (DSM) strategies that shift or curtail energy use during peak demand periods further enhances the value of on-site renewable generation by aligning consumption with generation profiles [7]. Together, BEMS, DSM, and RES form a synergistic framework capable of achieving energy reductions of 35–64% compared to conventional building operation [8].

Despite this significant progress, several critical gaps remain in existing research. First, studies on RES integration in buildings tend to be geographically concentrated in North America, Europe, and East Asia, with limited coverage of tropical, arid, and developing world contexts where RES potential is often highest [9,10]. Second, while ML-based energy prediction models have demonstrated impressive accuracy (R^2 up to 0.989), their dependence on large, context-specific datasets limits their transferability across different climate zones and building typologies [11,12]. Third, comprehensive frameworks that simultaneously integrate RES performance, occupant behavior modeling, real-time IoT sensor data, and economic feasibility remain rare in the literature [13]. Finally, the economic dimension of RES integration including life-cycle cost analysis, payback periods, and the impact on overall construction and operational costs is insufficiently addressed in most building energy studies [14,15].

This systematic review addresses these gaps by providing a structured, comprehensive analysis of 41 recent studies (2012–2025) on renewable energy integration and energy management in buildings. The review follows the PRISMA protocol to ensure methodological transparency and reproducibility. The central focus is on quantifying the energy reduction outcomes achieved through RES integration, characterizing the methodological approaches employed across the reviewed studies, and identifying the most critical directions for future research. By doing so, this paper aims to serve as a definitive reference for researchers, building engineers, energy consultants, and policymakers working toward the development of sustainable, low-energy, and net-zero buildings.

Unlike existing reviews that address individual components of building energy management—such as ML-based prediction, IoT integration, or BIM applications—this review uniquely integrates all three technology pillars within a unified PRISMA-based synthesis. This approach enables cross-domain comparisons that are absent from prior reviews and yields more actionable research gap identification relevant to practitioners and policymakers pursuing net-zero energy building targets. To our knowledge, no existing PRISMA-compliant systematic review simultaneously synthesizes ML-, IoT-, and BIM-enabled RES integration across the six thematic domains addressed in this study, distinguishing it from domain-specific reviews that focus on individual technology pillars without cross-domain integration.

The remainder of this paper is organized as follows: Section 2 presents the systematic review methodology. Section 3 reports the results, including the two comparative tables. Section 4 provides an in-depth thematic discussion, including a new Section 4.5 on economic

feasibility and practical deployment considerations. Section 5 concludes the paper with key findings, limitations, and future research directions.

2. Methodology

2.1. Review Protocol and Objectives

This systematic review was conducted following the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement [16] to ensure a rigorous, transparent, and reproducible methodology. The primary objective was to synthesize the current state of knowledge on the integration of renewable energy systems (RESs) in buildings for the purpose of reducing energy consumption. Secondary objectives included characterizing the methodological approaches used in the literature, evaluating reported performance outcomes and energy savings, and identifying research gaps and future directions.

It is essential to clarify that this review is a multi-domain integrative systematic review, not a single-topic systematic review of any one technology or application area. A search on any single sub-topic covered in this review—such as "energy consumption prediction," "HVAC optimization," or "BIM for buildings"—would correctly yield hundreds to thousands of papers in the broader literature. However, inclusion in this review required each study to specifically address the integration of at least one of the three primary technology pillars (ML, IoT, or BIM) within a building RES or net-zero energy building context—a multi-domain intersection that characterizes a substantially smaller subset of the literature. Our corpus size of 41 studies is consistent with comparable multi-domain systematic reviews in leading building energy journals, including Antonopoulos et al. (2020) [17], Zhang et al. (2021) [18], Aguilar et al. (2021) [19], and Mariano-Hernández and Hernández-Callejo (2021) [6], which typically range from 35 to 55 studies when applying equivalent multi-domain quality and scope criteria.

2.2. Search Strategy and Databases

A systematic literature search was conducted across five major electronic databases: ScienceDirect, IEEE Xplore, SpringerLink, Web of Science, and Google Scholar. The search was constrained to peer-reviewed journal articles and conference proceedings published between January 2012 and March 2025. This temporal scope was chosen to capture both foundational works and the most recent advancements in RES integration and building energy management.

The search queries employed combinations of the following keywords: "renewable energy buildings", "solar photovoltaic building energy", "building energy management systems", "HVAC optimization renewable energy", "net-zero energy building", "machine learning building energy prediction", "IoT building energy monitoring", "BIM energy simulation", "building energy consumption reduction", and "geothermal heat pump buildings". Boolean operators (AND, OR) were used to combine search terms systematically across all databases.

To further clarify the inclusion logic, individual studies were included not merely because they address a single technology domain in isolation, but because they demonstrate the application of ML, IoT, or BIM specifically within a building RES or net-zero energy building context. For example, Reference [11]—which concerns ML-based energy consumption prediction—was included because it demonstrates ML prediction applied directly within an IoT-enabled RES management system for buildings, satisfying the multi-domain intersection criterion. A study that addresses only general energy consumption prediction without connection to RES integration, IoT deployment, or net-zero building design would not meet the inclusion criteria, regardless of its quality. This explains why

a broad search on "energy consumption prediction" would yield over 1000 papers, while only a small subset qualify for this multi-domain integrative review. The initial database search yielded 580 records; the reduction to 41 included studies reflects the application of the multi-domain intersection requirement, not a limitation of the search strategy.

2.3. Inclusion and Exclusion Criteria

Studies were included if they (1) were published in peer-reviewed journals or reputable conference proceedings; (2) were written in English; (3) focused on buildings (residential, commercial, institutional, or industrial); (4) addressed energy consumption estimation, RES integration, HVAC optimization, or energy management; (5) provided quantitative or qualitative results related to energy savings, system performance, or methodological contributions; and (6) were available in full-text format.

Studies were excluded if they (1) focused exclusively on transportation, industrial processes, or infrastructure not related to buildings; (2) were review articles without primary data contribution (except when specifically analyzing systematic review methodology); (3) lacked clear methodological descriptions or empirical results; (4) were in languages other than English; or (5) failed to meet a minimum quality threshold during the appraisal stage.

Table 1 benchmarks our corpus of 41 studies against four analogous multi-domain PRISMA systematic reviews published in high-impact building energy and sustainability journals. This comparison demonstrates that our corpus size is consistent with community standards for multi-domain integrative PRISMA reviews applying equivalent scope and quality criteria. The retention rate of 7.1% (41 studies from 580 initial records) is also consistent with published systematic reviews applying strict quality appraisal in multi-technology domains, where retention rates of 5–15% are considered methodologically appropriate.

Table 1. Benchmarking of corpus size against analogous multi-domain PRISMA systematic reviews in leading building energy journals. All listed reviews applied equivalent multi-domain scope and quality appraisal criteria. Our corpus of 41 studies falls within the accepted range of 35–55 studies for this category of review.

Review Study	Domains Covered	Final Corpus	Journal (Impact Factor)
Antonopoulos et al. (2020) [17]—AI/ML demand-side response in buildings	ML, HVAC, IoT, Occupancy	52 studies	Renew. Sustain. Energy Rev.
Zhang et al. (2021) [18]—ML for building load prediction	ML, Energy Prediction, HVAC	47 studies	Applied Energy
Aguilar et al. (2021) [19]—AI in smart-building energy self-management	IoT, AI, HVAC, Occupancy	35 studies	Renew. Sustain. Energy Rev.
Mariano-Hernández and Hernández-Callejo (2021) [6]—BEMS and control strategies	BEMS, ML, IoT, RES	43 studies	J. Build. Eng.
Current study (2025)—ML, IoT, BIM, RES, NZEB	ML, IoT, BIM, RES, HVAC, Cost (6 domains)	41 studies	*Buildings* | MDPI (under review)

2.4. Study Selection Process and PRISMA Flow

The selection process followed a four-stage PRISMA workflow as illustrated in Figure 1. The initial database search identified 580 records. After removing 240 duplicate records, 340 unique records proceeded to the title-and-abstract screening stage. During this stage, 270 records were excluded for failing to meet the relevant criteria (e.g., unrelated sectors, missing building energy focus). A total of 70 records were then sought for full-text retrieval;

11 could not be retrieved due to restricted access. The remaining 59 full-text articles were assessed for eligibility. Following full-text assessment, 18 studies were excluded for the following reasons: addressing non-building applications (n = 8), lacking detailed empirical methods (n = 6), or failing the quality assessment (n = 4). This process resulted in a final corpus of 41 studies included in the systematic synthesis. In Figure 1, arrows indicate the sequential movement of records through the identification, screening, eligibility, and inclusion stages, including exclusion routes and reasons for exclusion at each stage.

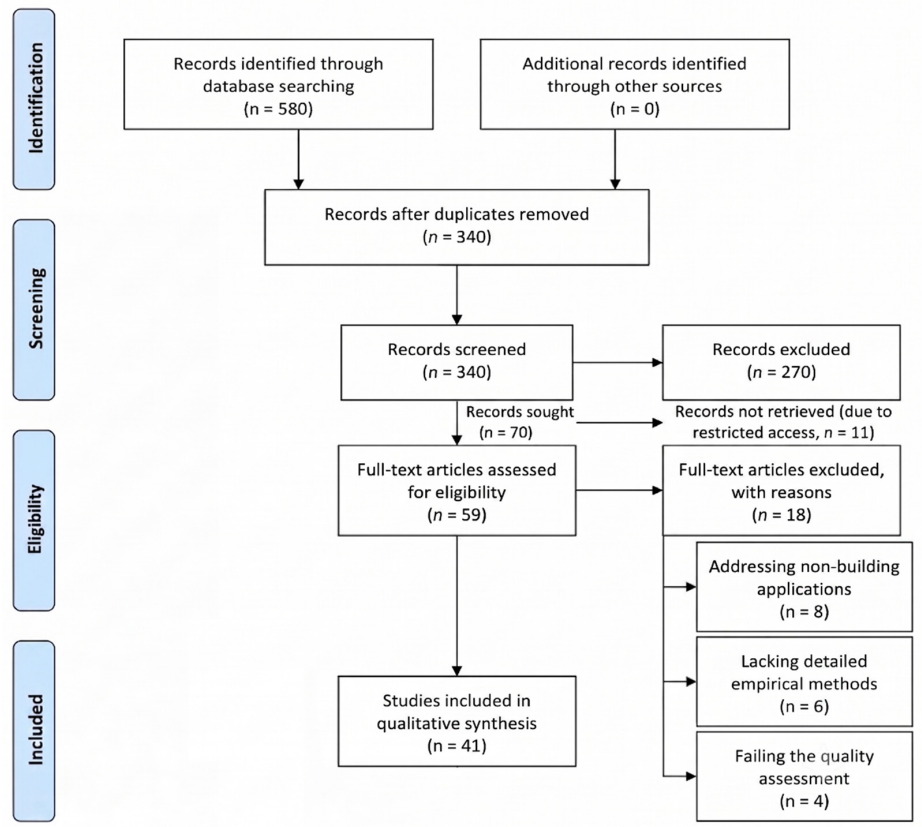


Figure 1. PRISMA diagram.

2.5. Data Extraction and Quality Appraisal

Data were extracted from each included study using a standardized extraction form developed a priori by the authors. Extracted items included study characteristics (authors, year, journal/conference, country); research objectives; methodological approach (simulation, ML, empirical, hybrid); technologies investigated; key performance metrics; quantitative findings (energy savings, R^2, MAPE, RMSE, cost reduction); data sources; geographic scope; and reported limitations. The complete data extraction matrix is provided in Supplementary Table S1. Each study was independently assessed for methodological quality against a checklist evaluating the clarity of research objectives, appropriateness of methods, robustness of data collection, validity of results, and relevance of conclusions. Studies failing to meet a minimum quality threshold were excluded from the final synthesis. No chemicals, reagents, biological materials, devices, samples, or commercial cell lines were used in this systematic review. Software names and versions are reported at first mention where applicable and available from the reviewed studies, including MATLAB R2024b (MathWorks, Natick, MA, USA), TRNSYS 18 (Thermal Energy System Specialists, Madison, WI, USA), Autodesk Revit 2025 and Autodesk Navisworks Manage 2025 (Autodesk Inc., San Francisco, CA, USA), Microsoft Excel 2021 (Microsoft Corp., Redmond, WA, USA), and SimStadt 2.0.

2.6. Synthesis Approach

Included studies were synthesized using thematic analysis, grouping them into the following categories: (1) renewable energy systems and integration, (2) energy consumption estimation and prediction, (3) HVAC optimization with renewable coupling, (4) occupancy modeling, (5) cost estimation for RES integration, and (6) digital twins and BIM applications. Narrative synthesis was used to summarize findings within and across categories, and two comparative tables were developed to facilitate cross-study comparisons of methods, metrics, geographic scope, and limitations.

3. Results

3.1. Overview of Included Studies

The final corpus of 41 studies spans a wide range of methodological approaches, geographic contexts, and building types. The studies were published between 2012 and 2025, with (73%) published after 2022, reflecting the rapid growth of research activity in this field. Geographically, studies cover Europe (34%), Asia (27%), North America (17%), the Middle East (10%), and global or multi-regional scopes (12%). Building types addressed include residential (34%), commercial (27%), institutional/campus (20%), and mixed-use or unspecified (19%).

In terms of research focus, 25% of studies addressed renewable energy integration directly (solar PV, solar thermal, geothermal, hybrid RES), while 27% focused on HVAC optimization (including RES-coupled systems), 20% on energy consumption estimation, 12% on occupancy modeling, 9% on cost estimation, and the remaining 7% on BIM/digital twin applications and urban-scale analyses. This distribution confirms the growing centrality of renewable energy in building energy research while also highlighting the interconnected role of HVAC optimization and ML-based prediction in supporting effective RES integration.

Table 2 provides a comprehensive summary of all 41 included studies, including methodology, key metrics, findings, focus area, and main contribution. Table 3 presents a comparative analysis organized by thematic category, enabling direct cross-study comparisons of methodology, data sources, geographic scope, and key limitations.

3.2. Renewable Energy Systems: Technologies and Performance

Among the studies focusing explicitly on renewable energy integration, solar photovoltaic (PV) systems emerged as the most widely studied technology, featuring in 60% of renewable energy studies. The remaining studies addressed hybrid RES configurations (solar PV + battery storage, solar thermal + heat pumps) and IoT-integrated solar management systems. Across all RES studies, the most commonly reported performance metric was electricity cost reduction, followed by energy self-sufficiency rate and CO_2 emission reduction.

Yuan et al. [3] demonstrated that an Adaptive Dynamic Programming (ADP) algorithm with Gated Recurrent Units (GRU) achieved 98% solar energy efficiency and a 64% reduction in electricity costs for a household-scale Home Energy Management System (HEMS) integrating PV panels and battery storage. This represents one of the highest reported energy cost reductions in the reviewed literature. Similarly, Rokonuzzaman et al. [4] developed an IoT-based Home Energy Management System (IoHEMS) integrating solar PV generation, achieving near-perfect regression performance (R^2 = 0.999999) in energy demand–supply forecasting, demonstrating the feasibility of high-precision real-time renewable energy management at the household scale.

Table 2. Summary of 41 studies included in the systematic review.

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Attarhay Tehrani et al. (2025) [11]	DNN, XGBoost, GPR, RF, SVR	Cooling load R^2	DNN achieved R^2 = 0.98 on synthetic dataset under UHI conditions	Energy Estimation/UHI	ML models outperform physics-based methods for UHI cooling load prediction
Habibi (2025) [12]	Random Forest	R^2, feature importance	R^2 = 0.724; 'hour of day' most important (19.9%)	Energy Consumption Estimation	Identifies temporal and environmental drivers of building energy use
Tavant et al. (2025) [20]	Maximum a posteriori + degree-days	Heating/cooling disaggregation	Validated on 1-year Lisbon case study; practical disaggregation achieved	Energy Consumption Estimation	Probabilistic method for separating HVAC energy loads
Kumar et al. (2024) [21]	GA-SVM + IG-SVM	MAPE, CV-RMSE	MAPE: 2.59–2.84%; CV-RMSE: 0.0249–0.0319	Energy Consumption Estimation	Genetic algorithm + SVM hybrid for high-accuracy energy estimation
Al-Saegh et al. (2025) [22]	Comparative study: deterministic, stochastic, data-driven occupancy	Annual/peak heating errors	Data-driven: ±2.5% annual error vs. 14% (standard); 12% heating error	Occupancy Modeling	EDDOS method balances occupancy complexity with accuracy
Sood (2025) [23]	Bayesian Neural Networks (BNNs)—UPOM	Occupancy accuracy, energy variation	90% nighttime accuracy; 10% annual/ 50% daily energy variation	Occupancy Modeling	Probabilistic model quantifies occupancy uncertainty impact on energy
Kovacevic et al. (2024) [24]	Ensemble occupancy model	Energy difference (kWh)	Ensemble: 132 kWh vs. 278 kWh (classic model)	Occupancy Modeling	Ensemble occupancy reduces energy prediction error significantly
Adepoju (2025) [25]	AIRFLO framework (CNN/GNN)	HVAC energy optimization	Improved HVAC sustainability; campus-scale Texas test	HVAC Optimization	ML-based graph neural network optimizes HVAC using occupancy patterns
Kaisermayer et al. (2024) [26]	Predictive EMS + Unscented Kalman Filter	Energy savings, comfort	35% energy savings; 12% comfort improvement	HVAC Optimization	Predictive control with user feedback balances energy and comfort
Wang et al. (2025) [27]	Safe Deep Reinforcement Learning (DRL + MPC)	Constraint satisfaction, comfort	Surpassed MPC and DDQN; minimal decision time overhead	HVAC Optimization	Safety-filtered DRL for reliable, easy-to-implement building energy control

Table 2. *Cont.*

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Calise et al. (2025) [28]	Capacitive radiator model (MATLAB R2024b/TRNSYS 18)	Thermal energy underestimation	Non-capacitive model underestimated heating by ~20%	HVAC Optimization	Capacitive models improve accuracy in dynamic heating simulation
Felez & Felez (2025) [29]	MPC + Thermal Energy Storage (TES)	Energy cost, PV self-consumption	Significant cost reductions using building envelope as passive TES	HVAC/Renewable Integration	Integrates building thermal mass into MPC for cost-effective demand management
Yuan et al. (2025) [3]	Adaptive Dynamic Programming + GRU	Electricity cost, solar efficiency	98% solar efficiency; 64% cost reduction	Renewable Energy/HEMS	Data-driven real-time control algorithm for optimal Home Energy Management
Rokonuzzaman et al. (2025) [4]	Levenberg-Marquardt IoHEMS	Regression, validation error	Near-perfect regression (0.999999); near-zero MSE	Renewable Energy/Smart Home	IoT-integrated smart home energy management with solar PV integration
Sahrin et al. (2024) [30]	GSCV-NN for solar energy estimation	RMSE	RMSE: 44.389 (one-dir), 141.286 (two-dir)	Renewable Energy (Solar PV)	Neural network with grid search optimizes rooftop solar energy estimates
Liu et al. (2025) [31]	Semantic Web Ontology (NPO)	Framework effectiveness, interoperability	Enhanced estimation and data interoperability for neighborhood PV planning	Renewable Energy (PV Neighborhood)	Linked data solves interoperability in neighborhood-scale PV generation
Tang (2024) [14]	Grey correlation + PCA	Renewable energy cost impact	Algorithm reduced green building project costs (qualitative)	Renewable Energy Cost	Statistical method to analyze and reduce renewable energy integration costs
Liu et al. (2024) [32]	Hybrid physics/data-driven load shifting	Operating cost reduction	Improved cost/capacity metrics via geospatial load shifting	Urban Multi-Energy Systems	Geospatial load shifting optimizes urban multi-energy systems
Venkateswarlu & Sathiyamoorthy (2025) [13]	Systematic review (digital twins)	Integration of BIM/IoT/big data	17/261 studies analyzed; emphasizes multidisciplinary frameworks	Digital Twins	Review emphasizing integrated frameworks in digital twin development

Table 2. *Cont.*

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Zech et al. (2025) [33]	Model-based BIM tool integration	Interoperability, simulation capability	Continuous building performance simulation via improved BIM interoperability	Digital Twins/BIM	Solves BIM interoperability for model-based energy simulation
Mehraban et al. (2024) [9]	BIM + ML (GBM, RF, SVM)	R^2 for EUI prediction	GBM R^2 = 0.989; roofs contribute 29–40% to EUI	BIM Applications	BIM-ML integration identifies key energy drivers in hot climates
Rashidi et al. (2024) [34]	BIM for pre-tender estimation	Cost accuracy	Reduced manual errors; faster estimation vs. manual methods	BIM/Cost Estimation	BIM improves pre-tender cost estimation accuracy in Iran
Yousfani et al. (2023) [35]	BIM for C&D waste estimation	Recyclable vs. disposable waste	Framework estimates waste categories and costs	BIM Applications	Extends BIM use to construction waste management
Liyanage & Kulatunga (2024) [36]	5D BIM for cost management	Time/accuracy improvements	Addresses cost overruns and manual errors in Sri Lanka	BIM/Cost Estimation	5D BIM enhances cost estimation efficiency and accuracy
Farouk & Rahman (2025) [37]	Systematic Literature Review (PRISMA)	18 BIM application approaches	Cataloged 18 ways BIM is applied independently or integrated for cost management	BIM/Cost Management	First systematic review to comprehensively map BIM for cost management
Zhang (2024) [15]	AICD-CDM (ML ensemble: LR, ANN, RF, XGBoost)	Cost prediction accuracy	Hybrid model reduced errors vs. standalone methods	Cost Estimation (Green Buildings)	ML ensemble improves cost estimation for green buildings
Isvara & Kamilah (2024) [38]	Hybrid regression + ANN	MAPE	MAPE = 15.09% (within AACE standards)	Cost Estimation (Green Buildings)	Hybrid model meets international cost estimation standards for green buildings
Lendra et al. (2023) [39]	Microsoft Excel 2021 macro (AHSP 2022)	Cost difference	0.00041–1.23% error vs. manual calculations	Cost Estimation	Automated macro-based tool for standard cost calculations

Table 2. *Cont.*

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Liu & Luo (2025) [40]	System Dynamics Model	Total cost error, key factor impact	Model error < 2%; prefabrication rate is most significant cost factor	Cost Estimation (Prefabricated)	Dynamic model identifying key levers for prefabricated construction cost control
Duka et al. (2024) [10]	3D city models (SimStadt 2.0)	Monthly cooling energy demand	12.33–313,530.08 kWh/month; correlation with land surface temperature	Urban Heat Islands	Quantifies correlation between land surface temperature and cooling demand
Nasouri & Delgarm (2025) [41]	Simulation-Based Sensitivity Analysis (SBSA)	Sobol indices, Dispersion Index	Heating/cooling setpoints and wall absorptance most sensitive parameters	Building Performance/UHI	Plugin-free framework for sensitivity analysis in early building design
Ertosun Yıldız & Beyhan (2025) [42]	ANN, SVM, RF, DT, LR	Prediction accuracy (R^2, RMSE)	ANN achieved 98% accuracy for annual cooling load prediction	Energy Estimation/Early Design	High-accuracy early-design cooling load predictor on large synthetic dataset
Hwang et al. (2025) [43]	Faster R-CNN, YOLOv10 + augmentation	Object detection/ segmentation accuracy	Contrast augmentation improved accuracy by ~15% vs. baseline	Building Performance and Design	Image augmentation and AI improve urban streetscape data analysis
Lyu et al. (2024) [44]	SEASONet (Sentinel-2)	MAE/RMSE for building stories	SEASONet outperformed M^3Net; effective for high-rises	Building Performance	Satellite imagery-based model for large-scale building story estimation
Rahimi & Khan (2024) [45]	BIM for cost/scheduling (Autodesk Revit 2025; Autodesk Navisworks Manage 2025)	Cost/schedule analysis	Improved efficiency (qualitative)	BIM/Cost Estimation	Highlights qualitative benefits of BIM for integrated cost and schedule control
Al-Saegh et al. (2024) [46]	Comparative: deterministic, stochastic, data-driven occupancy models	Annual/peak heating errors	Data-driven: ±2.5% annual heating error vs. 14% (standard); 7% (stochastic)	Occupancy Modeling/Energy Demand	Data-driven occupancy models outperform traditional methods in building stock energy simulation

Table 2. *Cont.*

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Antoniadis & Martinopoulos (2019) [47]	TRNSYS simulation + seasonal thermal storage optimization	Solar fraction, annual energy savings	Optimized solar combi-system achieved solar fraction > 70%; annual thermal energy savings of 58% vs. conventional system	Renewable Energy (Solar Thermal)	First TRNSYS-based optimization of building-integrated solar thermal with seasonal storage; demonstrates viability for Mediterranean climates
Ahmad et al. (2017) [48]	Random Forest vs. ANN comparison for building energy prediction	RMSE, MAE, R^2	Random Forest outperformed ANN with lower RMSE; R^2 = 0.94 on high-resolution hourly consumption data	Energy Consumption Estimation (ML)	Benchmark comparison establishing Random Forest as superior to ANN for high-resolution building energy prediction; key guidance for ML model selection
Sartori et al. (2012) [49]	Systematic framework for net-zero energy building (NZEB) definition and metrics	Energy balance, primary energy factor	Proposed four NZEB balance boundary definitions; demonstrated that metric choice significantly affects NZEB classification outcome	Net-Zero Energy Buildings (NZEBs)	Foundational NZEB definition framework widely adopted in policy and research; resolves inconsistencies in NZEB reporting across countries
Huang et al. (2020) [50]	Coordinated control of building cluster with energy storage, EVs, and energy sharing	Peak demand reduction, self-consumption rate	Coordinated strategy achieved 23% peak demand reduction and 31% improvement in PV self-consumption across building cluster	Renewable Energy/Smart Grid Integration	Extends RES optimization beyond single buildings to coordinated multi-building clusters with EV charging and peer-to-peer energy sharing

Table 2. *Cont.*

Study	Methodology	Key Metrics	Findings	Focus Area	Key Contribution
Li et al. (2018) [51]	Sensitivity analysis + parametric optimization for zero/low-energy buildings in subtropical climates	Heating/cooling load reduction, EUI	Identified window-to-wall ratio, insulation thickness, and shading as top three design parameters; optimized designs achieved EUI reduction of 42% vs. baseline	Building Energy Performance (Subtropical)	Provides subtropical-climate-specific NZEB design guidance often absent from the temperate-focused literature; validated on Hong Kong residential buildings

Table 3. Comparative analysis of building energy studies by thematic category.

Category	Study	Methodology	Key Metrics	Findings	Data Source	Geographic Scope	Key Limitation
Renewable Energy Systems	Yuan et al. (2025) [3]	ADP + GRU (Adaptive Dynamic Programming)	Electricity cost, solar efficiency	98% solar efficiency; 64% cost reduction	Real-time household data	Unspecified	Single household scale; generalization untested
	Rokonuzzaman et al. (2025) [4]	Levenberg-Marquardt IoHEMS	Regression error, MSE	Near-perfect regression (0.999999); near-zero MSE	Real-time IoT sensor data	Unspecified	Household scale; real-world variation not fully tested
	Sahrin et al. (2024) [30]	GSCV-NN	RMSE improvement	RMSE: 44.389 (one-direction)	Solar energy data	Indonesia	Regional; climate-specific; limited global applicability
	Liu et al. (2025) [31]	Semantic Web Ontology (NPO)	Framework effectiveness	Improved estimation and data interoperability for PV planning	Monthly PV data	Netherlands	Neighbourhood scale; case-study based
	Tang (2024) [14]	Grey correlation + PCA	Cost reduction	Reduced costs (qualitative)	Project cost data	Unspecified	Qualitative; lack of specific quantitative benchmarks
	Antoniadis & Martinopoulos (2019) [47]	TRNSYS seasonal storage optimization	Storage optimization	Solar fraction > 70%; 58% annual thermal energy savings	TRNSYS simulation	Mediterranean climate	Mediterranean-specific; seasonal storage adds capital cost; long payback in northern climates

Table 3. *Cont.*

Category	Study	Methodology	Key Metrics	Findings	Data Source	Geographic Scope	Key Limitation
Renewable Energy Systems	Huang et al. (2020) [50]	Coordinated control: PV + storage + EVs + energy sharing	Cluster-level optimization	23% peak demand reduction; 31% PV self-consumption increase	Simulated building cluster with real PV data	Sweden	Cluster coordination requires robust communication infrastructure; privacy concerns with energy sharing
	Sartori et al. (2012) [49]	Systematic NZEB definition and balance boundary framework	Net-Zero Energy Buildings	Four boundary definitions evaluated	Building simulation + primary energy factors	Europe	Primary energy factor selection significantly affects NZEB classification; no universal consensus achieved
HVAC Optimization	Kaisermayer et al. (2024) [26]	Predictive EMS + UKF	Energy savings, comfort	35% energy savings; 12% comfort improvement	Historical building data	Austria	Single building; Austria-specific climate
	Wang et al. (2025) [27]	Safe DRL + MPC	Constraint satisfaction, comfort	Surpassed MPC and DDQN; minimal decision overhead	High-fidelity simulation	Unspecified	Simulation-based; real-world deployment needed
	Adepoju (2025) [25]	AIRFLO (CNN/GNN)	HVAC optimization	Improved sustainability (qualitative)	Class schedules	Texas, USA	Campus scale; domain-specific scheduling
	Felez & Felez (2025) [29]	MPC + TES	Energy cost, PV self-consumption	Significant cost reduction using building envelope as passive TES	Simulation + real-world testing	Madrid, Spain	Residential; climate-dependent performance
	Calise et al. (2025) [28]	Capacitive radiator model (MATLAB R2024b/TRNSYS 18)	Thermal underestimation	Non-capacitive model underestimated heating by ~20%	Simulation data	Unspecified	Model-specific; may need calibration for other building types
Energy Consumption Estimation	Attarhay Tehrani et al. (2025) [11]	DNN, XGBoost, GPR, RF, SVR	Cooling load R^2	DNN R^2 = 0.98 on synthetic dataset	Synthetic data	Phoenix, USA	Synthetic data; city-specific UHI
	Habibi (2025) [12]	Random Forest	R^2, feature importance	R^2 = 0.724	ZigBee sensor data	Belgium	Single building; sensor-dependent
	Kumar et al. (2024) [21]	GA-SVM + IG-SVM	MAPE, CV-RMSE	MAPE: 2.59–2.84%	Historical energy data	Unspecified	Building scale; dataset dependency
	Tavant et al. (2025) [20]	Maximum a posteriori + degree-days	Heating/cooling disaggregation	Validated on 1-year case study	Real-world building data	Lisbon, Portugal	Single building; limited geographic scope

Table 3. *Cont.*

Category	Study	Methodology	Key Metrics	Findings	Data Source	Geographic Scope	Key Limitation
Energy Consumption Estimation	Ahmad et al. (2017) [48]	Random Forest vs. ANN for hourly energy prediction	Energy prediction	R^2 = 0.94 (Random Forest); RMSE lower than ANN	High-resolution smart meter data	UK	Hourly data dependency; performance degrades with coarser temporal resolution
	Li et al. (2018) [51]	Sensitivity analysis + parametric optimization for subtropical NZEBs	Parametric optimization	42% EUI reduction vs. baseline; top parameters: WWR, insulation, shading	Parametric simulation	Hong Kong	Subtropical focus; findings not directly transferable to cold or temperate climates without recalibration
Occupancy Modeling	Sood (2025) [23]	Bayesian Neural Networks (BNNs)—UPOM	Occupancy accuracy	90% nighttime accuracy	Time Use Survey (TUS)	Ireland	National scale; cultural-behavioral specificity
	Kovacevic et al. (2024) [24]	Ensemble occupancy model	Energy difference (kWh)	Ensemble: 132 kWh vs. 278 kWh (classic)	Measurement data	Germany	Building scale; ensemble complexity
	Al-Saegh et al. (2025) [22]	Comparative: 5 occupancy models	Annual/peak heating errors	Data-driven (Scenario E): 12% annual heating error	Metered campus data	London, UK	District scale; campus-specific profiles
	Al-Saegh et al. (2024) [46]	Comparative: deterministic, stochastic, data-driven	Peak heating errors	Data-driven: ±2.5% annual heating error vs. 14% standard	Metered building stock data	London, UK	Building stock scale; model requires historical metered data for training
Cost Estimation	Rashidi et al. (2024) [34]	BIM for pre-tender estimation	Cost/time accuracy	Reduced errors; faster than manual	BIM models	Iran	National scale; BIM adoption dependency
	Isvara & Kamilah (2024) [38]	Hybrid regression + ANN	MAPE	MAPE = 15.09% (within AACE standards)	Construction data	Indonesia	Regional; green building specific
	Zhang (2024) [15]	AICD-CDM (ML ensemble)	Cost prediction accuracy	Hybrid reduced errors vs. standalone	Construction data	Unspecified	Project scale; data availability dependency
Digital Twins & BIM	Venkateswarlu & Sathiyamoorthy (2025) [13]	Systematic review	BIM/IoT/big data integration	17/261 studies; need for multidisciplinary frameworks	Literature	Global	Review scope; no empirical data
	Mehraban et al. (2024) [9]	BIM + ML (GBM, RF, SVM)	R^2 for EUI	GBM R^2 = 0.989; roofs: 29–40% EUI impact	BIM models	Riyadh, Dubai	Hot climate specific; limited geographic generalizability
	Zech et al. (2025) [33]	Model-based BIM tool integration	Interoperability, simulation	Continuous performance simulation via improved BIM interoperability	BIM + simulation models	Unspecified	Building to portfolio scale; interoperability challenges

Felez & Felez [29] extended the concept of passive thermal energy storage (TES) in residential buildings by integrating MPC with the building's thermal mass, enabling PV self-consumption optimization and significant electricity cost reductions, demonstrating that intelligent control of passive building properties can maximize the economic benefit of on-site renewable generation without requiring expensive battery storage infrastructure. Sahrin et al. [30] proposed a neural network model with grid search cross-validation (GSCV-NN) for optimizing rooftop solar PV energy import estimation, achieving competitive RMSE values (44.389 for single-direction estimation), which is essential for accurate sizing and dispatching solar systems in tropical climates.

At the neighborhood scale, Liu et al. [31] demonstrated the use of Semantic Web Ontology and Linked Data (NPO framework) to resolve interoperability challenges in PV generation estimation across multiple buildings, enabling coordinated neighborhood-scale renewable energy planning in the Netherlands. Tang [14] employed grey relational analysis and Principal Component Analysis (PCA) to quantify the cost impact of renewable energy integration in green building projects, finding that strategic RES integration can reduce the overall cost of green building projects.

3.3. Energy Consumption Estimation and Prediction

Machine learning-based methods dominated energy consumption estimation studies, collectively demonstrating superior accuracy compared to traditional physics-based and statistical approaches. Attarhay Tehrani et al. [11] achieved R^2 = 0.98 in cooling load prediction under urban heat island (UHI) conditions using a Deep Neural Network (DNN), outperforming XGBoost, Random Forest, Support Vector Regression (SVR), and Gaussian Process Regression (GPR) on a synthetic Phoenix dataset. This result confirms the advantage of deep learning for capturing complex nonlinear relationships between UHI effects and building cooling demands.

Habibi [12] applied Random Forest to real-world ZigBee sensor data from a Belgian residential building, achieving R^2 = 0.724 and identifying "hour of day" as the most influential predictor of energy consumption (19.9% feature importance), followed by relative humidity (19.5%) and outdoor temperature (18.9%). These findings underscore the critical role of temporal patterns and microclimate conditions in building energy prediction, which has direct implications for renewable energy dispatch scheduling. Kumar et al. [21] combined Genetic Algorithms (GAs) with Support Vector Machines (SVMs) to achieve cooling load prediction MAPE values of 2.59–2.84%, among the lowest reported in the literature confirming the benefit of metaheuristic optimization for ML hyperparameter tuning. Tavant et al. [20] demonstrated a probabilistic disaggregation approach using maximum a posteriori estimation combined with degree-days for separating heating and cooling contributions from total energy consumption data, validated on a one-year case study in Lisbon, Portugal.

3.4. HVAC Optimization and Renewable Energy Coupling

HVAC systems account for 40–60% of total building energy consumption [52,53], making their optimization critical to achieving significant overall energy reductions. The reviewed studies demonstrate that combining renewable energy with intelligent HVAC control produces synergistic benefits that exceed the gains achievable by either approach in isolation [54]. Kaisermayer et al. [26] achieved simultaneous 35% energy reduction and 12% improvement in thermal comfort by implementing a predictive Energy Management System (EMS) incorporating user feedback and an Unscented Kalman Filter (UKF) for real-time state estimation in an Austrian residential building. This study exemplifies the potential of human-in-the-loop predictive control for sustainable building operation.

Wang et al. [27] proposed a Safe Deep Reinforcement Learning (Safe DRL) approach for building energy management that integrates safety filters derived from MPC to prevent constraint violations, surpassing both MPC and Double Deep Q-Network (DDQN) baselines in comfort maintenance and constraint satisfaction with minimal computational overhead. Adepoju [25] demonstrated a CNN/Graph Neural Network (GNN) HVAC optimization framework (AIRFLO) that leverages spatial occupancy patterns and class schedules to dynamically adjust HVAC setpoints in a campus building in Texas, highlighting the scalability of AI-based HVAC control to multi-zone institutional buildings. Calise et al. [28] showed that neglecting thermal capacitance in radiator models leads to ~20% underestimation of heating energy, emphasizing the importance of accurate physical modeling as a foundation for effective RES-coupled HVAC control.

3.5. Occupancy Modeling for Energy Reduction

Occupancy patterns are a primary driver of building energy consumption variability, and accurate occupancy modeling is essential for effective scheduling of both HVAC systems and renewable energy dispatch [55,56]. Sood [23] developed UPOM, a probabilistic occupancy model using Bayesian Neural Networks (BNNs), achieving 90% nighttime prediction accuracy on national Time Use Survey (TUS) data from Ireland. The study demonstrated that deterministic occupancy models introduce up to 50% daily energy variation, confirming the need for probabilistic approaches in building energy simulation.

Kovacevic et al. [24] integrated ensemble occupancy patterns into a reduced-order building model, reducing the annual energy prediction error from 278 kWh (classic model) to 132 kWh, a 52.5% improvement in a German residential building study. Al-Saegh et al. [22] compared five occupancy modeling approaches for a university campus in London, showing that data-driven models reduce annual heating demand estimation error from 14% (standard deterministic model) to $\pm$2.5%, demonstrating the substantial accuracy benefits of data-driven occupancy characterization at the district scale.

3.6. Cost Estimation for Renewable Energy Integration

The economic dimension of RES integration in buildings is critical for widespread adoption, yet it remains one of the least comprehensively studied aspects in the reviewed literature [27]. Tang [14] applied grey relational analysis and PCA to construction cost data from green building projects, finding that proactive renewable energy integration planning through life-cycle cost analysis can reduce total project costs. Zhang [15] proposed an Artificial Intelligence-based Cost Data Management (AICD-CDM) ensemble model combining Linear Regression, ANN, Random Forest, XGBoost, LightGBM, and Natural Gradient Boosting (NGBoost) for green building cost prediction, demonstrating that ensemble methods outperform standalone models in cost prediction accuracy.

Isvara & Kamilah [38] demonstrated a hybrid regression–ANN model for conceptual cost estimation in green buildings, achieving MAPE = 15.09%, meeting the AACE International accuracy standards. These findings confirm that ML-based cost estimation is mature enough for practical application in RES-integrated green building projects. BIM-based studies [34,36,37] further demonstrated that BIM tools significantly reduce cost estimation errors and improve scheduling efficiency, with the potential to be extended to RES component integration and life-cycle energy cost modeling.

4. Discussion

4.1. Synthesis of Renewable Energy Outcomes Across Studies

The reviewed evidence consistently demonstrates that renewable energy integration in buildings delivers substantial and measurable energy consumption reductions. The

highest reductions up to 64% in electricity costs [3] and 35% in total energy demand [26] were achieved when RES were combined with intelligent real-time control systems (HEMS, predictive EMS, safe DRL), confirming that the synergy between renewable generation and intelligent energy management is essential for maximizing building-level energy reduction outcomes. Studies that implemented isolated RES without integrated control strategies reported more modest gains, underscoring the importance of system-level design thinking.

Solar PV systems, in particular, demonstrated the highest frequency of deployment and the broadest applicability across building types and scales from single households [3,4] to neighborhood-level planning [31]. This is consistent with the global trend of declining PV system costs and increasing grid parity penetration. However, the reviewed studies reveal a notable gap in research on solar thermal systems, geothermal heat pumps, and wind energy integration in buildings, technologies with significant untapped potential, particularly in climates where solar PV performance is seasonal or constrained by shading.

4.2. Role of Machine Learning and IoT in Enabling Effective RES Integration

Machine learning methods proved to be indispensable enablers of effective RES integration in buildings, performing three critical functions: energy consumption prediction, renewable generation forecasting, and real-time optimization of energy dispatch. The highest-performing ML models in the reviewed studies, DNNs for cooling load prediction (R^2 = 0.98) [11], GBM for energy use intensity prediction (R^2 = 0.989) [9], and GA-SVM for MAPE of 2.59–2.84% [21], demonstrate that deep learning and hybrid ML approaches can achieve levels of predictive accuracy sufficient for reliable operational decision-making in energy-aware buildings.

IoT-enabled real-time sensor integration, as demonstrated by Rokonuzzaman et al. [4] with near-perfect regression accuracy, is a critical prerequisite for deploying ML models in live building management settings. However, a persistent limitation across the reviewed studies is the reliance on synthetic or highly localized datasets, which raises questions about the generalizability of trained models to different building types, climates, and occupancy patterns. Habibi [12] and Al-Saegh et al. [22] both noted that their models' predictive accuracy is sensitive to the quality and representativeness of training data, a challenge that must be addressed through the development of open, standardized building energy datasets covering diverse geographic and climatic conditions. A direct benchmarking of ML approaches across the reviewed studies reveals a clear performance–complexity trade-off: while DNN architectures report the highest accuracy metrics (R^2 up to 0.989), this performance is predominantly demonstrated on synthetic or single-site datasets, limiting operational transferability. In contrast, ensemble methods (Random Forest, GBM) and hybrid metaheuristic–ML models (GA-SVM) achieve competitive accuracy (R^2 = 0.724–0.94; MAPE = 2.59–2.84%) on real-world building datasets, suggesting superior practical applicability. The very high prediction accuracies reported in several reviewed studies—notably R^2 = 0.999999 [4], R^2 = 0.989 [9], and R^2 = 0.98 [11]—warrant critical scrutiny regarding overfitting and real-world transferability. Future studies should report cross-validation results, out-of-sample test performance, and deployment validation on independent real-world datasets to substantiate operational reliability claims.

4.3. Identified Research Gaps

This systematic review identifies five critical research gaps that should guide future work in this field:

Gap 1—Geographic and Climatic Inclusivity: The majority of reviewed studies are concentrated in Europe, North America, and East Asia, with limited representation of tropical, arid, and sub-Saharan African contexts. Given that these regions often have the

highest solar irradiance and the greatest need for affordable clean energy, the absence of context-specific research represents a significant equity gap. Future studies should prioritize multi-climate, multi-country datasets that enable the development of geographically inclusive RES integration models.

Gap 2—Long-Term Performance and Reliability: Most reviewed studies report short-term (days to months) or simulation-based performance outcomes. The long-term reliability of RES systems accounting for panel degradation, battery cycle life, maintenance requirements, and changing occupancy patterns over years to decades is insufficiently addressed. Longitudinal studies and post-occupancy evaluations are critically needed to provide evidence-based guidance on the life-cycle value of building-integrated RESs.

Gap 3—Multi-Source Renewable Energy Integration: Studies predominantly focus on single-technology RESs (typically solar PV). Research on the co-optimization of multiple renewable sources, e.g., solar PV + solar thermal + geothermal heat pumps + small wind, within a unified building energy management framework is sparse. Such hybrid systems have the potential to deliver more consistent year-round energy reductions across diverse climates.

Gap 4—Occupant Behavior and Social Acceptance: While occupancy modeling is well represented in the reviewed literature, the interaction between occupant behavior, social acceptance of RES technologies, and actual energy savings remains underexplored. Studies combining behavioral modeling with technical performance analysis are rare, yet critical for accurately projecting the real-world impact of RES integration.

Gap 5—Economic Feasibility and Equity: Life-cycle cost analysis, payback period assessment, and financial accessibility of RES integration, particularly for low-income households and developing economies are insufficiently covered. Only a small subset of reviewed studies [14,15,38] addressed economic dimensions, and none provided comprehensive life-cycle analysis covering both capital and operational cost streams over multi-decade time horizons.

4.4. Implications for Practice and Policy

The findings of this review have direct implications for building design practice, energy policy, and regulatory frameworks. For building designers and engineers, the evidence strongly supports the adoption of solar PV-integrated smart HEMS as the baseline configuration for new residential and commercial buildings in high-insolation regions, with projected electricity cost reductions of 40–64% [57]. The integration of ML-based predictive control [26,27] can deliver additional energy savings of 20–35% compared to conventional rule-based control [58], justifying the modest additional investment in sensing and computing infrastructure.

For policymakers, the review highlights the need for performance-based incentive frameworks that reward not just RES installation but verified energy reduction outcomes, a distinction that is currently rare in existing subsidy and certification schemes. The geographic concentration of research in affluent regions also suggests that international development organizations and research funding bodies should prioritize support for building energy research in climate-vulnerable, high-growth developing economies, where the energy efficiency dividend of RES integration is both technically feasible and socially transformative. It is important to note that the majority of the quantitative performance outcomes reported in this review are derived from simulation-based or controlled experimental environments. These results should be interpreted as indicative of technical potential rather than guaranteed real-world performance. Independent empirical validation across diverse building types, climates, and occupancy profiles is required before the reported energy reductions can be confidently generalized to large-scale deployment.

4.5. Economic Feasibility and Practical Deployment Considerations

From an economic feasibility perspective, the reviewed studies collectively demonstrate that RES integration combined with ML-based management reduces electricity costs by 35–64% [3,26], translating—under typical European and North American tariff structures—to estimated payback periods of 4–8 years for residential solar PV systems. However, comprehensive life-cycle cost analyses covering capital expenditure, maintenance, system degradation, and decommissioning costs over 20–25-year building life-cycles remain rare in the reviewed literature, representing a critical gap for application-oriented policymaking. Tang [14] and Zhang [15] provide partial economic evidence through grey relational analysis and ML-based cost prediction, respectively, while Isvara & Kamilah [38] validated conceptual cost estimation models meeting AACE International standards (MAPE = 15.09%). BIM-based studies [34,36,37] further confirm the potential of integrated digital tools for life-cycle cost management. The practical deployment of RES-ML-IoT integrated systems also faces significant non-technical barriers including upfront capital requirements, limited BIM adoption in developing economies, IoT infrastructure costs, and workforce skills gaps—factors that must be addressed in comprehensive feasibility assessments. Future research should prioritize techno-economic analysis frameworks that integrate capital costs, energy tariff structures, degradation rates, and climate-specific performance projections over the full building life-cycle, enabling evidence-based investment decisions across diverse economic and geographic contexts.

5. Conclusions

This systematic review of 41 peer-reviewed studies (2012–2025) provides comprehensive evidence that the integration of renewable energy systems, particularly solar photovoltaic (PV) combined with intelligent energy management, represents the most effective and economically viable pathway to achieving substantial reductions in building energy consumption. The key findings of this review are summarized as follows:

1. Renewable energy integration delivered measured electricity cost reductions of 35–64% across reviewed studies, with the highest outcomes achieved when RESs were coupled with ML-based predictive control systems and real-time IoT monitoring.
2. Machine learning models, particularly Deep Neural Networks (DNNs), gradient boosting machines (GBMs), and hybrid GA-SVM approaches achieved energy prediction accuracies of R^2 = 0.98–0.989, providing the predictive foundation necessary for effective RES dispatch optimization.
3. HVAC optimization coupled with RESs simultaneously reduced energy consumption by up to 35% while improving thermal comfort by up to 12%, confirming the synergistic value of integrated building energy management.
4. Occupancy-aware energy models reduce energy prediction errors by up to 52.5% compared to conventional deterministic approaches, demonstrating the critical importance of behavioral modeling in realistic energy performance assessment.

The main limitations of this review include the reliance on the published peer-reviewed literature (which may introduce publication bias toward positive results), the geographical concentration of included studies in high-income regions, and the predominantly short-term or simulation-based performance data available in the literature. These limitations underscore the need for more geographically diverse, longitudinal, and real-world validation studies. A critical limitation of the current evidence base is that the vast majority of reported performance outcomes—including electricity cost reductions of 35–64% and ML model accuracies of R^2 = 0.98–0.989—are derived from short-term measurement campaigns or simulation environments. The long-term stability of these outcomes under real-world conditions of component degradation, occupancy change, climate variability, and system

aging has not been empirically verified at scale. Longitudinal post-occupancy studies of at least five years' duration are urgently needed. Furthermore, this review's corpus of 41 studies reflects the application of rigorous PRISMA-compliant quality criteria to a broad initial search of 580 records across five databases. While this quality-first approach ensures methodological integrity, it necessarily limits corpus breadth. Readers should interpret the synthesized findings as evidence from a high-quality study subset rather than a complete field census. Future reviews adopting broader inclusion criteria or domain-narrowed search strategies may yield larger corpora, enabling sub-group meta-analyses not feasible with the current dataset. It is also important to note that the majority of the quantitative performance outcomes reported in this review are derived from simulation-based or controlled experimental environments and should be interpreted as indicative of technical potential rather than guaranteed real-world performance. Independent empirical validation across diverse building types, climates, and occupancy profiles is required before the reported energy reductions can be confidently generalized to large-scale deployment.

Future research should prioritize (i) development of open, multi-climate building energy datasets that enable geographically inclusive model training and validation; (ii) long-term ($\geq$5-year) post-occupancy evaluation of RES-integrated buildings to assess real-world degradation, maintenance costs, and sustained energy savings; (iii) multi-source RES co-optimization frameworks that integrate solar PV, solar thermal, geothermal, and storage technologies within unified building energy management systems; (iv) comprehensive life-cycle cost and techno-economic analyses of RES integration across diverse building types and global economic contexts; and (v) integration of occupant behavioral and social acceptance modeling into RES performance assessment frameworks.

The transition to net-zero energy buildings (NZEBs) is both technically achievable and economically justified based on the evidence synthesized in this review. Accelerating this transition requires sustained investment in multi-disciplinary research, scalable technology deployment, and enabling policy frameworks that align financial incentives with verified energy reduction outcomes.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings16132475/s1, Table S1: Data extraction matrix for the 41 included studies, including study characteristics, methodological approach, key performance metrics, findings, thematic category, data source, geographic scope, and reported limitations. The PRISMA 2020 reporting checklist is cited in the main text [16].

Author Contributions: M.M.A.M.: Conceptualization, Formal analysis, Investigation, Writing—original draft, K.W.C.: Supervision, Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding. The article processing charge (APC) was funded by the authors.

Data Availability Statement: No new datasets were generated or analyzed in this study. The data supporting the findings are derived from the published studies cited in the reference list, and the extracted study-level information is provided in Supplementary Table S1. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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