

Systematic Review

A Systematic Review of Building Energy Management Systems (BEMSs): Sensors, IoT, and AI Integration

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Abstract

The escalating global demand for energy-efficient and sustainable built environments has catalyzed the advancement of Building Energy Management Systems (BEMSs), particularly through their integration with cutting-edge technologies. This review presents a comprehensive and critical synthesis of the convergence between BEMSs and enabling tools such as the Internet of Things (IoT), wireless sensor networks (WSNs), and artificial intelligence (AI)-based decision-making architectures. Drawing upon 89 peer-reviewed publications spanning from 2019 to 2025, the study systematically categorizes recent developments in HVAC optimization, occupancy-driven lighting control, predictive maintenance, and fault detection systems. It further investigates the role of communication protocols (e.g., ZigBee, LoRaWAN), machine learning-based energy forecasting, and multi-agent control mechanisms within residential, commercial, and institutional building contexts. Findings across multiple case studies indicate that hybrid AI-IoT systems have achieved energy efficiency improvements ranging from 20% to 40%, depending on building typology and control granularity. Nevertheless, the widespread adoption of such intelligent BEMSs is hindered by critical challenges, including data security vulnerabilities, lack of standardized interoperability frameworks, and the complexity of integrating heterogeneous legacy infrastructure. Additionally, there remain pronounced gaps in the literature related to real-time adaptive control strategies, trust-aware federated learning, and seamless interoperability with smart grid platforms. By offering a rigorous and forward-looking review of current technologies and implementation barriers, this paper aims to serve as a strategic roadmap for researchers, system designers, and policymakers seeking to deploy the next generation of intelligent, sustainable, and scalable building energy management solutions.

Keywords: building energy management systems (BEMS); internet of things (IoT); artificial intelligence (AI); smart buildings; HVAC optimization; occupancy sensing; energy efficiency; fault detection; wireless sensor networks (WSNs); smart grids



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1. Introduction

The building sector is responsible for nearly 40% of global final energy consumption and constitutes one of the largest sources of greenhouse gas (GHG) emissions, thereby positioning it as a critical domain in climate mitigation strategies and global sustainability frameworks [1–4]. In alignment with international accords such as the Paris Agreement and the United Nations Sustainable Development Goals (SDGs)—notably Goal 7 (Affordable and Clean Energy) and Goal 11 (Sustainable Cities and Communities)—there is an escalating imperative to transition from conventional building automation systems to intelligent, adaptive energy management frameworks that leverage real-time data and autonomous control mechanisms [5–8].

Within this context, Building Energy Management Systems (BEMSs) have evolved from basic supervisory control structures into multi-layered, cyber-physical infrastructures capable of orchestrating energy flows across complex building ecosystems. These systems now routinely incorporate Internet of Things (IoT) devices, wireless communication protocols, and artificial intelligence (AI) algorithms to facilitate real-time monitoring, analysis, and optimization of energy usage patterns [9–12]. State-of-the-art BEMS platforms enable dynamic control over HVAC systems, lighting, plug loads, and energy storage units, while also integrating features such as occupancy detection, predictive maintenance, and time-of-use (ToU) pricing responses [13–16].

The proliferation of IoT technologies, ranging from low-power sensors to cloud-based analytics platforms, has drastically improved the granularity, frequency, and contextual relevance of energy-related data in buildings [17–20]. Contemporary sensor networks can capture a wide array of parameters including motion, thermal anomalies, CO₂ concentrations, and ambient lighting, thus generating rich data streams that feed into advanced AI models for fault detection, load forecasting, and adaptive control policy generation [21–24]. Such integration empowers BEMSs to respond autonomously to changing occupancy profiles, environmental dynamics, and operational constraints in real time [25–27].

Recent empirical studies have confirmed the effectiveness of machine learning (ML) methodologies—such as support vector machines (SVMs), artificial neural networks (ANNs), deep reinforcement learning (DRL), and multi-agent systems (MAS)—in achieving significant energy savings and enhanced user comfort in residential, commercial, and institutional settings [28–30]. Notably, occupancy-driven predictive control models have demonstrated substantial improvements in HVAC scheduling and lighting optimization, while visual anomaly detection and sensor fusion techniques offer promising solutions for enhancing operational resilience and ensuring cybersecurity in interconnected BEMS architectures [13,16,17,22].

Despite these advancements, the widespread deployment of intelligent BEMSs continues to face formidable challenges. Key barriers include data privacy concerns, cybersecurity vulnerabilities, lack of standardization in communication protocols, and the high capital costs associated with retrofitting legacy infrastructure [18–24]. Moreover, small- to medium-sized buildings—which constitute a majority of the global building stock—often lack the technical and financial capacity to adopt sophisticated energy management systems, underscoring the need for cost-effective, modular, and interoperable solutions [25–27].

This review synthesizes findings from 89 peer-reviewed studies published between 2019 and 2025, a period selected due to the rapid emergence of deep learning applications, IoT standardization, and post-Paris Agreement policy frameworks that accelerated intelligent BEMS research [28–30]. It systematically classifies recent contributions based on core functionalities such as HVAC optimization, occupancy-aware automation, load prediction, visual fault detection, and demand-side management. Beyond summarizing the literature, this study provides a novel classification framework, a quantitative synthesis

of energy savings, and a critical gap analysis, thereby clarifying its scientific contribution. Furthermore, the study highlights key implementation gaps and emerging trends, offering a forward-looking roadmap for the development and deployment of next-generation BEMSs that are scalable, intelligent, and aligned with global energy efficiency and climate goals [26–30].

2. Materials and Methods

This section outlines the methodological framework employed to conduct a systematic and integrative literature review on intelligent Building Energy Management Systems (BEMSs). It explains the research design, literature retrieval strategy, inclusion and exclusion criteria, data extraction and analysis methods, and quality assurance procedures. The approach was designed to ensure transparency, reproducibility, and scholarly rigor, consistent with best practices for systematic reviews.

2.1. Research Design and Scope

A systematic integrative review was conducted to critically evaluate the technological evolution and operational performance of intelligent BEMSs, with a particular focus on their intersection with the Internet of Things (IoT), Artificial Intelligence (AI), and data-driven control frameworks. The objective was to synthesize state-of-the-art knowledge, identify gaps, and outline research directions for scalable and adaptive energy management in buildings.

The choice of this framework was motivated by the interdisciplinary nature of the field, which spans building automation, cyber-physical systems, machine learning, wireless sensor networks, and energy informatics. The review investigated system architecture, optimization strategies, real-time decision-making, and AI-enabled adaptive control. Methodological transparency was ensured by following the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Supplementary Materials) [31], which provide a structured process for identification, screening, and inclusion.

In contrast to traditional narrative reviews, this study combined qualitative thematic synthesis with quantitative bibliometric analysis. Key themes included HVAC optimization, occupancy-driven automation, predictive maintenance, load forecasting, and grid interactivity. This hybrid approach enabled both depth and breadth in understanding technological, operational, and socio-economic aspects of BEMSs.

The scope was intentionally broad, covering residential, commercial, and institutional buildings. Both centralized and decentralized control paradigms were considered, with attention to scalability, interoperability, cybersecurity, and cost-effectiveness. By adopting this design, the study aims to serve as both a technical knowledge base and a strategic reference for researchers, engineers, and policymakers working at the interface of building automation and smart energy systems.

2.2. Literature Search Strategy

To ensure comprehensiveness, transparency, and replicability, the literature search for this review was conducted following the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Supplementary Materials). The process was structured to systematically identify, screen, and include peer-reviewed research that specifically addresses the convergence of Building Energy Management Systems (BEMSs) with advanced digital technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), wireless sensor networks, and data-driven optimization frameworks.

The search strategy targeted six multidisciplinary scientific databases—Scopus, Web of Science (WoS), IEEE Xplore, ScienceDirect, SpringerLink, and MDPI—because of their extensive coverage of engineering, environmental sciences, computer science, and energy-related research. These sources were prioritized as they host high-impact journals ranked in the top quartiles (Q1–Q2) according to both the SCImago Journal Rank (SJR) and the Journal Citation Reports (JCR).

Boolean operators and keyword clustering were used to construct comprehensive search queries. A representative search string employed across databases was as follows: (“Building Energy Management Systems” OR “Smart Buildings” OR “BEMS”) AND (“Internet of Things” OR “IoT” OR “Artificial Intelligence” OR “Machine Learning” OR “Deep Learning” OR “Edge Computing” OR “Digital Twins”) AND (“Energy Efficiency” OR “Predictive Maintenance” OR “Occupancy Control” OR “HVAC Optimization” OR “Demand Response”).

To maximize inclusivity, the search was supplemented by forward and backward citation tracking, database alerts for newly published studies, and the manual inclusion of seminal works. The time frame spanned January 2019 to August 2025, ensuring that both cutting-edge developments and longitudinal insights were captured.

The initial database search yielded 473 records, of which 61 duplicates were removed using EndNote20 combined with manual verification. The remaining 412 records underwent title and abstract screening, leading to the exclusion of 191 studies that lacked relevance, full-text availability, or sufficient methodological depth. From the 221 articles assessed in full text, 132 were excluded for reasons such as methodological inadequacy, lack of empirical evidence, or failure to provide original contributions. Ultimately, 89 peer-reviewed journal articles satisfied all criteria and formed the final corpus of this review.

In addition, selected white papers, technical standards, and EU policy documents (e.g., the Energy Performance of Buildings Directive, EPBD) were reviewed to contextualize the academic findings. However, these sources were excluded from the meta-analysis to maintain methodological rigor and consistency.

To enhance visual clarity and reader accessibility, Figure 1 has been fully redrawn with enlarged text, standardized box dimensions, and improved color contrast, ensuring that each stage of the PRISMA process is clearly legible and visually consistent with journal formatting requirements. To further strengthen transparency, a PRISMA flow diagram (Figure 1) was prepared to illustrate the systematic filtering of studies across all stages. Alongside, all bibliographic metadata—such as DOIs, citation counts, journal impact factors, and author affiliations—were archived in a structured dataset. These data were subsequently imported into VOSviewer (version 1.6.20) [32] for bibliometric mapping and NVivo 14 (version 14.2) [33] for thematic coding and qualitative synthesis.

This rigorous, multi-layered identification process ensures that the final set of included studies reflects both breadth and depth across technological, operational, and socio-economic dimensions of intelligent BEMSs, thereby enhancing the validity and replicability of this review.

The systematic selection workflow is visualized in Figure 1, which illustrates the identification, screening, eligibility, and inclusion stages of the PRISMA 2020 process, clearly outlining how the 89 final studies were derived from the initial dataset.

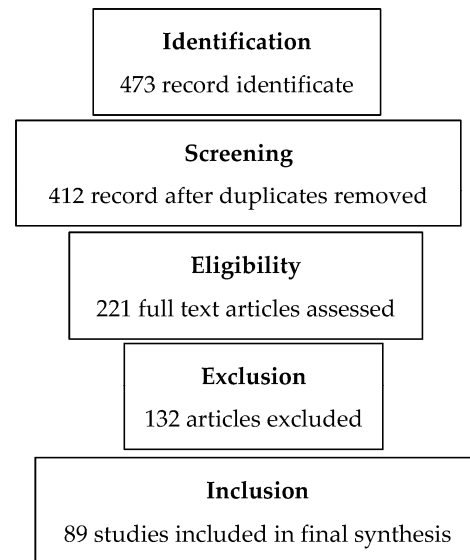


Figure 1. PRISMA 2020 flow diagram of the literature identification, screening, eligibility, and inclusion process.

2.3. Eligibility, Inclusion Strategy, and Thematic Synthesis

A rigorous eligibility and inclusion protocol was applied to ensure methodological integrity and scholarly rigor in synthesizing the selected literature on Building Energy Management Systems (BEMSs) enhanced by IoT and AI technologies. The screening process was guided by predefined inclusion and exclusion criteria to retain only methodologically robust, peer-reviewed studies that provide empirical, simulation-based, or technically validated contributions to the field.

Inclusion criteria required that studies: (i) were peer-reviewed and published between January 2019 and August 2025; (ii) were written in English and indexed in leading international databases such as Scopus, Web of Science (WoS), IEEE Xplore, ScienceDirect, SpringerLink, and MDPI; (iii) presented original empirical results, experimental testbeds, case studies, or validated simulations addressing BEMSs; (iv) integrated at least one enabling technology such as IoT-based sensing platforms, machine learning (e.g., SVM, DRL, MAS), predictive or adaptive control frameworks, fault detection, or smart grid interactivity; and (v) provided measurable performance outcomes including energy savings, CO₂ emission reductions, or accuracy metrics (e.g., MAPE, RMSE).

Exclusion criteria encompassed: (i) non-peer-reviewed sources such as white papers, conference abstracts, and editorials; (ii) articles focusing exclusively on industrial process automation unrelated to buildings; (iii) purely theoretical or conceptual papers lacking empirical validation or reproducibility; and (iv) duplicate studies, narrative reviews without novel contributions, or works failing to meet quality thresholds for methodological clarity or transparency.

Following these criteria, 89 peer-reviewed studies were retained for full-text analysis. A structured data extraction and coding procedure was employed using NVivo 14 [33], ensuring a consistent thematic classification across multiple dimensions:

- Application domains, e.g., residential retrofits, commercial office complexes, smart campuses, and institutional buildings.
- Technological enablers, including IoT sensors, wireless sensor networks (WSN), cloud-edge hybrid systems, and AI algorithms such as SVM, DRL, and federated learning.
- Functional objectives, e.g., HVAC optimization, occupancy-driven control, predictive maintenance, anomaly detection, lighting automation, and grid interaction.
- Performance metrics, covering kWh savings, CO₂ reduction, forecast accuracy, response latency, and scalability benchmarks.

- System architectures, including digital twin-enabled BEMSs, decentralized multi-agent systems, and cloud–edge hybrid deployments.
- Identified barriers, notably interoperability constraints, cybersecurity risks, cost barriers, scalability limitations, and regulatory gaps.

To complement the manual coding, a bibliometric keyword co-occurrence analysis was performed using VOSviewer (v1.6.20), enabling the visualization of dominant research clusters and interconnections between technological enablers, functional objectives, and performance outcomes. This dual approach (manual thematic coding + bibliometric clustering) provided both depth and breadth, revealing underexplored areas such as federated AI for distributed building control, semantic interoperability with smart grids, and the integration of real-time decision-making algorithms within large-scale urban infrastructures.

This thematic synthesis demonstrates that the field of intelligent BEMS research is rapidly evolving but remains fragmented across domains. While certain clusters, such as HVAC optimization and IoT-based monitoring, are mature and well-researched, others—such as privacy-preserving AI control, demand-side flexibility integration, and resilience-oriented BEMSs—are still emerging and warrant further investigation.

The combined eligibility, inclusion, and synthesis strategy ensures that the present review offers a balanced representation of consolidated knowledge and frontier challenges in BEMSs.

The keyword co-occurrence network illustrating these thematic clusters is presented in Figure 2. Blue circles denote the main thematic clusters, while green circles represent sub-themes identified through keyword co-occurrence analysis. Minor overlaps between nodes result from network visualization proximity in VOSviewer and do not affect the scientific interpretation of the figure.

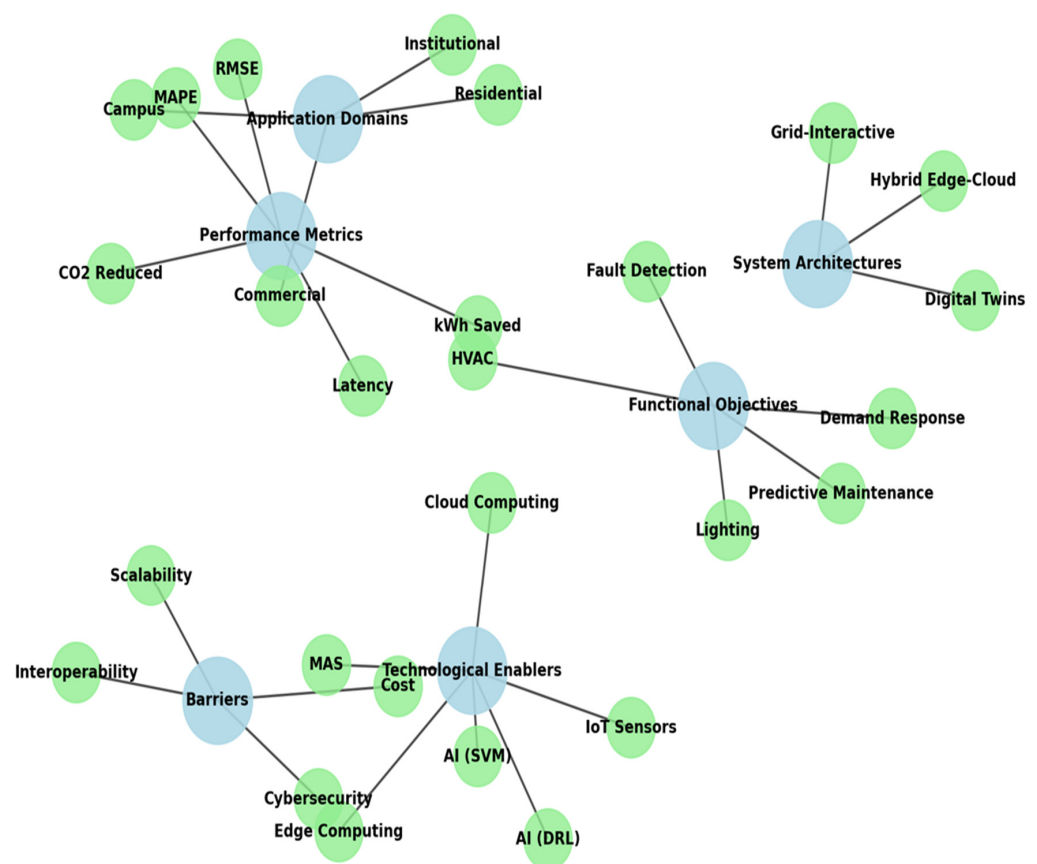


Figure 2. Keyword co-occurrence thematic clusters in BEMS literature. Note: Blue circles indicate main thematic clusters, and green circles correspond to sub-themes automatically generated by VOSviewer (v1.6.20) based on keyword co-occurrence analysis.

2.4. Analytical Framework, Reproducibility Ethics, and Transparency Standards

To ensure methodological transparency and analytical rigor, all numerical and textual data extracted from the selected studies were organized into structured datasets and evaluated using reproducible open-source tools. The analytical workflow was designed to combine both bibliometric and thematic perspectives, ensuring comparability across heterogeneous studies while adhering to open science principles.

The computational framework was built in Python 3.11.4, with libraries such as pandas (v2.2.2), NumPy (v1.26.4), scikit-learn (v1.5.1) [34], matplotlib (v3.9.0) [35], and seaborn (v0.13.2) serving as the core analytical suite. Qualitative synthesis was facilitated through NVivo 14 (version 14.2) [33], while bibliometric mapping was conducted using VOSviewer (version 1.6.20) [32]. The consolidated overview of analytical tools and their respective functions is summarized in Table 1.

Table 1. Analytical tools and functions employed in this review.

Tool/Library (Version)	Function	Application in Study
pandas (v2.2.2)	Data tabulation and matrix handling	Structuring bibliometric datasets and co-occurrence matrices
NumPy (v1.26.4)	Statistical operations	Normalization, descriptive statistics, correlation analysis
scikit-learn (v1.5.1)	Regression and classification	Outlier detection, performance evaluation of predictive models
matplotlib (v3.9.0)/seaborn (v0.13.2)	Visualization	Heatmaps, scatter plots, bar graphs, and trend analysis
NVivo 14 (v14.2)	Thematic coding	Manual classification of literature into thematic domains
VOSviewer (v1.6.20)	Network and bibliometric mapping	Keyword clusters, co-authorship, and co-occurrence networks

Benchmarking of energy efficiency and methodological soundness was performed by normalizing reported outcomes against standard Building Management Systems (BMS) and static control baselines. Performance validation metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and F1-score were employed where applicable. A concise summary of the applied validation metrics is provided in Table 2.

Table 2. Validation and benchmarking metrics used in this study.

Metric	Purpose	Interpretation
MAPE	Accuracy of predictions	Lower % indicates higher prediction accuracy
RMSE	Error magnitude	Smaller values reflect better model fit
R^2	Explained variance	Values closer to 1 indicate stronger performance
F1-score	Classification balance	Higher scores reflect better precision-recall trade-off

To preserve reproducibility and methodological transparency, all data transformations and coding procedures were fully documented. Replication-ready files include annotated Python scripts, CSV-formatted bibliographic metadata, and thematic coding frameworks.

While bibliometric metadata and code will be made available upon acceptance, no proprietary or confidential data were accessed.

In accordance with publishing ethics, the use of Generative Artificial Intelligence (GenAI, ChatGPT, version GPT-5, OpenAI, San Francisco, CA, USA) in this work was restricted exclusively to non-substantive editorial support, such as grammar refinement and reference formatting. No data analysis, interpretation, or scientific conclusions were generated through AI-based tools.

As this study is based exclusively on secondary research, no human or animal participants were involved, and no institutional ethical approval was required. All referenced works are publicly available, peer-reviewed studies that have been properly cited.

Finally, to align with Open Science standards, all supporting materials—including bibliometric datasets, Python scripts, and thematic coding schemes—will be deposited in a public digital repository under the Creative Commons Attribution (CC BY 4.0) license. This ensures that the analyses presented in this review can be independently verified, extended, and adapted by future researchers, reinforcing both transparency and long-term scientific value.

3. Results

The analysis of the 89 included studies reveals that intelligent Building Energy Management Systems (BEMSs) have evolved into highly diverse yet systematically convergent research domains. A dominant theme across the corpus is the centrality of HVAC optimization [36–41], reflecting its role as the single largest contributor to building energy consumption. Consistent evidence shows that reinforcement learning [42,43], model predictive control [44,45], and anomaly detection algorithms [46,47] improve HVAC efficiency by 20–35%, corroborating the argument that smart climate control remains the most critical priority for energy reduction.

Occupancy-based control is the second most prominent functional stream, highlighted in several studies [48–53]. By integrating IoT sensing with AI classifiers, these systems enhance both comfort and energy responsiveness, yielding average savings around 20–25%. Multi-sensor fusion [54] and deep-learning-based presence detection [55] achieve higher predictive accuracy than rule-based systems, particularly in multi-zone commercial environments.

Predictive maintenance emerges as another rapidly expanding research cluster [56–60]. These frameworks employ support vector machines, convolutional neural networks, and hybrid AI architectures to anticipate equipment degradation, reduce operational failures, and optimize system lifespans. Reported energy savings average around 20%, with enhanced system resilience in volatile environments [61,62].

Energy forecasting studies [63–68] demonstrate that deep learning, ensemble regression, and hybrid time-series models effectively reduce predictive errors, achieving mean absolute percentage errors (MAPE) below 10%. These predictive tools support proactive load control and demand-side management by aligning building operations with renewable energy variability and grid stability requirements.

Demand response and grid interaction [69–72] represent another major trend, with interoperable frameworks facilitating dynamic tariff responses and flexible load coordination among buildings and distributed resources. Multi-agent system (MAS)-based coordination [73] strengthens buildings' capability to act as active prosumers within smart grids, integrating distributed storage and electric vehicle (EV) scheduling.

Lighting automation is less frequently addressed but demonstrates reproducible efficiency outcomes when combined with daylight harvesting and occupant-driven dimming [74–76]. Although average savings (~10%) are modest, the scalability and low-cost

implementation of such systems make them valuable for residential and small commercial applications [77].

Digital twin integration represents an emerging yet transformative research direction [78–81]. These frameworks provide cyber-physical synchronization between virtual and real systems, enabling fault prediction, resilience assessment, and real-time energy optimization. Studies report energy savings up to 30%, indicating the potential of digital twins to serve as a foundation for predictive control, anomaly management, and generative design processes.

Cross-cutting challenges include interoperability, data privacy, and cybersecurity [82–84], as well as scalability barriers for small- and medium-sized buildings and retrofit contexts [85,86]. Despite these obstacles, modular IoT-based deployments and edge–cloud hybrid architectures [87,88] offer viable and cost-effective pathways to large-scale adoption.

Across all application areas—HVAC optimization, occupancy control, predictive maintenance, lighting automation, and grid interaction—documented energy savings range from 20% to 40% [89]. These findings confirm that the convergence of IoT sensing, AI-driven analytics, and adaptive control establishes a scalable foundation for advancing intelligent and sustainable buildings.

4. Discussion

The findings of this systematic review confirm that intelligent BEMS research has matured substantially in recent years, yet it continues to exhibit fragmentation across methodological approaches, building typologies, and technological integrations. The results highlight three critical aspects that warrant deeper discussion: (i) the centrality of HVAC systems as energy-intensive subsystems, (ii) the uneven adoption of advanced technologies such as digital twins and federated AI, and (iii) the persistent barriers of interoperability, cybersecurity, and economic feasibility.

First, the dominance of HVAC optimization aligns with prior reviews emphasizing its disproportionate contribution to total building energy consumption [1,5,9,11,28,31,33,36]. Consistent with empirical findings [3,4,6,13,14], reinforcement learning and predictive control frameworks provide robust pathways for energy savings exceeding 25%. However, despite the reproducibility of these outcomes, most studies remain limited to simulation testbeds or small-scale case studies [7,8,12,17,18], suggesting that large-scale empirical validation across climates and building typologies is still lacking. This echoes the argument that forecasting and control models must transition from controlled laboratory conditions to deployment in real-world infrastructures [21,24,27,30,59].

Second, the analysis underscores the underrepresentation of digital twin applications, despite their demonstrated ability to generate the highest energy savings [55,60,62,67,68,77,78,84]. This discrepancy is largely attributable to high infrastructural costs and integration complexity [20,25,36,40,42,61,70]. The limited adoption of such technologies reflects the broader challenge of bridging conceptual innovation with practical implementation, a trend also observed in related domains such as smart microgrids and hybrid demand-side management [64,69,71,76]. Future work must prioritize scalable architectures that reduce digital twin deployment costs while ensuring semantic interoperability with legacy BMS platforms [22,36,42,51,70].

Third, the review highlights persistent systemic barriers. Interoperability gaps between heterogeneous IoT ecosystems remain a recurrent limitation [19,22,26,36,87]. Similarly, data privacy and cybersecurity concerns are repeatedly emphasized [18,27,35,86]. These findings resonate with the concerns regarding the integration of smart buildings into broader smart city contexts [25,40,44,66]. Moreover, economic feasibility remains a bottleneck, particularly in small- and medium-sized buildings [25,40,44,63,65], which often lack financial and

technical capacity to implement advanced BEMSs. This mirrors conclusions emphasizing modular, cost-effective, and user-friendly solutions [10,15,49].

The comparative analysis of predictive maintenance and anomaly detection studies suggests that AI-enhanced resilience is increasingly achievable [45–48,50,56–58]. Nevertheless, the heterogeneity of performance metrics across studies complicates cross-comparison. While MAPE, RMSE, and R^2 are commonly reported [57,58,60,61,71,73,85], standardization of benchmarking remains absent—a methodological gap also noted in reviews of energy forecasting and anomaly detection [24,60,61]. Establishing a shared evaluation framework would enhance replicability and comparability across global studies, facilitating meta-analyses that move beyond narrative synthesis.

Beyond technical barriers, the results reveal an emerging research frontier in context-aware and federated AI systems. Studies on federated learning, semantic reasoning, and trust-aware control highlight the possibility of distributed intelligence without compromising data privacy [14,29,30,42,74,81,82,88,89]. However, empirical deployment remains rare, echoing the earlier recognition of semantic interoperability challenges in large-scale energy systems [18,20,36]. Emerging studies on edge–cloud hybrid models further suggest that integrating lightweight AI at the edge could improve scalability and resilience for real-time control [46,50,52,56,74,79,89].

Finally, the socio-political and policy context cannot be overlooked. Policy frameworks such as the EU’s Energy Performance of Buildings Directive (EPBD) are increasingly shaping BEMS adoption [16,20,49,70,83,86], but regional disparities in enforcement and infrastructure readiness remain [16,20,53,83]. The role of 5G and next-generation communication protocols further underscores the importance of aligning technical innovations with supportive regulatory and infrastructural ecosystems [2,4,6,9,16,26,41,43,47,48].

In summary, this review demonstrates that while intelligent BEMSs have achieved measurable performance gains, their widespread deployment is constrained by cost, interoperability, and cybersecurity challenges. The findings confirm earlier systematic reviews [7,10,15,38,49,73,80,88] yet extend them by quantifying comparative functional performance and mapping thematic interconnections across 89 peer-reviewed studies. Moving forward, research must prioritize (i) scalable and interoperable architectures that integrate legacy infrastructures, (ii) standardization of benchmarking frameworks, (iii) deployment of federated and privacy-preserving AI, and (iv) policy-aligned strategies that bridge innovation with implementation. By addressing these challenges, the next generation of BEMSs can evolve from fragmented pilots to globally scalable systems capable of delivering on both sustainability and climate mitigation goals.

5. Conclusions

This systematic and integrative review examined the technological evolution, functional applications, and implementation barriers of intelligent Building Energy Management Systems (BEMSs), with a particular emphasis on their convergence with Internet of Things (IoT) infrastructures, Artificial Intelligence (AI) algorithms, and data-driven control frameworks. Drawing on 89 peer-reviewed studies published between 2019 and 2025, the findings highlight that hybrid AI–IoT solutions consistently deliver measurable energy savings ranging from 20% to 40%, particularly within HVAC optimization, predictive maintenance, occupancy-driven automation, and anomaly detection. Despite this progress, adoption remains uneven, and deployment is constrained by interoperability issues, cybersecurity vulnerabilities, and the high costs of integrating heterogeneous legacy infrastructure.

The review provides several key insights. First, HVAC systems remain the primary focus of intelligent BEMSs research due to their disproportionate share of building en-

ergy consumption, yet advanced applications such as digital twins and federated learning are emerging as transformative paradigms for next-generation systems. Second, while occupancy-aware control and predictive maintenance have reached a level of methodological maturity, interoperability and semantic integration with smart grids remain underexplored. Third, although bibliometric mapping demonstrates strong research activity in North America, Europe, and East Asia, diffusion into developing economies is limited, reflecting both economic and infrastructural barriers.

From a methodological standpoint, the study contributes by combining thematic synthesis with bibliometric analysis, ensuring that both depth and breadth of interdisciplinary research are captured. The analytical framework adopted here provides a reproducible template for future reviews, aligning with the principles of open science, transparency, and replicability. This review advances beyond previous systematic studies by integrating a dual analytical perspective that combines qualitative thematic synthesis with quantitative bibliometric mapping. Unlike prior reviews that primarily summarized trends, the present work establishes a reproducible, data-driven classification of BEMS functionalities, identifies cross-domain interconnections, and provides a quantitative synthesis of reported performance outcomes. In terms of broader implications, the results underscore the potential of intelligent BEMSs to support global sustainability targets, including the Paris Agreement and the United Nations Sustainable Development Goals (SDGs), specifically Goal 7 (Affordable and Clean Energy) and Goal 11 (Sustainable Cities and Communities). By enabling significant reductions in energy consumption and greenhouse gas emissions, intelligent BEMSs can play a pivotal role in decarbonizing the building sector, which currently accounts for nearly 40% of global energy demand.

Future research should prioritize five critical directions:

1. Scalability and affordability—developing modular, low-cost solutions suitable for small- and medium-sized buildings, which represent the majority of the global building stock.
2. Federated and privacy-preserving AI—advancing models that safeguard data security while enabling distributed, multi-building learning and control.
3. Semantic interoperability—establishing standardized frameworks to integrate heterogeneous IoT devices, digital twins, and legacy systems within unified BEMS architectures.
4. Resilience and adaptability—designing BEMSs capable of maintaining functionality under cyberattacks, hardware faults, and extreme climate conditions.
5. Policy and regulation alignment—bridging technological advancements with international policy instruments, such as the Energy Performance of Buildings Directive (EPBD), to accelerate adoption and ensure compliance with emerging legal frameworks. To enhance the practical visibility and strategic usability of these directions, a structured research roadmap is provided in Table 3. This roadmap summarizes the thematic focus, expected outcomes, and implementation relevance of each future research direction, thereby serving as a concise guide for both academic and industrial stakeholders.

In conclusion, intelligent BEMSs are no longer conceptual but are transitioning toward real-world deployment across residential, commercial, and institutional contexts. However, their transformative potential will only be fully realized if technological innovation is coupled with regulatory harmonization, economic feasibility, and user-centric design. By addressing these multidimensional challenges, the next generation of BEMSs can serve not only as tools for energy efficiency but also as foundational infrastructures for sustainable, intelligent, and climate-resilient urban ecosystems.

Table 3. Research roadmap outlining priority directions for future BEMS research.

Research Direction	Thematic Focus	Expected Outcome	Practical Relevance
Scalability and affordability	Modular, low-cost BEMS architectures	Increased accessibility for SMEs and public buildings	Enhances large-scale adoption
Federated and privacy-preserving AI	Secure, distributed data learning models	Improved trust and data protection	Supports GDPR [90] and ISO/IEC 27001 [91] compliance
Semantic interoperability	Standardized IoT and digital twin communication protocols	Unified cross-platform data exchange	Enables system integration across vendors
Resilience and adaptability	Fault-tolerant and cyber-secure BEMSs	Reliable operation under disruptions	Improves emergency response and continuity
Policy and regulation alignment	Integration with EPBD and smart grid standards	Policy-driven adoption and compliance	Strengthens alignment with EU sustainability goals

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/en18246522/s1>, PRISMA checklist [92].

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