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Artificial Intelligence Applications in Sustainable Buildings: A Systematic Synthesis of Machine and Deep Learning Approaches

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Abstract. Artificial intelligence (AI) is increasingly used to support sustainability-oriented decisions in building design, construction, and operation. This paper presents a systematic literature review of peer-reviewed journal articles at the intersection of AI (machine learning and deep learning) and sustainable buildings. Searches were conducted primarily in Scopus and complemented by SpringerLink and Google Scholar. Following PRISMA-based screening and eligibility assessment, 59 articles published between 2016 and 2023 were retained for synthesis. The review maps AI applications to the three sustainability pillars, identifies dominant application domains, and summarizes the most frequently adopted algorithms and software tool chains. Environmental sustainability dominates literature, with energy prediction and optimization as the most common use cases. Social sustainability research concentrates on indoor environmental quality and thermal comfort, while economic sustainability remains comparatively limited and is largely focused on cost prediction. Overall, tree-based machine learning models and conventional artificial neural networks appear most prevalent, typically reporting positive performance in predictive and optimization tasks. The review concludes with research gaps and practical directions for future work, including better coverage of social and economic outcomes, more transparent and explainable models, and tighter integration with BIM and life-cycle assessment workflows.

Introduction

Sustainable building design aims to reduce environmental impacts while supporting occupant well-being and economic feasibility. Digitalization has expanded the availability of building performance data (from simulation, BIM, and sensing), enabling data-driven methods to complement conventional analytical approaches. AI techniques, particularly machine learning (ML) and deep learning (DL), have been used to predict energy demand, optimize envelopes and system parameters, and support occupant-centric control strategies. Human-centric regenerative design perspectives further motivate the integration of computational tools into design workflows [1]. Despite rapid growth in the number of publications, the literature remains fragmented across application domains, sustainability dimensions, and algorithmic choices. This review consolidates recent evidence to answer four research questions: (1) how AI is applied across the environmental, social, and economic pillars; (2) which ML and DL models are most frequently used; (3) which building sustainability issues are most often targeted; and (4) which model families appear to perform best in reported applications. The main contributions are: (i) a PRISMA-informed synthesis of 59 journal articles [1]-[56]; (ii) a taxonomy of AI methods and software pipelines used in sustainable building research; and (iii) a discussion of research gaps relevant to conference and practice-oriented audiences.

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Methods

A systematic literature review protocol was adopted to ensure transparent study identification, screening, and synthesis. The review focused on journal articles written in English and reporting primary research (empirical, experimental, or computational). Conference proceedings, book chapters, and narrative reviews were excluded to maintain methodological consistency.

A. Search Strategy: Searches were conducted in Scopus and complemented with SpringerLink and Google Scholar using Boolean queries combining sustainability terms (e.g., "sustainable building", "green building") with AI terms (e.g., "machine learning", "deep learning", "artificial intelligence").

B. Screening and Eligibility: Records were de-duplicated and screened by title and abstract, followed by full-text eligibility checks. The process followed PRISMA logic, resulting in an initial pool of 283 records and a final corpus of 59 studies.

C. Data Extraction and Synthesis: For each included study, metadata and analytical attributes were extracted (publication year, country, research design, target sustainability issues, AI model type, and software tools).

Descriptive statistics were used to summarize distributions, and qualitative synthesis was used to interpret thematic patterns and data.

Results and Discussion

Publication and methodological trends:

The PRISMA screening process yielded 59 eligible journal articles from an initial pool of 283 records. The evidence base is recent and rapidly expanding publications increased steadily from 2016 (n=1) to a peak in 2023 (n=19), with 88% of studies published between 2020–2023 (n=52). Geographically, contributions were concentrated in a small number of countries, led by China (21/59), followed by Iran (5) and Italy (3). This distribution suggests that AI for sustainable buildings is globally investigated but remains uneven in research output.

In terms of research design, correlational studies were most common (31%), followed by experimental/causal (26%), exploration (25%), and descriptive designs (18%) (Figure 1).

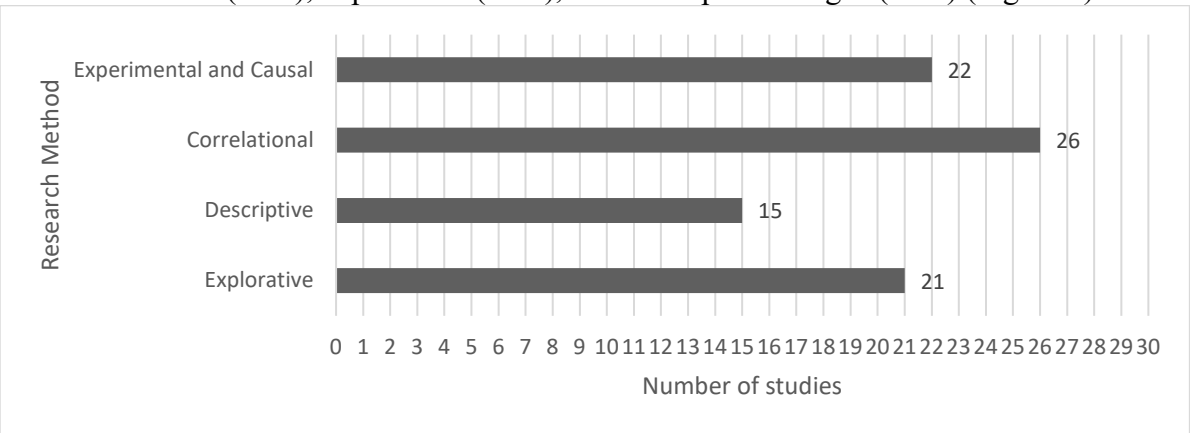

Figure 1: Research Methods

Most studies were quantitative (59%), while qualitative-only approaches were less frequent (13%); mixed methods accounted for 28%. Case study implementation remains limited: 24% (14/59) reported real-world case studies, whereas most studies relied on broader datasets or simulations as shown in figure 2. Overall, the literature is dominated by data-driven predictive

modeling, frequently evaluated through simulation environments rather than full-scale field deployment.

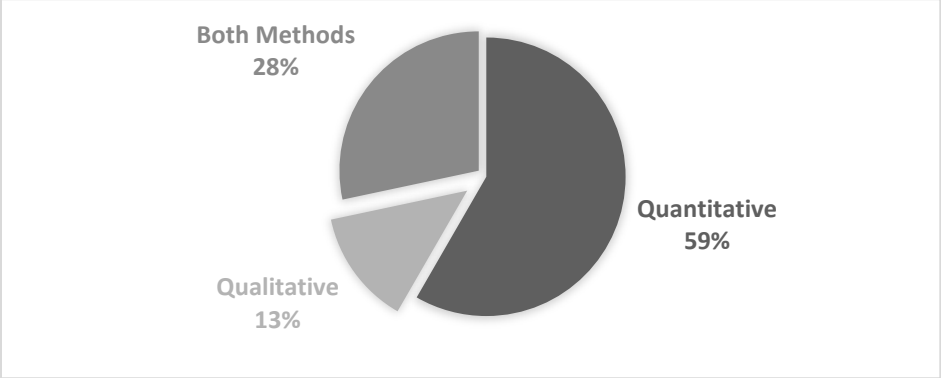

Figure 2: Research Types

Sustainability aspects addressed in the literature:

Across the reviewed studies, AI applications targeted a wide range of sustainable building issues, spanning energy systems, envelope and insulation, indoor environmental quality (IEQ), HVAC and ventilation control, life-cycle assessment, emissions reduction, materials selection, and cost estimation (Table 1). Energy-related applications were the most prominent (22/59; 37%), followed by thermal comfort-focused research (9 studies).

Table 1: Sustainability Pillars Issues

Sustainability core dimension	CODE	List of sustainability issues/aspects/factors :	Paper ID :	NO:	TOTAL	Frequa	Percentage
ENVIRONMENTAL SUSTAINABILITY	S1	Sustainable materials	2,3,5,42	4	47	8.47%	65%
	S2	Energy load/consumption/storage/loss/efficency	4,6,9,11,14,16,17,18,20,21,22,25,26,27	22		37.29%	
	S3	Life cycle assessment /Green performance assessment	6,31,47,24,48,59	6		10.17%	
	S4	Greenhouse gas emissions	7,31,41,59	4		6.78%	
	S5	Insulation technique	9,58	2		3.39%	
	S6	Renewable energy resources	26,30,45,46,51,53,55	7		11.86%	
	S7	Landscape Environment	32	1		1.70%	
	S8	Lighting control	52	1		1.70%	
SOCIAL SUSTAINABILITY	S9	Façade Esthetics	1,	1	19	1.70%	27%
	S10	Building climate control (Indoor) (Natural Ventilation) (Air Conditioning	8,19,28,30,36,37,45	7		11.86%	
	S11	Thermal comfort satisfaction	15,20,22,23,29,39,42,50,56	9		15.25%	
	S12	Human Centric	34,49	2		3.38%	
ECONOMICAL SUSTAINABILITY	S13	Construction/building Cost	10,12,13,33,38,43	6	6	10.16	8%

When grouped under the three pillars of sustainability, the evidence shows a clear imbalance. Environmental sustainability dominated (~65% of studies), social sustainability was secondary (~27%), and economic sustainability was least represented (~8%). This pattern indicates that AI research in sustainable buildings has primarily prioritized measurable performance outcomes (energy and emissions) over occupant-centered and economic considerations.

Environmental applications commonly address energy management and efficiency, life cycle and performance evaluation, materials optimization, and emissions reduction. Reported success rates were generally favorable: energy management appeared in 37.3% of studies with ~68% success, LCA/green performance evaluation appeared in ~10.7% with ~83% success, and materials/emissions-related applications showed success rates around 75% in the reviewed subset.

Social themes emphasized occupant experience, particularly thermal comfort and indoor climate control. Thermal comfort was discussed in 15.3% of studies, while AI-enabled climate control systems appeared in ~11.9% (reported success ~71%).

The comparatively smaller volume of work in this pillar suggests an opportunity to expand beyond comfort prediction to broader well-being and behavioral outcomes.

Economic applications focused mainly on cost prediction and optimization for green buildings. Where reported, ML-based cost prediction achieved ~66.7% success across relevant studies, and

at least one XGBoost model reported very high predictive accuracy ($R^2 \approx 0.96$). Despite strong results, this pillar remains underexplored relative to environmental performance.

Machine learning models: dominance of tree-based predictors:

ML methods were widely used and were classified by intended use and by fundamental task (Table 2). By intended use, decision-tree algorithms were the most prevalent (~36%), followed by regression models (~21%) and gradient boosting methods (~13%) (Table 2). Empirically, tree-based predictors were frequently reported as effective in building-performance contexts: simple decision trees showed positive outcomes in 84.5% of the studies in which they appeared, while Random Forest achieved a 66.7% positive impact rate in the subset reported. Beyond trees, several non-linear regressors (e.g., SVR and GPR) were reported with consistently positive outcomes in the studies where they were used, while basic linear regression showed mixed performance, suggesting limited suitability for complex, non-linear building datasets.

Collectively, these patterns reinforce that robust, non-linear learners dominate practical AI deployment in this domain, likely due to their ability to capture complex interactions among climate, geometry, materials, and operational variables. From the "fundamental type" perspective, predictive models represented the largest share (~47%), with classification (~19%) and regression-focused tasks (~14%) also common (Table 2). This confirms that the primary role of ML in sustainable building research is forecasting key outcomes (energy, comfort proxies, cost) to support design and operational decision-making.

Table 2: Machine Learning Models

CODE	Group 1:	Machine Learning Algorithms	Paper ID:	NO:	TOTAL	Frequancy in Papers Percentac	Scope/Use :
	Gradient Boosting Methods 1:				8	13.50%	
M1		Gradient boosting (GBR)	3,16	2			Predictive Models
M2		Extreme gradient boost regressor (XGBR)	3,23	2			Predictive Models
M3		LightGBM	10,25	2			Predictive Models
M4		XGBOOST	10,13	2			Predictive Models
	Decision Tree Algorithms/Models 2:				22	37.20%	
M5		Decision Tree algorithms/models	1,9,15,24,27,29,31	13			Predictive Models
M6		FLR, C4.5, IBK, OneR	55	1			Decision Making
M7		Random Forest (RF)	11,15,20,32,38,43	6			Data Classification
M8		Random Tree (RT)	11,13	2			Data Classification
	Ensemble Learning Methods 3:				3	5%	
M9		Adaptive Boosting regressor (ABR)	3	1			Predictive Models
M10		Reinforcment learning	26	1			Decision Making
M11		Multi-linear Random Forest Regression (MRFR)	7	1			Predictive Models
	Regression Models 4:				13	22%	
M12		Linear Regression	43,54	2			Predictive Models
M13		Ridge and Lasso	43	1			Predictive Models
M14		Support Vector Regression (SVR)	12,15,16,20,51,52	6			Regression Tasks
M15		Extreme Learning Machine (ELM)	36	1			Regression Tasks
M16		Gaussian Process Regression (GPR)	8,9,22	3			Probabilistic Models
	Classification and Clustering Models 5:				7	11.86	
M17		PLS-DA	2	1			Predictive Models
M18		LCSA-ML Model	6	1			Data Processing/extr
M19		Linear Discriminant Analysis (LDA)	7,33	2			Data Processing/extr
M20		Support Vector Machine (SVM)	9,31,54	3			Data Classification
	k-Nearest Neighbor (k-NN) 6:				2	3.38%	
M21		k-Nearest Neighbor (k-NN)	19,20	2			Predictive Models
	Multi-objective Optimization 7:				3	5%	
M22		Multi-objective optimization (MOPSO)	39,42,47	3			Decision Making
	Other Models/Techniques 8:				2	3.38%	
M23		Boolean Ant Colony Optimization (BACO)	7	1			Predictive Models
M24		Multivariate adaptive regression splines (MARS)	54	1			Predictive Models
	Topic Modeling 9:				1	1.60%	
M25		Latent Dirichlet Allocation (LDA)	17	1			Probabilistic Models

Deep learning models: concentrated in comfort and prediction tasks:

Deep learning appeared in 28 of 59 papers (~47%) (Table 3). By architecture type, ANN models were dominant (~59%), while DNN and other neural network variants each accounted for ~10%. Sequence and spatial architecture (RNN/LSTM and CNN) were less frequent (~6% each).

Transformer-based and TCN approaches were rare (~3% each) and, in the limited instances reported, produced neutral-to-negative outcomes, suggesting that cutting-edge architectures are not yet established in this application space.

By application type, DL usage was overwhelmingly predictive (75%), with a smaller share used for feature extraction/data processing (18%) (Table 3). In practice, this supports a consistent interpretation: DL is primarily used when researchers expect complex, non-linear relationships (often occupant-related or time-dependent) and when sufficient data streams (e.g., sensor or simulation time series) are available.

Table 3: Deep learning Models

CODE	Column1	Deep Learning algorithms	Paper ID:	NO:	TOTAL	FREQUANCY IN PAPERS	Scope/Use :	Postive Effect Papers ID	Percentag	Negative Effect Papers ID	Percenta	Neutral Effect Papers ID	Percenta
	Recurrent Neural Networks (RNN) 1:				2	3.20%							
D1		LSTM Models	4,44	2			Data processing/estr	0	0%	0	0%	4,44	100%
	Convolutional Neural Networks (CNN) 2:				2	3.20%							
D2		You only look once (YOLO	48	1			Data processing/estr	48	100%	0	0%	0	0%
D3		Region-based convolutional neural network (R	48	1			Probabilistic Models	48	100%	0	0%	0	0%
	Deep Belief network (DBN) 3 :				1	1.60%							
D4		Deep Belief network (DBN)	5	1			Predictive models	5	100%	0	0%	0	0%
	Deep Neural Networks (DNN) 4:				3	5%							
D5		Deep Neural Networks (DNN)	12,13,45	3			Predictive models	12,13	66.66%	45	33.33%	0	0%
	Transformers-Based Models 5 :				1	1.60%							
D6		Bidirectional Encoder Representations from Tr	17	1			Data Classification	0	0%	17	100%	0	0%
	Temporal Convolutional Neural Networks (TCN) 6 :				1	1.60%							
D7		Deep temporal convolutional neural network	57	1			Data Processing/est	0	0%	0	0%	57	100%
	General Terms 7 :				3	5%							
D8		Neural network algorithm (NNA)	18,21,59	3			Predictive Models	18,21,59	100%	0	0%	0	0%
	Artificial Neural Networks (ANN) 8 :				19	32.20%							
D9		Artifical neural network (ANN)	1,11,14,15,16,28,30,	14			Predictive models	1,11,14,15,16,28,36,39,42,46,53	78.57%	30,34		14,20%	7%
D10		Backpropagation Neural Networks (BPNN):	35	1			Data processing/estr	0	0%	35	100%	0	0%
D11		Adaptive-Network based Fuzzy Inference Syste	11	1			Predictive models	11,	100%	0	0%	0	0%

Research themes and tools: a simulation-to-AI workflow:
Six dominant research themes were identified (Table 4), led by predictive modeling for sustainable design (61%), followed by AI in green building practices (13%) and materials classification/rating (8%). Smaller thematic clusters included integrated AI workflows, LCSA–ML integration, and BIM–ML approaches.

Table 4: Scope of the studies

Scope of the overall studies (two strings correlated)	Paper ID	No.
Developing Machine learning models to predict or benefit of sustainable architecture.	1,6,7,8,9,10,12,13,15,16,18,19,20,21,22,23,24,25,26,27,29,30,31,33,36,37,39,41,43,44,45,46,50,51,53,54,55,56,57,59,60	41
Machine Learning or Deep learning models to classify and assess sustainable materials.	2,3,5,42,46,	5
Deep learning integrated with machine learning in applications of sustainable architecture.	4,28,35,38,48,	5
Machine Learning integrated with tools like LCSA to assess sustainable buildings.	6,24,30,47,	4
Integrating Machine Learning and BIM towards the benefits of green architecture.	25,37,58	3
The use of artifical intelligence models in the sustainable architecture and green buildings.	1,11,14,17,28,32,34,49,52	9

The digital tool ecosystem (figure 3) further indicates a typical pipeline. Data analysis/programming tools were most common (33%), with MATLAB/Simulink frequently reported (~12 papers). Energy/environment simulation tools comprised 22% (notably EnergyPlus and DEST), and design/simulation platforms accounted for 17% (e.g., Design Builder, Rhino/Grasshopper). BIM tools represented 14% (e.g., Revit). Taken together, the evidence indicates a recurring workflow: (i) model and simulate building performance, (ii) extract and curate datasets, (iii) train ML/DL predictors, and (iv) interpret/visualize results for design or operational decisions (figure 3).

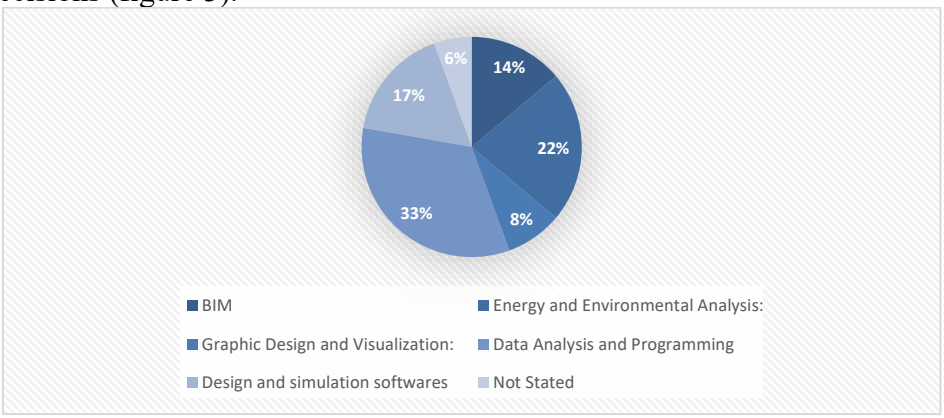

Figure 3: Overall Scopes of the studies

Cross-variable synthesis: models, pillars, and tools align in predictable clusters:
The correlation synthesis (Table 5) highlights three recurring clusters. First, environmental sustainability studies frequently used ML predictive models, particularly tree-based algorithms, often coupled with energy/environmental simulation tools; this cluster represents ~53% (33/59) of the sample.

Second, social sustainability studies commonly used DL predictive models (especially ANN) and relied on design/simulation tools to evaluate comfort and control strategies. Third, economic sustainability studies primarily employed ML predictors (often boosting and ensemble trees) for cost estimation and optimization.

According to the dataset, study outcomes were predominantly positive: approximately three-quarters of studies reported that AI methods met the intended objectives, with fewer neutral and negative outcomes. The prevalence of positive results supports the maturity of predictive modeling for energy and cost tasks; however, the scarcity of economic and broader social sustainability applications indicates a research gap that may limit holistic sustainability decision-making if not addressed.

Table 5: *Pillars, and tools align in predictable clusters*

Groups :	Digital Media used :	Paper ID:	NO:	TOTAL NO:	uancy of Papers Perc	Postive Paper:	Percen	Negative Paper	Percen	Neutral Paper:	Percent
BIM				5	8.47%						
	Autodesk Revit	25,32,37	3			25,32,37	100%	0	0%	0	0%
	Autodesk Autocad	34	1			34	100%	0	0%	0	0%
	ArchiCAD	34	1			34	100%	0	0%	0	0%
Energy and Environmental Analysis:				8	13.55%						
	EnergyPlus and DEST	21,44,57,6	4			6,21	50%	0	0%	44,57	50%
	PV Stimulation Software	11	1			11	100%	0	0%	0	0%
	Energy analysis	6	1			6	100%	0	0%	0	0%
	Meteonorm	39	1			39	100%	0	0%	0	0%
	Intelligent thermal Comfort management ITCM	20	1			20	100%	0	0%	0	0%
Graphic Design and Visualization:				3	5.00%						
	GIMP2.1	1	1			1	100%	0	0%	0	0%
	Remote Sensing	34	1			34	100%	0	0%	0	0%
	MS Excel	10	1			10	100%	0	0%	0	0%
Data Analysis and Programming				12	20.33%						
	MATLAB and Simulink	1,11,14,26,36,51,6	7			1,6,11,14,26,36,51	100%	0	0%	0	0%
	The R Software	27	1			27	100%	0	0%	0	0%
	Python	31	1			31	100%	0	0%	0	0%
	IBM Software	1,34	1			1,34	100%	0	0%	0	0%
	Commerical Statistical product services solutions	53	1			53	100%	0	0%	0	0%
	CT Scanning software	2	1			2	100%	0	0%	0	0%
	RapidMiner	38	1			0	0%	0	0%	38	100%
Design and simulation softwares				6	10.16%						
	Sketchup	31	1			31	100%	0	0%	0	0%
	Grasshopper	6,59	1			6,59	100%	0	0%	0	0%
	Design Builder	19,25,29,60	3			19,29,60,25	100%	0	0%	0	0%
	Design Expert	29	1			29	100%	0	0%	0	0%
Not Stated		52,55	2	2	3.38%	52	50%	0	0%	55	50%

Conclsuion

This systematic literature review examined 59 studies on AI applications (machine learning and deep learning) in sustainable architecture. The results show a clear surge in research since 2020 and confirm that AI is increasingly shaping sustainable building design and operation. Most work focuses on environmental sustainability, especially energy efficiency and carbon reduction, where decision trees and ensemble models frequently deliver strong predictive performance. Social sustainability (e.g., thermal comfort and indoor environmental quality) is also supported, particularly through deep learning, while economic sustainability remains less explored despite promising cost-estimation results.

Overall, roughly three quarters of the reviewed reported positive outcomes, underscoring AI's potential to improve decision-making and building performance. Future research should better balance environmental goals with social and economic dimensions and explore hybrid approaches that integrate ML/DL with simulations, IoT sensor data, and real-time building management systems. As data availability and smart-building infrastructure expand, AI is likely to become a core driver of resilient, energy-efficient, and human-centric buildings that support sustainable urban development.

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