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Systematic Review

Artificial Intelligence-Enabled Heating, Ventilation, and Air Conditioning Systems Toward Zero-Emission Buildings: A Systematic Review of Applications, Challenges, and Future Directions

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Abstract

Heating, ventilation, and air conditioning (HVAC) systems are among the largest energy consumers in buildings, making their intelligent operation fundamental to achieving zero-emission performance and advancing climate neutrality. With recent progress in artificial intelligence (AI), new opportunities have emerged to optimize HVAC operations by enabling predictive, adaptive, and autonomous control. Several studies have explored aspects of AI-driven net-zero emission performance for building HVAC systems. However, a systematic assessment that consolidates these findings and identifies future directions is still needed. This review addresses this gap by analyzing the current state of research on AI-enabled HVAC systems in the context of zero-emission building performance, with particular attention to residential, commercial, and educational settings. In addition, it provides recommendations for future research while underscoring the importance of AI methods in achieving zero-emission performance of building HVAC systems. Based on this review, five primary application domains of AI-enabled building HVAC systems were identified and analyzed: predictive maintenance, scheduling, adaptive optimization, renewable energy integration, and IoT-enabled control. Existing research gaps are identified, including privacy-preserving AI methods, modular and interoperable frameworks, climate-adaptive and occupant-aware strategies, and computationally efficient architectures. Future directions in the field of the AI-enabled HVAC system integrations, along with lifecycle assessment, are highlighted to enable resilient, zero-emission building performance.

Keywords: AI; HVAC systems; zero-emission; energy efficiency; occupant comfort; building automation

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1. Introduction

The building sector is a major contributor to global energy consumption and building energy-related greenhouse gas emissions, representing roughly 30% of total global energy consumption and more than 26% of energy consumption-related global emissions [1]. Of these emissions, about 8% originate directly from building operations, while nearly 18% result indirectly from the generation of electricity and heat consumed within buildings [1]. If current energy consumption trends persist, the sector's share could rise to as much as 50% by 2050 [2]. Consequently, the adoption of effective environmental policies and the

implementation of measures aimed at achieving sustainable objectives, particularly those necessary to limit the rise in global warming to below 2 °C, are essential [3].

In response to the urgent need to address such challenges and reduce the environmental footprint of the building sector, innovative concepts and strategies have been developed to enhance energy performance and minimize emissions. Among these, the pursuit of zero-emission buildings (ZEBs) has emerged as a promising solution, aligning closely with global climate commitments and sustainable development goals [4]. By 2030, it is expected that all new buildings will achieve net-zero operational carbon, with at least a 40% reduction in the embodied carbon of new constructions and major renovations [5]. This paradigm shift redefines the role of buildings from being major energy consumers and emission sources to becoming integral components of a low-carbon future [6]. Among the various energy-intensive systems within buildings, heating, ventilation, and air conditioning (HVAC) systems are among the most significant. These systems are responsible for more than 40% of the total energy consumed in buildings [7]. Given their substantial contribution to energy use and carbon emissions, improving the efficiency and intelligence of HVAC systems is crucial to meeting national and international decarbonization targets. However, traditional HVAC technologies often operate based on static control strategies and predefined schedules, lacking adaptability to dynamic internal and external conditions [8]. As a result, they frequently fail to optimize energy use effectively or maintain consistent indoor comfort under varying occupancy and climatic patterns, posing a significant barrier to achieving true zero-emission performance.

To overcome these limitations in traditional HVAC systems, there is an increasing emphasis on the development of intelligent, adaptive, and highly efficient solutions. The integration of intelligent control mechanisms is becoming essential in modern buildings, particularly as they evolve into complex systems requiring real-time coordination of diverse parameters such as temperature, humidity, occupancy, outdoor climate, and renewable energy integration [9,10]. These emerging needs have motivated the exploration of advanced digital solutions capable of enhancing both energy and operational efficiencies. In this context, the integration of artificial intelligence (AI) has emerged as a transformative technology in the building sector, providing powerful tools for predictive control, fault detection, system optimization, and intelligent energy management in building HVAC systems [11,12]. Notably, recent studies have demonstrated the potential of AI-driven HVAC systems to improve energy efficiency and occupant comfort while addressing gaps in previous research [13,14]. Consequently, the integration of AI-driven solutions is increasingly recognized as essential for the next generation of sustainable, zero-emission buildings. AI-enabled HVAC systems can analyze large volumes of data from sensors and building management systems, learn occupant preferences and system behavior, predict heating and cooling demands, detect faults proactively, and optimize control strategies in real time [14–16]. These capabilities support the creation of intelligent, self-adaptive environments that not only reduce energy consumption but also enhance occupant comfort and facilitate the transition toward zero-emission buildings.

Accordingly, AI-based HVAC applications have recently attracted significant research attention, despite certain limitations (as explored in Section 4). In response, a number of review studies on the analysis of existing AI approaches has been published. While the body of literature on AI applications in buildings is steadily growing, there remains a notable lack of comprehensive and focused reviews that specifically examine the role of AI in HVAC systems through the lens of decarbonization and sustainability. Existing reviews often focus on buildings in general or on broader smart building concepts, or they examine only a limited range of AI methods—without addressing how these techniques align with the urgent global objective of achieving zero-emission targets. This fragmentation creates

a pressing need for a systematic synthesis of the state-of-the-art research on AI-driven HVAC technologies, their current capabilities in zero-emission building contexts, practical limitations, and future research opportunities.

To tackle this gap, this paper presents a systematic review of cutting-edge AI applications in HVAC systems, with an emphasis on their role in enabling energy-efficient, zero-emission building operations. The objectives are to (1) identify and categorize the main application domains of AI-enabled building HVAC systems to achieve zero-emission performance, (2) analyze current research trends and practical implementations, (3) highlight the key technical and operational challenges, and (4) outline promising future directions for research and development. The remainder of this article is structured as follows: Section 2 provides a review on the related previous studies and highlights this study contributions. Section 3 describes the methodology used for the systematic literature review. Section 4 provides a comprehensive analysis of key findings from previous studies on AI methods applied to building HVAC systems. Section 5 presents a discussion on relevant limitations and challenges, as well as potential future opportunities. Finally, Section 6 concludes the review with key findings and insights.

2. Related Previous Reviews

Most review studies have primarily focused on zero-energy buildings [17–26] while comparatively less attention has been given to the zero-emission performance of buildings [27–29]. Importantly, zero-energy buildings are often considered a stepping stone toward zero-emission buildings, since achieving net-zero energy demand through efficiency and renewable generation provides the basis for subsequently addressing embodied and operational carbon emissions. Although these studies provide valuable insights into definitions, policy frameworks, cost-performance evaluations, balance calculation methodologies, and bibliometric analyses. They do not examine the integration of advanced AI techniques in building HVAC systems, an essential dimension for enabling the transition from zero-energy to zero-emission buildings, which is the central focus of this review. Table 1 positions these previous reviews within the broader research landscape and highlights their thematic coverage, thereby clarifying the gap that motivates the present study. For instance, Marszal et al. [17] focused on the existing zero energy building definitions and calculation methodologies. Similarly, Wells et al. [18] discussed Australian net ZEB policies and their implications, while Feng et al. [19] examined net-zero energy buildings in hot and humid climates. Belussi et al. [20] provided an overview of zero-energy building performance and related technical solutions. Taherahmadi et al. [21] emphasized the importance of consistent zero-energy building definitions. Ürge-Vorsatz et al. [22] examined the potential for a net-zero global building sector; however, their work was limited to best practices and policy concerns.

Table 1. Key findings for relevant review studies, including objectives, covered aspects and review methodology.

Review Study	Year	Objectives	Covered Aspects	Review Methodology
[17]	2011	Review on zero energy building definitions and calculation methodologies	Existing definitions, calculation methodologies	Narrative literature review
[18]	2018	Review of net zero-energy buildings with insights into the Australian context	NZEB concepts, definitions, building energy policy, international policies	Conceptual review

Table 1. *Cont.*

Review Study	Year	Objectives	Covered Aspects	Review Methodology
[19]	2019	Review the development of net zero-energy buildings with a focus on recent developments in hot and humid climates	Analyzes 34 study cases, summarizing design strategies, technology options, and energy performance	Narrative literature review
[20]	2019	Review on the performance of ZEBs and energy efficiency solutions	Definitions, energy efficiency measures, barriers to Implementation	Narrative literature review
[21]	2020	Literature review of net zero-energy building definitions	Existing definitions of ZEBs, Lifecycle zero buildings, energy policymaking	Conceptual review
[22]	2020	Review on recent advances in net-zero strategies for the global building sector	Energy efficiency, cost studies, existing policies and programs	Narrative literature review
[23]	2022	Assess progress, gaps, and challenges in global net-zero building pathways	International approaches, Design strategies, Knowledge-sharing initiatives	Comparative review
[24]	2023	Provide a comprehensive understanding of the role of data-driven approaches in advancing net-zero and positive-energy buildings	Data-driven algorithms for prediction and optimization, Renewable integration, building performance optimization	Systematic review
[25]	2025	Review on design strategies with insights into the Egyptian context	Design concepts, technological innovations, Energy efficiency	Narrative literature review
[26]	2025	Review how urban digital twins are integrated with zero-energy buildings	Integrating digital twins with zero-energy buildings for climate change mitigations	Bibliometric analysis/Systematic review
[27]	2022	Explore the current state of research on net-zero emission buildings and provide recommendations for future research directions	Technologies, new vs. existing buildings, residential vs. commercial buildings, economic and environmental aspects	Bibliometric/Qualitative analysis
[28]	2024	Examines the shift of educational institutions to zero-carbon, resilient, smart campuses	Concepts, sustainability initiatives, smart technology integration, resilience strategies	Bibliometric analysis
[29]	2025	Review net-zero energy building concepts, focusing on definitions, energy-efficient technologies, renewable integration, and implementation methods	Concepts/ definitions of NZEB, energy-efficient technologies, renewable integration, implementation methods	Narrative/ Comprehensive Literature Review

Furthermore, Satola et al. [23] explored international net-zero energy building approaches, although their study was limited to building legislation, policies, and voluntary frameworks. In contrast, Mousavi et al. [24] evaluated state-of-the-art research related to data-driven prediction and optimization applications to achieve net-zero and positive-energy buildings. Extending beyond policy and predictive approaches, Ibrahim et al. [25] discussed design concepts and technological innovations that promote energy efficiency. From a digitalization perspective, Bibri et al. [26] reviewed the previous efforts from the perspective of integrating digital twins and zero-energy buildings to mitigate climate changes. Similarly, Ohene et al. [27] analyzed previous efforts using quantitative and qualitative bibliometric analyses to assess the current state of research on ZEBs, identify gaps and provide recommendations for potential future directions. At the community scale,

Abulibdeh [28] explored the transformation of community-scale educational institutions into zero-carbon buildings, while Parvin et al. [29] focused on the concepts and definitions of net ZEBs, energy technology integration, and implementation methods. While these reviews provide a solid knowledge of net-zero emission buildings (nZEBs), systematic perspectives, particularly those integrating HVAC technologies and AI applications to achieve zero-emission performance, remain underexplored.

Based on the gaps identified in the aforementioned literature, the contributions of this review are as follows: (1) provide a systematic review of the current state of research on AI applications to promote the net-zero emission performance of building HVAC systems; (2) reveal different aspects of AI-enabled building HVAC system research, including predictive maintenance, scheduling strategies, adaptive HVAC optimization, integration with renewable sources, and IoT-based AI-HVAC; and (3) discuss relevant limitations and challenges and provide recommendations on research gaps and future opportunities. By addressing these research aspects, this review seeks to significantly impact the net-zero emission building industry by strengthening the widespread adoption of AI-based solutions and supporting the global transition toward more sustainable intelligent nZEBs.

3. Methodology

To ensure transparency and reproducibility, the review methodology adopted three key steps in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRIMSA) statement [30]. As illustrated in Figure 1, the process follows a structured approach to identify, screen, evaluate, and analyze relevant studies on AI-driven HVAC systems in the context of ZEB transitions. The three steps are as follows: First, identification, relevant studies were retrieved from major databases (Google Scholar, Scopus, ScienceDirect, Springer, IEEE, Wiley, and MDPI) using an advanced search strategy (as explained in Section 3.3). A total of 230 records were identified, with 45 irrelevant records removed before screening. Second, screening, the remaining studies underwent a refined screening process, resulting in 100 selected articles, while 85 were excluded based on scope relevance. Third, eligibility, a full-text eligibility assessment was conducted, leading to the exclusion of 45 articles. Ultimately, 48 studies were included in this systematic review.

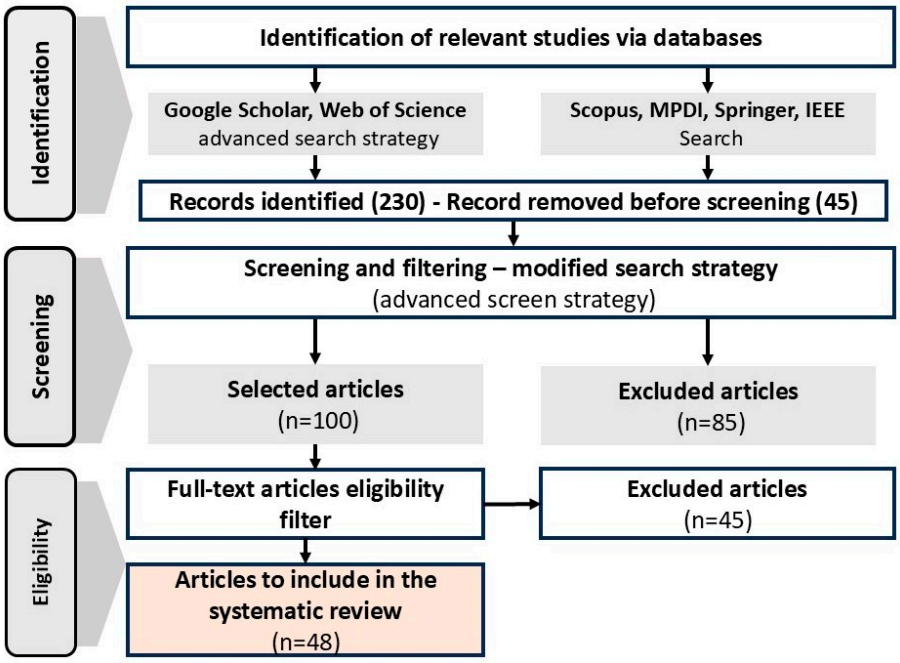


Figure 1. Systematic review methodology strategy followed to select the relevant research articles.

This methodology consists of three main sections: scope definition, selection criteria, and search strategy/data sources. A detailed description of each section is provided below.

3.1. Scope Identification

The scope of this review is defined as an examination of the current body of peer-reviewed research on integrating AI methods with diverse building HVAC systems, particularly regarding their role in achieving nearly zero-emission performance while supporting the climate neutrality and occupant comfort. This includes AI-driven applications in ZEB HVAC systems, such as dynamic load forecasting, real-time optimization, predictive maintenance, demand response management, occupancy-based control, indoor thermal comfort and air quality management, and the integration of distributed renewable energy systems, along with their associated benefits, including enhanced energy efficiency and reduced carbon emissions.

In line with the defined scope, the review focuses on literature published between 2015 and 2025, capturing the most relevant advancements alongside the increased use of AI methods in the sector of buildings. AI applications in educational, residential, and commercial buildings are included, adopting a global perspective to reflect diverse technological, regulatory, and climatic contexts. Research articles focusing solely on conventional HVAC systems without AI integration are excluded. To guide this review, the following research questions are formulated: What are the current applications of AI in HVAC systems for achieving zero-emission performance of buildings? What challenges hinder the adoption of AI-enabled HVAC systems? What future research directions can optimize the widespread adoption of diverse AI methods in building HVAC systems?

3.2. Selection Criteria

To ensure that this review aligns with the stated objectives, four key criteria were predefined for the precise selection of the relevant literature. First, the article must clearly state that the existing research work directly addresses issues related to AI-driven building HVAC systems. Articles that only highlight the significance of AI in improving building HVAC performance, without employing explicit AI methods (e.g., machine learning, deep learning, or deep reinforcement) were excluded. These studies, while valuable for understanding broader efficiency strategies, were not included because the focus of this review is on applied AI methods rather than conceptual or descriptive discussions. Second, the research work must apply one or more AI methods to address specific tasks such as HVAC energy consumption prediction, performance optimization, control and monitoring, real-time management, or the maximization of renewable energy integration. Articles that employ AI without clearly specifying the method used or the targeted task were excluded to maintain methodological transparency and reproducibility. Third, the research must address the previously mentioned issues related to HVAC systems in educational, residential or commercial buildings, either individually or in groups. These building types were deliberately chosen because they represent the majority of HVAC-related energy consumption in the built environment and are well-documented in the literature. Industrial and other specialized buildings were excluded, as their operational patterns, HVAC designs, and energy management requirements differ substantially, which would dilute the focus of this review. Fourth, all articles must be written in English and published in internationally recognized, peer-reviewed journals or reputable conference proceedings to ensure scientific reliability. These four criteria form the basis for conducting a thorough systematic review to analyze the current state-of-the-art research on AI-enabled HVAC systems. They also justify the scope of this review by clearly explaining which studies were excluded and why.

3.3. Search Strategy and Data Sources

Based on both the defined scope and criteria of this review, and as illustrated in Figure 1, a structured search strategy was developed to involve five main steps, outlined as follows: (1) Keywords were formulated across three dimensions (i) AI methods (e.g., ML, DL, RL, hybrid optimization algorithms, and data-driven models), (ii) HVAC applications (e.g., performance optimization of HVAC systems, energy prediction of building HVAC systems, and scheduling strategies), and (iii) Zero-emission context (e.g., low-carbon buildings, net-zero energy buildings, zero-emission buildings, and smart energy management). Boolean operators were applied to systematically combine the search terms across eight major databases (Google Scholar, Web of Science, Scopus, ScienceDirect, Springer, IEEE Xplore, Wiley, and MDPI). The search was restricted to peer-reviewed publications (journal articles and conference proceedings published) in English, covering the period 2015–2025 to ensure the inclusion of recent advancements. (2) all articles were screened against the predefined inclusion criteria (Section 3.2). Studies that did not involve explicit AI methods or did not address HVAC-related applications for energy efficiency and emissions reduction were excluded. (3) The articles cited by a paper that passed the screening test based on the above criteria were identified as additional candidate research in this review. (4) All articles selected in steps 1 and 2 were reviewed to extract information on scope, AI technique applied, and HVAC context. (5) The selected articles were systematically analyzed to assess the advantages and limitations of AI-driven HVAC systems, identify research gaps, and highlight future research opportunities. All initial search results were imported into a reference management tool (e.g., Mendeley and EndNote) to remove duplicates and streamline the screening process.

4. Results

This section presents a systematic analysis of different application aspects for how AI methods have been employed in the field of HVAC systems of buildings, focusing on educational, residential, and commercial settings. The reviewed studies are categorized into five main domains of AI-enabled building HVAC systems: predictive maintenance, scheduling, adaptive optimization, integration with renewable energy sources, and AI-enabled smart HVAC systems powered by IoT. Each subdomain reflects a distinct application pathway toward achieving zero-emission buildings through AI-enhanced operational efficiency, adaptability, and energy intelligence. By examining previous research in terms of the methods, scope, and outcomes, this section highlights the extent of AI adoption and technological maturity within each category.

4.1. Predictive Maintenance

Table 2 presents the findings of previous studies on AI-driven predictive maintenance applications for HVAC systems across diverse building types. The studies are categorized according to publication year, type of study (experimental, theoretical, or combined) predictive methods employed, study objectives, HVAC system type, and major observations. As shown in Table 2, the reviewed studies employed a wide range of ML and DL algorithms, such as XGB, LSTM, ELM-KNN, and knowledge-infused neural networks, indicating a strong trend toward the use of AI techniques in fault detection, diagnosis, and energy prediction tasks. A key observation is that most of these studies focused primarily on predicting heating and cooling energy usage or carbon emissions in building HVAC systems, typically addressing a single optimization objective, i.e., energy efficiency or system reliability. In many of these applications [31–40], outdoor weather conditions obtained from local meteorological stations served as essential input variables for enhancing model performance. These variables included temperature, relative humidity, wind speed, global

horizontal radiation, solar irradiance, and solar radiation. In some cases [32,33], indoor parameters such as temperature and humidity were also considered. This input selection is justified by the strong physical correlations between these environmental variables and building energy consumption. However, thermal comfort considerations for building occupants, such as thermal sensation and acceptance assessments under varying ambient conditions or different climate contexts, were generally not addressed. In addition, the issue of energy demand in relation to building function remained insufficiently addressed. These aspects, along with HVAC system operational parameters, are critical for exploring the trade-off between achieving energy efficiency and maintaining indoor comfort, which remains an underexplored area in predictive maintenance research.

Table 2. Outcomes of predictive and maintenance studies on HVAC systems in the context of educational, residential and commercial buildings.

Study	Year	Type of Study	Predictive Method	Task (Objectives)	HVAC System (Type)	Observations
[31]	2019	Combined	DRL (DDPG)	short-term energy consumption prediction for an office building HVAC system	Ground source heat pump	Enhanced short-term forecasting accuracy, achieving MAE, RMSE, and R^2 values of 3.858, 19.092, and 0.992, respectively
[32]	2020	Combined	LSTM, BPNN, SOM-LSTM, SOM-RBF, SOM-BPNN	Predicts overheating risks during the cooling season for a library building	Fan coil unit with energy recovery ventilator system	SOM-LSTM provides high accuracy over 95% for indoor temperature and 90% for carbon density, respectively
[33]	2021	Combined	LSTM, NILM	Forecasts the HVAC energy usage for net-zero energy houses	Residential electric HVAC system integrated with distributed energy resources	Forecasting accuracy, with hourly and daily CVRMSE values of 29.4% and 11.1%, respectively
[34]	2021	Combined	XGB, SVM	Reveals and diagnoses faults in screw chillers	Chilled water system with screw chillers	XGB detects 97.26% faults, and 96.89% accuracy in fault diagnosis
[35]	2022	Combined	EML, KNN, EML-KNN	Diagnoses multiple faults in screw chillers	Chilled water system with screw chillers	ML-ELM-KNN diagnoses multiple faults without training data, achieving 94.41% accuracy
[36]	2023	Combined	SVR, RF, ANN, KINN	Introduces a knowledge-infused NN, incorporating self-assessment capabilities to diagnose faults in HVAC systems	Water-cooled screw and centrifugal chillers	KINN improves predictions for out-of-distribution test cases, with average accuracy reaching 0.621
[37]	2024	Combined (simulation-based experimentation)	PSO-SVM, PSO-BPNN, SVM, BPNN	Achieves zero-carbon buildings by considering CO_2 emissions, thermal comfort, and economic indicators	Idealed variable air volume terminal unit with variable supply temperature and humidity	PSO-SVM showed higher accuracy, with R^2 values of 0.977, 0.925, and 0.903 for predictions of CO_2 emissions, incremental cost, and comfortable time, respectively
[38]	2024	Experimental	LSTM	Analysis of changes in cooling demand and condenser heat recovery over a 20-year period for a hypothetical hotel	Variable speed chiller system	Achieved strong performance, with an R^2 value up to 0.979 and 94.6%
[39]	2024	Combined	XGB	Predicts the energy consumption of a VRF heat pump in a commercial building	Variable refrigerant flow heat pump	High prediction performance, with RMSE less than 0.2 kW
[40]	2025	Combined	ANN, RF, XGB, RBF, DT, AutCode	Evaluation of the effectiveness of AI in monitoring CO_2 emissions from HVAC systems in traditional and nearly zero-energy buildings	Heating and refrigeration HVAC (NR)	Heating and cooling emissions in building LUCIA are 20 and 10 kg CO_2/m^2, increasing by 9 in FUHEM, highlighting AI's importance in sustainability and CO_2 emissions reduction
[41]	2025	Combined	Hybrid ANN-PSO, Standard ANN	Estimates residential energy consumption by integrating architecture and HVAC processes with an approach combining environmental impacts	Thermostatic Radiator Valves (NR)	Hybrid model achieved an R^2 of 0.99, while the standard ANN model achieved R^2 values between 0.95 and 0.97 in test datasets
[42]	2025	Combined	ELM-GA, ELM-SA	Enhances the efficiency of variable air volume systems in office buildings	Variable air volume	High prediction accuracy, with R^2 values of 0.73–0.74 and RMSE values of 1.8–1.9 for both models

Another observation is the use of hybrid models that combine multiple AI methods to enhance fault detection and diagnosis capabilities in HVAC systems [34–36], as well as to improve the accuracy of energy consumption forecasting in buildings [41,42]. These models typically utilize various combinations of system-specific-operational parameters to identify faults at both the system and component levels. Commonly used variables included evaporation and condenser temperatures, condensing and evaporating pressures, condensation temperatures, and compressor power consumption. Such models have achieved notable accuracy levels, with fault detection and diagnosis rates reaching up to 96.89% and 97.26%, respectively. Despite the significance of AI-based hybrid models and their promising outcomes, further research is needed to develop models that incorporate both ambient indoor and outdoor environmental conditions across seasonal variations, while also accounting for HVAC operational parameters under real-world scenarios [43]. Advancing this field will require the integration of more sophisticated AI methods, such as transfer learning and attention mechanisms. Together, computational cost, response time, and accuracy of these methods are critical aspects of ZEB HVAC systems research. Moreover, deploying these models through edge computing platforms can increase their practicality, enabling real-time diagnostics and control to better balance thermal comfort and energy efficiency.

4.2. HVAC System Scheduling

Recent advancements in AI have substantially reshaped the scheduling of building HVAC systems, enabling dynamic, data-driven operation that align energy usages with occupancy patterns and real-time grid demands under varying ambient weather conditions (see Figure A1). In this context, as presented in Table 3, several previous studies have demonstrated the effectiveness of AI-driven scheduling strategies, particularly those employing ML, DL, DRL, in improving energy efficiency, reducing operational costs, lowering energy use-related carbon emissions, and enhancing indoor comfort across various types of building HVAC systems. A notable trend in the reviewed studies is the integration of demand response (DR) strategies within HVAC scheduling frameworks. For instance, Ahmed et al. [44] implemented a hybrid LSA-ANN and PSO-ANN framework to optimize the "On/Off" scheduling of household appliances, achieving a 9.71% reduction in peak-hour energy usage during DR events. Similarly, Javaid et al. [45] employed a deep neuro-fuzzy optimizer for residential load and cost optimization, demonstrating improved energy performance under time-of-use (ToU) pricing schemes in both summer and winter seasons. More advanced scheduling strategies have also been applied in the context of combined cooling, heating, and power systems. Zhou et al. [46] proposed a multi-layered approach that integrates ANN-based load forecasting with MPC and dynamic programming to enable active, cost-optimal dispatch. This approach delivered notable operational benefits, including a 93% faster convergence rate and a 3.66% reduction in energy costs. These outcomes underscore the potential of anticipatory, data-driven scheduling in improving the performance and efficiency of multi-energy systems.

On the other hand, other studies [47–50] have concentrated on optimizing the operation of hybrid energy systems that combine HVAC equipment with renewable energy sources. They typically employed time-series datasets, including indoor temperature, occupancy status, and outdoor climate variables, to improve the balance of renewable self-consumption/renewable-consumption. Within this domain, advanced DRL-based frameworks dynamically regulate the scheduling of connected electrical devices, particularly HVAC systems, to minimize energy costs while preserving occupant comfort. Such frameworks integrate state-aware decision-making (considering real-time energy demand, price signals, and user preferences), reward-guided optimization (ensuring savings without

sacrificing comfort), and online adaptive learning (continuously refining schedules based on evolving consumption patterns). These research efforts provide substantial opportunities for scheduling AI-enhanced HVAC systems to achieve energy cost reduction, enhanced comfort, and improved integration of renewable sources. However, most implementations remain simulation-based experimentation, with limited real-world deployment. Moreover, in some studies, the type of building HVAC systems considered is either unspecified, ideal, or based on previous work, as shown in Table 3. Instead, research should focus on validating these models in operational environments, enhancing interoperability with existing building management systems, and ensuring scalability across different building types and climatic zones [51].

Table 3. Results of previous studies on HVAC system scheduling driven by AI in the context of educational, residential and commercial buildings.

Study	Year	Type of Study	Scheduling Method	Task (Objectives)	HVAC System (Type)	Observations
[44]	2016	Combined	Hybrid LSA-ANN, PSO-ANN	Optimization of DR scheduling by predicting the optimal ON/OFF statuses of home appliances	Air conditioner (NR)	Reduced peak-hour energy use by 9.71% during DR events, considering four appliances over 7 h
[45]	2019	Combined (simulation-based experimentation)	DNN, fuzzy logic (hybrid deep neuro-fuzzy optimizer)	Efficient load and cost optimization for residential consumers	Air conditioners (NR) (Air Handling Units and Variable Air Volume system)	Enhanced energy efficiency for consumers by leveraging Time-of-Use pricing rates across summer and winter seasons
[46]	2021	Combined (simulation-based experimentation)	ANN-based load forecasting integrated with MPC and dynamic programming	Enable active, economically optimal dispatch for CCHP systems	Combined cooling, heating and power system	93% faster convergence, 3.66% cost savings, 8-h forecast optimal
[47]	2023	Combined (simulation-based experimentation)	Model-based RL using Q-learning, DQN, DDPG	Optimize zero-energy house operations, accounting for PV use and energy cost	PV–battery energy system (split air conditioning system)	Improved PV self-consumption to 49.4% and self-sufficiency to 36.7%, cutting energy costs 7.2% over rule-based control
[48]	2024	Combined (simulation-based experimentation)	Learning-based robust optimization (shape learning + calibration)	Investigates carbon-aware scheduling to achieve net-zero emissions in multi-energy building systems	Building-integrated multi-energy systems	Up to 8.2% cost savings relative to traditional methods, with robust net-zero achievement
[49]	2025	Combined (simulation-based experimentation)	Transferable Reward-Shaping DRL (RSDRL)	Scheduling demand-side of building HVAC system, while maintaining comfort	Multi zone variable air volume system (NR)	Achieved up to 19.2% energy savings, high satisfaction indices, and reduced peak load by 6.45%
[50]	2025	Combined (simulation-based experimentation)	DRL, MC-TD3	Develops an optimal scheduling strategy for a novel off-grid zero-energy building system	Ground source heat pump	Lowered operational costs by 23% to 78% compared to alternative RL methods

4.3. Adaptive HVAC Optimization

Unlike the scheduling strategies described in Section 4.2, which are primarily based on predictive models and predefined scenarios (e.g., energy price signals and demand response events) to determine when and for how long HVAC systems should operate, adaptive HVAC optimization concentrates on how these systems should function in real time (See Table A1). As illustrated in Figure 2, this paradigm systematically leverages datasets capturing external weather fluctuations, indoor environment parameters, and occupant behavior patterns to dynamically adjust thermostat setpoints, airflow rates, and equipment operating models. These datasets are typically acquired in real-time through continuous streams from sensor networks deployed across both interior and exterior zones of the target building. In this context, operating within a closed-loop control framework, adaptive optimization facilitates instantaneous decision-making that concurrently balances energy efficiency, thermal comfort, indoor air quality, and operational costs. By responding to prevailing conditions rather than adhering to static schedules, it delivers fine-grained,

occupant-centric control while enhancing system resilience to unforeseen variations in building loads or environmental factors.

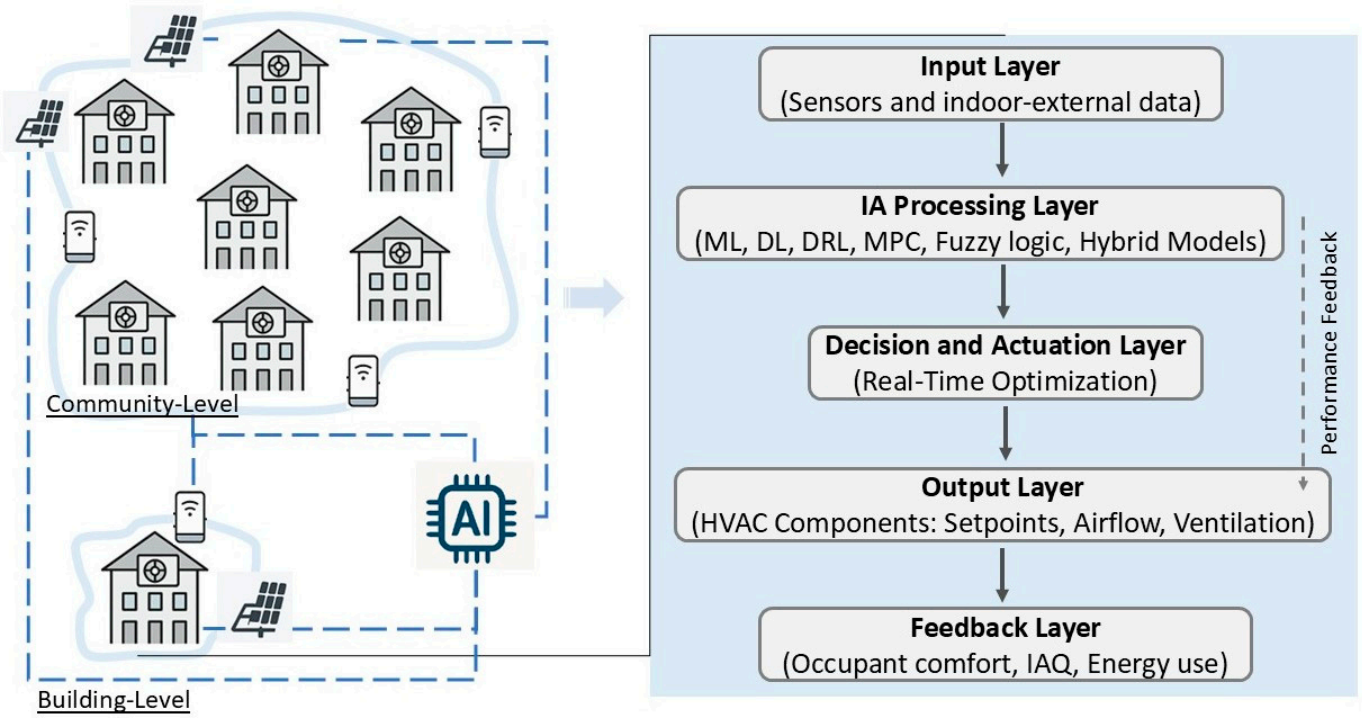


Figure 2. Representative layered architecture illustrating adaptive HVAC optimization paradigm driven by AI methods.

As shown in Table 4, the reviewed studies indicate that enhancing AI-driven adaptive optimization can yield substantial efficiency gains, with reported energy savings ranging from 2–14% in modest implementations to as high as 65% in advanced ones. Methods such as DRL-based MPC, and hybrid AI–physics models dominate the high-performing cases, reflecting their ability to navigate complex, nonlinear building dynamics without requiring explicit system models. Hybrid AI–physics models combine data-driven learning with physical building equations, ensuring that solutions respect real-world constraints, such as thermal limits, HVAC capacities, or energy budgets. DRL and MPC naturally handle time-dependent sequential decisions, whereas standard ML models (e.g., SVR or XGBoost) usually make static predictions without accounting for sequential feedback. A key differentiator of adaptive control is its ability to integrate personalized comfort models into real-time decision-making processes. Occupant-centric approaches [52–55] often employ PMV indices or direct user feedback to tailor HVAC operation, thereby achieving simultaneous improvements in comfort and energy performance. Multi-objective optimization studies [56,57] demonstrate that adaptive strategies can enhance IAQ, such as by lowering CO_2 concentration peaks, without imposing substantial energy penalties. However, some aggressive optimization schemes [58] reveal a trade-off, delivering up to 63% energy savings but at the expense of a measurable reduction in comfort metrics.

Another notable trend is the extension of adaptive optimization beyond immediate control of HVAC systems. Studies such as [59] integrated seasonal passive systems (e.g., solar chimneys) into the control loop, aligning real-time operation of HVAC systems with whole-building energy strategies and resilience objectives. Despite promising results, most studies on adaptive optimization remain simulation-based, with limited large-scale field validation. Interoperability with existing building management systems and scalability across diverse climatic and operational contexts remain major obstacles [60,61]. Further,

the deployment of personalized comfort models raises concerns about data privacy, user acceptance, and model generalization. In conclusion, adaptive optimization of HVAC systems represents a shift from predictive programming to responsive, context-aware control. By enabling real-time, multi-objective decision-making, it offers a powerful pathway toward occupant-centric, low-carbon building operation, provided that challenges related to interoperability, privacy, and field deployment are addressed [62,63].

Table 4. Adaptive HVAC optimization results driven by AI methods in the context of educational, residential, and commercial buildings.

Study	Year	Type of Study	Optimization Method	Task (Objectives)	HVAC System (Type)	Observations
[52]	2020	Combined	ANN-based PBDR (Price-Based Demand Response)	Optimize HVAC operation based on occupant preferences in response to real-time pricing signals	Variable Air Volume multizone air-handling units with zone-specific thermostat settings	Maintaining preferred thermal conditions in all zones with 7.19–26.8% peak energy demand reductions
[53]	2022	Combined	Integrated ANN-based, occupant-centric HVAC control with MPC	Maximize energy efficiency in multizone commercial building spaces	Not Reported	Achieves energy savings of at least 10% while improving occupant comfort
[54]	2025	Combined (simulation-based experimentation)	Hybrid PMV-based ML {SVR, RF, XGB}	Develop ECO-FOCUS framework integrating sensors for occupant-centric energy control	Variable Air Volume terminal units fitted with supply air diffusers	Savings of 29.3% at the room level and between 1.5% and 97% at the zone level, respectively
[55]	2025	Combined (simulation-based experimentation)	Hybrid PMV-based multilayer perceptron NN	Optimize energy, IAQ, and comfort within ASHRAE standards	Packaged multizone variable air volume systems	Optimized strategies cut discomfort, reduce CO_2, and improve energy efficiency
[56]	2024	Combined (simulation-based experimentation)	DRL (DQL, DQN)	Maximize energy efficiency while preserving occupant comfort	Multiple variable air volume systems, integrated with air handling units	Achieved 37% energy savings, while minimizing temperature deviations
[57]	2025	Combined (simulation-based experimentation)	Encoder–decoder LSTM-driven FTML optimizer {MPC}	Minimize HVAC energy use while enhancing indoor air quality and occupant comfort	Air-source-heat-pump system and fan-coil units	Reduced peak carbon dioxide concentration by 10.4% and energy demand by 3.2%
[58]	2023	Combined	Hybrid DRL, DQL	Maximize thermal comfort while minimizing energy costs	Air-sourced heat pump with duct and primary-air unit	63% savings at the cost of a 15.3% reduction in room thermal comfort reward
[59]	2025	Combined (simulation-based experimentation)	Hybrid BO-XGB-GA	Investigate solar chimney and VRF integration for comfort, energy reduction	Variable refrigerant flow system with air-heat-exchangers	Optimized solar chimney–VRF system enhances resilience, especially during extreme heat
[64]	2021	Combined	DNN-based Order Preferences	Minimize peak demand and cost while maintaining occupant comfort	Electric baseboard heaters with smart thermostats	With smart thermostats, the payback period decreases by 10.87 years
[65]	2023	Combined	DBN, DELM, KNN	Maximize performance across operating modes and cross-condition scenarios	Water-cooled screw chiller system with chilled water distribution	Satisfactory performance, with 98% and 88% accuracy in temperature and load tests, respectively
[66]	2024	Combined	DRL, DQL, DQN	Compare energy saving performance SHRAE 36 vs. DRL-based control	a rooftop unit combined with a variable air volume	DRL-based control reduces total HVAC energy consumption by 54%
[67]	2024	Combined (simulation-based experimentation)	Hybrid ANN-based simulation and AG	Optimize seasonal HVAC operation by coordinating storage and heat recovery using intelligent control	Forced-air coupled with wastewater and exhaust air heat pumps with radiators	Enhanced performance with a 33.7% reduction in total energy supply
[68]	2024	Experimental	RL, DPC, DDPC	Compare three advanced real-time HVAC control strategies in a building	Variable air volume, integrated with air handling units	Energy savings of 50%, 48%, and 30.6% were achieved by DDPC, RL, and DPC, respectively
[69]	2024	Combined (simulation-based experimentation)	DR, PPG	Develop optimized control approaches for HVAC systems	Packaged-DX-air system with VAV and electric-reheating-coil	Reduced energy use by 2–14% and improved indoor comfort

Table 4. *Cont.*

Study	Year	Type of Study	Optimization Method	Task (Objectives)	HVAC System (Type)	Observations
[70]	2024	Combined (simulation-based experimentation)	LSTM-PPO (DAL-PPO {DRL})	Improve HVAC control by better managing disturbances and temporal dynamics efficiently	Not Reported	8% energy savings accompanied by 15% reductions in both predicted mean vote and CO_2 levels
[71]	2025	Combined	Python-based script integrated with NSGA-II optimization {LR, RF, DT, GB, GB, SVR, XGB, KNN}	Investigate AI integration for automated energy prediction and optimization	Ideal variable air volume terminal unit with variable supply air temperature and humidity control	Achieved up to 65% energy efficiency improvement and heating load reduction of 13.5 GJ

4.4. Integration with Renewables

In the previous section, several literature contributions on AI-based adaptive HVAC systems were discussed. This section examines key findings on how AI methods enhance the integration of renewable energy sources and storage devices within building HVAC systems. As presented in Table 5, the reviewed studies predominantly focus on maximizing building self-sufficiency by improving HVAC performance in conjunction with onsite energy storage and the management of demand–supply balances. The management of demand–supply balances is typically conducted through HVAC system control during periods of peak demand when onsite generation is limited, or via the coordinated exchange between solar PV and wind energy sources to ensure optimal energy use and maintain building self-sufficiency. In this context, various AI-based methods, including hybrid methods and optimization algorithms, have been employed to improve HVAC energy efficiency while aligning demand with fluctuations in renewable energy generation. The reviewed studies indicate that the most effective AI-driven renewable energy integration strategies combine predictive forecasting of renewable generation with adaptive HVAC operation and storage scheduling. For instance, DL, DRL and hybrid AI–physics approaches have emerged as dominant methods, as they can anticipate fluctuations in solar or wind availability and adjust HVAC loads proactively. Studies such as [72–74] demonstrated that coupling PV generation forecasts with predictive thermal load models enables buildings to precondition spaces during periods of high renewable availability, thereby reducing grid reliance during peak demand hours. Notably, hybrid algorithms that combine MPC with AI-based forecasting methods demonstrate robust performance in managing the inherent uncertainty of renewable generation.

In addition, recent studies highlight the potential of AI frameworks to coordinate HVAC systems with distributed energy resources, storage units, and smart grids [75,76]. Techniques such as predictive control, multi-agent reinforcement learning, and real-time optimization enable HVAC loads to adjust dynamically in response to fluctuations in renewable generation, energy prices, and grid signals. By integrating DR strategies, buildings can actively participate in grid services while maintaining occupant comfort, demonstrating the capability of AI-driven frameworks to manage complex, interconnected energy systems efficiently.

Table 5. Renewable integration results and HVAC system synergies enabled by AI in buildings according to the reviewed literature.

Study	Year	Type of Study	Integrated Method	Task (Objectives)	HVAC System (Type)	Observations
[72]	2023	Combined (simulation-based experimentation)	LSTM, MPC	Maximize self-sufficiency by increasing PV self-consumption	VAV systems equipped with dedicated outdoor air FCUs	Framework matched load with PV, boosting self-consumption and self-sufficiency
[73]	2023	Combined (simulation-based experimentation)	DRL	Develop hybrid RL framework for comfort, cost, and PV use	Not Reported	Multi-agent DRL enables complex renewable energy system optimization effectively
[74]	2023	Combined (simulation-based experimentation)	MPC, FSMC, GA	Minimize HVAC environmental footprints while ensuring thermal comfort	Retrofitted hybrid HVAC with BIPV and CCHP	Intelligent controllers achieved up to a 95% reduction in carbon dioxide emissions
[75]	2024	Combined (simulation-based experimentation)	Self-attention LSTM combined with DRL	Optimize household energy storage and reduce peak load	Household energy storage and appliance control system (including AC)	HEMS significantly reduces peak loads and household energy costs
[76]	2024	Combined (simulation-based experimentation)	RL, DNN	Optimize smart home energy use with PV and storage	Not Reported	Proposed approach reduces smart home energy use by 12%
[77]	2025	Combined (simulation-based experimentation)	ANN-assisted Graywolf algorithm	Optimize hybrid solar-biofuel system for efficiency and sustainability	Hybrid CCHP with PVT, biomass, chiller, thermal storage	Optimization improved efficiency, cost, and emissions over baseline
[78]	2025	Combined (simulation-based experimentation)	Surrogate ML models {RF, XGB, LightGB, DT, LR, KNN, AdaR, RidR, BayR}	Maximize PV self-consumption and self-sufficiency	Multi-split VRF system with two-pipe configuration	Fast surrogate model enables real-time, efficient HVAC control

In the same context, as illustrated in Figure 3, building HVAC systems integration with renewables focuses on using AI-driven control strategies to synchronize HVAC energy demand with renewable generation, thereby minimizing grid dependency and maximizing self-consumption. Although Figure 3 is schematic, it provides a conceptual overview of how AI-driven HVAC control can coordinate with onsite renewable generation and storage, helping readers visualize the system-level interactions discussed in this subsection. This requires precise renewable energy estimates, typically generated using AI-based approaches, such as machine learning and deep learning models, to reliably predict future solar or wind generation over short-time horizons These forecasts are then used to adjust the setpoints and operating modes of HVAC systems dynamically. For instance, Wang et al. [77] proposed an ANN-assisted GrayWolf algorithm optimization to integrate distributed solar PV modules with a biofuel-driven boiler, addressing the energy demands of a CCHP system. Similarly, Barrio et al. [78] proposed a surrogate model-based approach that integrates building energy modelling (BEM), PV production, and weather data with machine learning models to meet the requirements of VRF systems while maximizing self-consumption. Despite significant contributions in the reviewed literature, the practical deployment of AI-assisted HVAC-renewable energy integration remains at an early stage and faces several challenges. These include interoperability issues among renewable sources, storage devices, and building management systems, as well as a critical dependence on accurate renewable energy forecasts [79,80]. Combining predictive forecasts, adaptive control, and optimized storage management can help overcome these challenges and enable low-carbon, autonomous building operation. However, designing zero-emission HVAC systems under multiple uncertainties, varying parameters, and coupled interactions remains a key challenge [81].

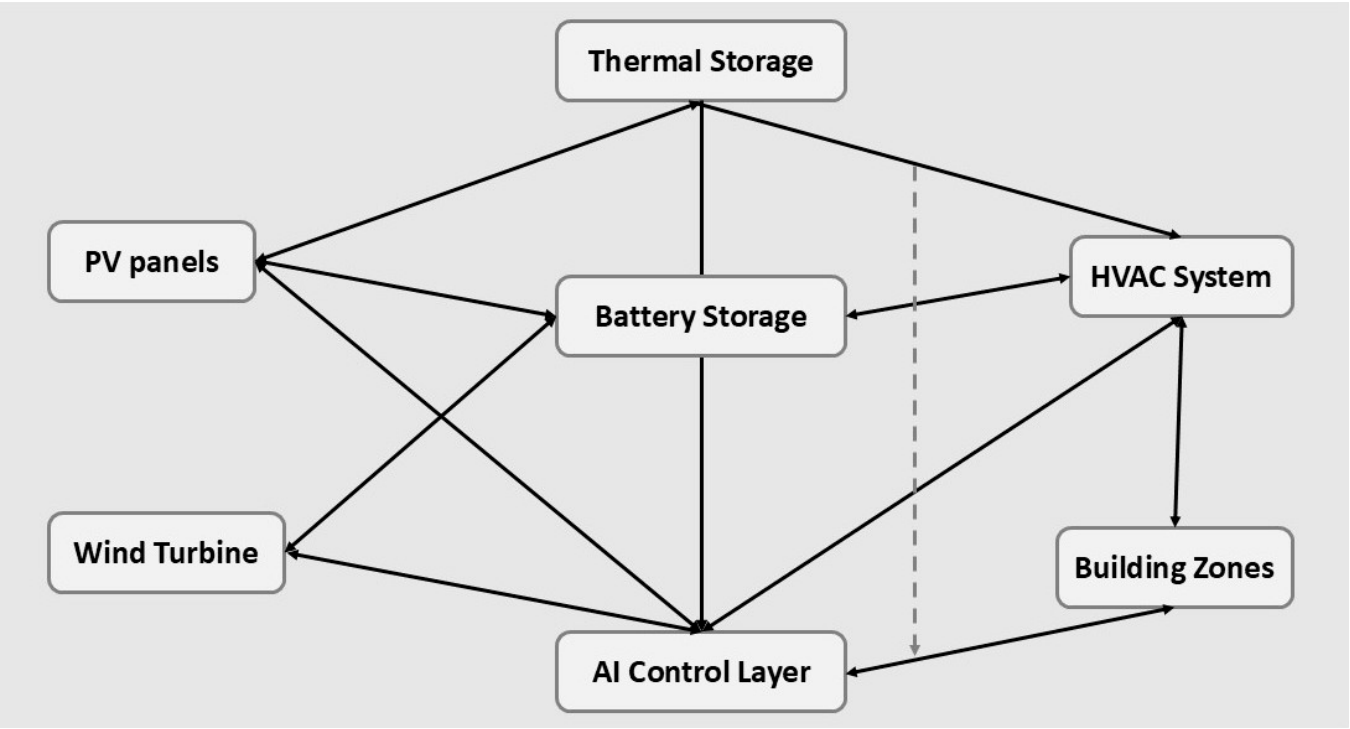


Figure 3. Conceptual integration of HVAC systems with renewable energy sources by AI-driven synergy.

4.5. Smart HVAC Systems and IoT

In parallel with the adaptive control strategies of Section 4.3 and the renewable-integrated approaches of Section 4.4, this section examines the role of AI in enhancing Internet of Things (IoT)-enabled HVAC systems for achieving smart, nearly/zero-emission building operations. As illustrated in Figure 4, which provides a general architectural framework for such systems, IoT-enabled HVAC in the indoor environment of buildings prioritizes continuous sensing, ubiquitous connectivity, and AI-enhanced decision-making. This synergy facilitates enhanced monitoring, rapid fault detection, and coordinated multi-system control, thereby broadening the scope and improving the precision of building energy management. Within this context, research efforts remain relatively limited compared to the broader AI-HVAC field; nevertheless, several studies have provided notable contributions. As summarized in Table 6, several researchers have integrated IoT technologies, distributed smart sensors, HVAC systems, and, in some cases, renewable energy resources to develop AI-driven agent frameworks that reduce the carbon footprint of building HVAC operations and detect cyber-attacks through monitoring deviations in energy performance. This dual emphasis on efficiency and resilience underscores the growing importance of the Internet of Things as an operational enabler and a cybersecurity safeguard. Recent studies have further advanced these systems by incorporating attention mechanisms into IoT-based HVAC control. For instance, Su and Wang [82] proposed an agent-based distributed real-time optimal control strategy for HVAC systems within IoT-enabled sensor networks, while Li et al. [83] developed an event-driven multi-agent distributed optimal control approach for smart buildings. Zhuang et al. [84] demonstrated that attention-enhanced LSTM networks achieved outperformed classical AI models in capturing temporal dependencies within IoT data streams, thereby achieving superior forecasting accuracy for building energy demand and improving control responsiveness and energy efficiency.

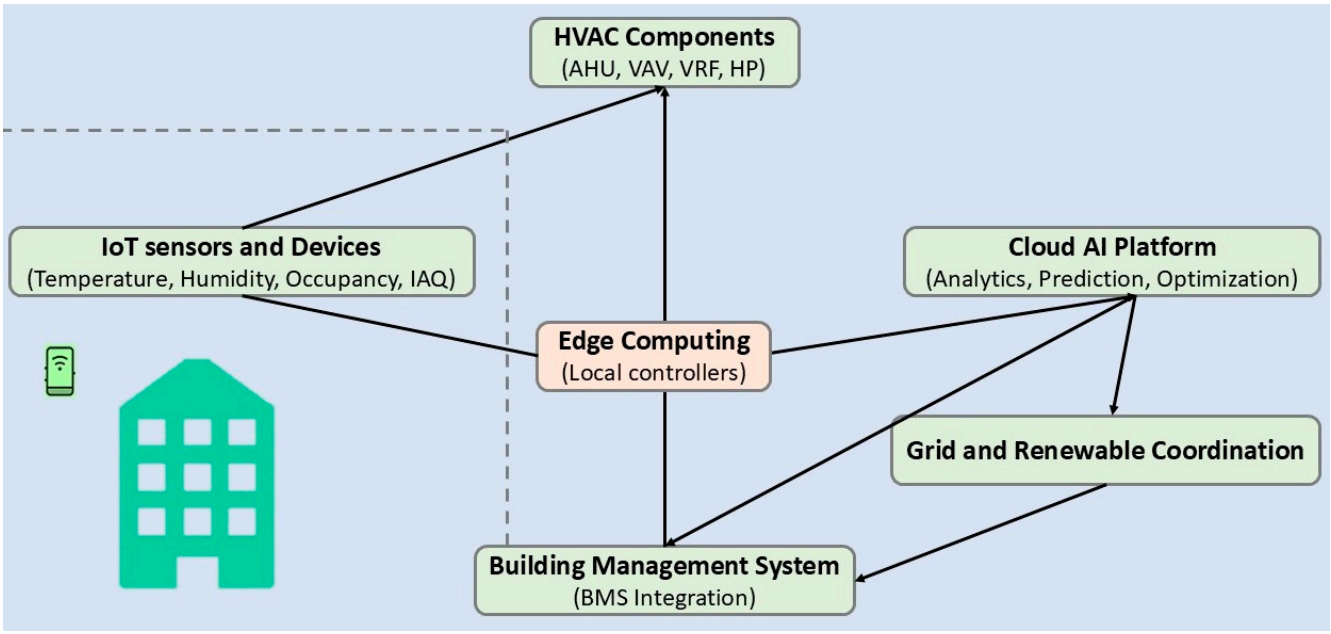


Figure 4. Conceptual AI-enabled smart HVAC systems integrated with IoT devices within the building domain.

Table 6. Reviewed literature findings on AI- and IoT-driven HVAC system applications in the context of educational, residential, and commercial buildings.

Study	Year	Type of Study	Integrated AI Method	Task (Objectives)	HVAC System (Type)	Observations
[82]	2020	Combined	GA {Agent-based optimal control strategy}	Develop AI–IoT agent-based control for HVAC systems	Central-cooling system with centrifugal-chillers, pumps and towers	Optimized agent-based control efficiently reduces energy despite component performance variations
[83]	2021	Combined	AI-inspired multi-agent strategy using classical distributed optimization algorithms	Maximize HVAC system performance while minimizing IoT sensor energy	Variable air volume and dedicated outdoor-air HVAC systems	Proposed strategy maintains HVAC performance while reducing IoT sensor energy
[84]	2023	Combined	LSTM-based time-series forecasting {included BiLSTM, CNN, RNN} with RL	Optimize HVAC performance and energy in IoT buildings	IoT-integrated variable air volume system with air handling units	Attention-based models improve forecasts, boosting HVAC optimization
[85]	2023	Combined (simulation-based experimentation)	Combination of RF with K-Means clustering	Optimize HVAC scheduling in net-zero PV-battery buildings balancing comfort and storage	Variable refrigerant flow and direct expansion units integrated with IoT	Demand compliance improves battery retention 17.9% in rain, maintaining comfort levels
[86]	2025	Combined (simulation-based experimentation)	Physics-informed dynamic Bayesian network (PIDBN)	Detect cyber-attacks via energy performance deviations	Smart building air handling units	PIDBN outperforms traditional methods in attack detection
[87]	2025	Combined (simulation-based experimentation)	Multi-faceted deep learning framework (M-FSB-DLF)	Enhance smart building efficiency, security, and sustainability	AI-optimized air handling units with adaptive controls	M-FSB-DLF improves energy management by 96.2%.

Furthermore, Liang et al. [85] developed an IoT-based energy management framework that optimally integrates HVAC devices with PV-battery systems in net-zero buildings while maintaining demand compliance. In parallel, Chen et al. [86] introduced a physics-informed dynamic Bayesian network (PIDBN) to strengthen resilience against cyber-attacks in HVAC operations. Arun et al. [87] concluded that supporting smart energy systems in buildings with advanced DL models integrated with a network of sensor trackers for data acquisition can enhance security systems by 94.8%, energy management by 96.2%, occupancy optimization by 74.3%, energy efficiency by 64.5% and urban sustainability with 96.2%. Building on these contributions, the significance of IoT technologies lies in their ability to provide high-resolution, real-time datasets, covering temperature, humidity,

air quality, occupancy, and equipment status that serve as critical inputs for AI-driven control algorithms. By leveraging such data streams, AI models can more effectively anticipate demand shifts, detect anomalies, and coordinate real-time HVAC operations with other building subsystems, such as lighting, shading, and storage, while also maximizing renewable energy integrations to support zero-emission performance [88–90]. IoT-based architectures would enable decentralized/edge-computing solutions, allowing low-latency decision-making without continuous reliance on cloud connectivity. However, large-scale adoption still faces challenges, including cybersecurity risks, interoperability with legacy building management systems, and the costs associated with widespread IoT deployment. Overcoming these challenges requires standardized communication protocols, robust security measures, and scalable sensor integration strategies that support AI-enhanced, IoT-driven HVAC systems in diverse buildings, facilitating a balance between occupant comfort and environmental sustainability [88,91].

5. Discussion

While the previous sections presented and analyzed the current state of research on the adoption of AI-driven methods in promoting the zero-emission performance of building HVAC systems, this section discusses the limitations and challenges of such research and highlights potential opportunities for future innovation.

5.1. Relevant Limitations and Challenges

After a thorough analysis of the literature, it is evident that despite notable research progress in applying AI to HVAC systems in order to achieve improved energy efficiency, better occupant comfort, and reduced carbon dioxide emissions, their widespread adoption remains constrained by a set of interdependent challenges. These challenges are mainly associated with the interoperability, security, and scalability of AI-enabled smart HVAC systems, which have been significantly underexplored in the reviewed literature, thereby hindering their large-scale adoption in buildings. As illustrated in Figure 5, the challenges can be categorized into six main domains. These domains include the scalability, security and data privacy, interoperability, generalizability and robustness, renewable integration, and computational and infrastructure. Each of these domains is directly reflected in the findings of previous Sections 4.1–4.5, as discussed below.

The first challenge concerns the development contexts and scalability of AI-driven HVAC systems. As seen in Sections 4.1 and 4.2, predictive and scheduling strategies often deliver strong performance in single-building case studies or controlled simulations. However, their effectiveness is likely diminished when scaled to larger, more diverse building and climate contexts, as well as different occupant comfort preferences. In reality, the effectiveness of deploying AI-driven building HVAC systems is significantly influenced by building characteristics, occupant behavior, localized climate conditions, and comfort preferences [92–94]. As discussed in Sections 4.1 and 4.2, AI-based deployment models often rely on limited datasets combining meteorological conditions, occupancy data, and system operational parameters (e.g., thermostats, energy prices), typically reflecting small indoor environment scales. In real deployment contexts, data streams may be incomplete, noisy, or unavailable, limiting the ability to build universal datasets and reducing the overall HVAC system performance [95,96]. Achieving sustainable, optimal performance thus requires large, diverse datasets that capture a variety of building sizes, HVAC configurations, occupant behaviors, and comfort preferences under heterogeneous real-world conditions.

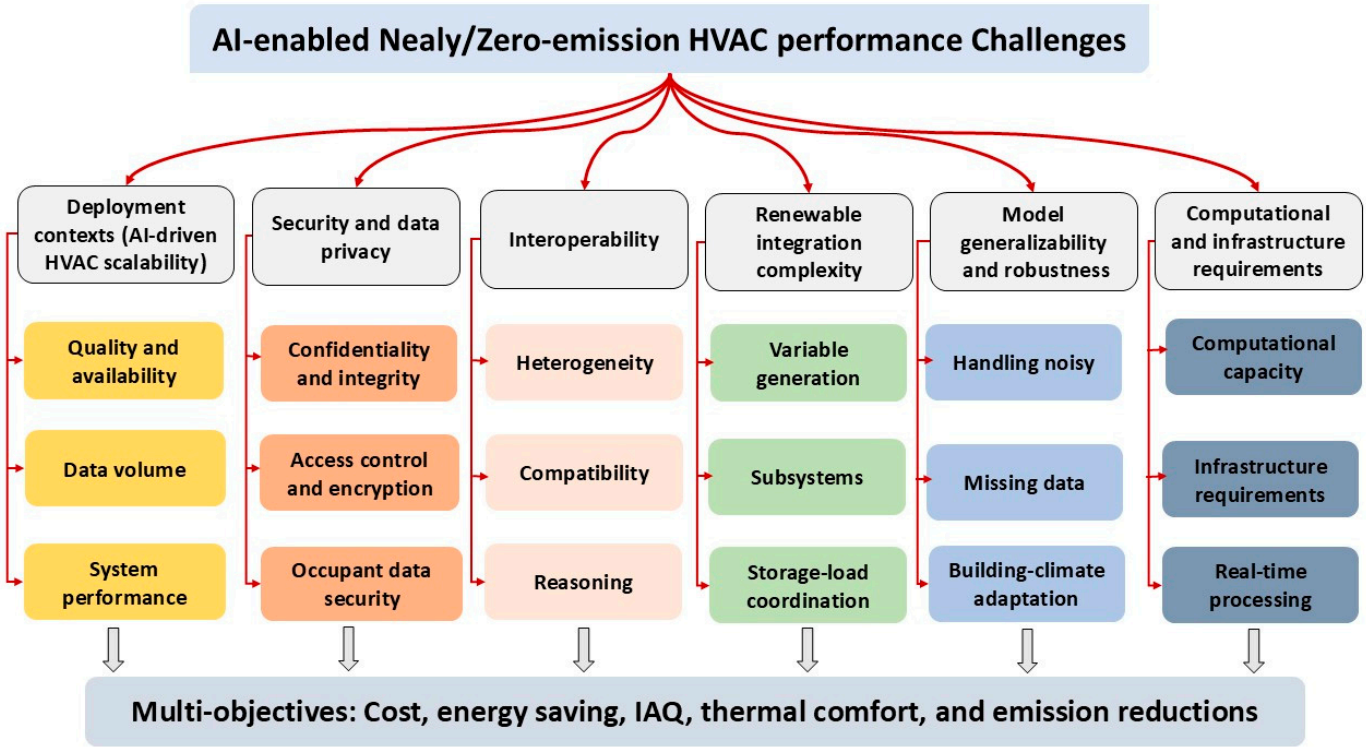


Figure 5. Principal challenges in achieving nearly zero-emission AI-driven HVAC system performance in buildings.

The second challenge arises from security and data privacy concerns associated with AI-enabled HVAC systems. These systems rely on sensitive occupant information (e.g., occupancy schedules and comfort preferences), operational data (e.g., thermostat set-points, humidity levels, and energy records), and building performance metrics (e.g., indoor air quality and thermal performance) to optimize energy use and comfort. For instance, unauthorized access, data breaches, or cyberattacks may compromise the safety of occupants and violate privacy regulations, limiting building owners' willingness to adopt AI-based HVAC solutions. Specifically, cyber-attacks (See Figure 6) can have far-reaching consequences by infiltrating and manipulating operations via building automation system networks; they can disrupt thermal comfort, reduce energy efficiency, and threaten energy system stability [86,97,98]. Additionally, strict data protection policies may considerably limit data collection and sharing, reducing the diversity and richness of datasets needed for robust model development. Handling such issues requires privacy-preserving approaches, such as federated learning, encryption, and anonymization, alongside strong cybersecurity measures to safeguard occupant trust and system reliability [99–101]. In addition to security and privacy, a third challenge concerns the interoperability of AI-enabled HVAC systems with other building systems and energy resources. Effective operation requires seamless integration with building management systems and other subsystems such as lighting, water heating, and security, together with energy resources encompassing renewable generation (e.g., rooftop photovoltaics), energy storage (e.g., batteries and thermal storage), and electric vehicles functioning as flexible loads or mobile storage [102–104]. However, variability in communication protocols, hardware platforms, and software standards can hinder integration, causing suboptimal control, data exchange errors, and increased complexity [105–107]. Ultimately, this reduces reliability and limits the scalable deployment of AI-driven HVAC systems across diverse buildings.

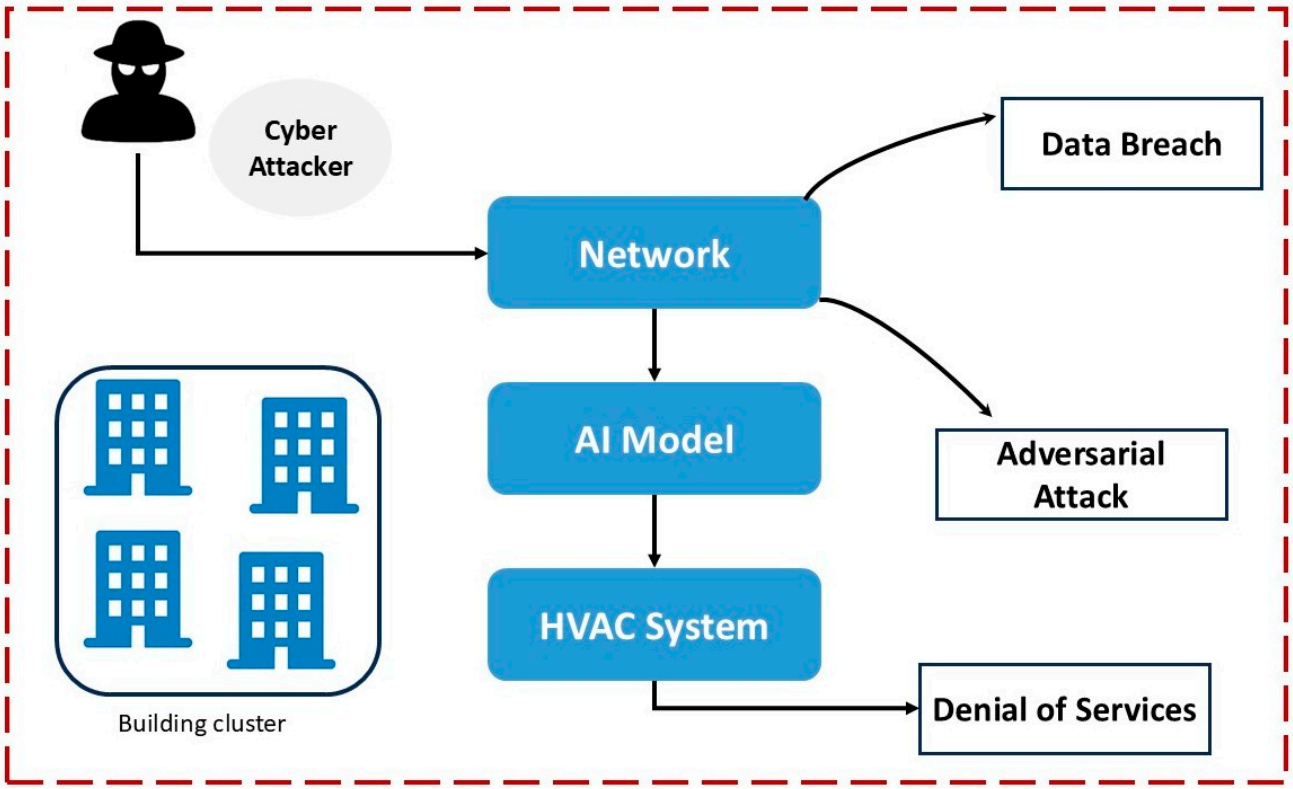


Figure 6. Conceptual depiction of cyber-attacks targeting AI-enabled building HVAC systems.

The fourth challenge lies in the generalizability and robustness of AI-enabled HVAC solution models. Often, these models (See Table A2) are limited to context-specific datasets, performing well under controlled conditions but potentially failing when applied to new building HVAC systems with varying occupancy patterns and different climatic conditions. This lack of generalizability and robustness can lead to inconsistent thermal comfort, inefficient energy use, and reduced reliability in real-world deployments [108,109]. In parallel to this challenge, another critical barrier arises from the computational and infrastructure demands of AI-enabled HVAC systems, particularly in building renovations and existing low-carbon HVAC systems. Advanced AI models pose substantial demands for processing power, low-latency data handling, and reliable connectivity, which are difficult to meet in resource-constrained or legacy buildings, thereby limiting large-scale deployment. Furthermore, their high computational requirements increase energy consumption and operational costs, ultimately reducing overall efficiency [110,111]. This requires the development of lightweight model architectures, edge computing strategies, and cloud-assisted frameworks that balance performance, energy efficiency, and scalability across diverse building types. By systematically incorporating lightweight AI models and edge-computing deployment, future research can reduce computational overhead and lifecycle environmental impacts while maintaining robust performance. Such approaches enable real-time control and decision-making, ensuring that AI-enabled HVAC systems contribute effectively to sustainable, low-carbon, and resilient building operations. Collectively, these challenges highlight the difficulty of integrating AI-enabled HVAC systems with broader sustainability goals at present. Effective operation must not only maintain thermal comfort and energy efficiency but also support zero-carbon objectives, renewable integration, and overall building sustainability. This requires coordinated interaction with distributed energy resources, energy storage systems, and smart grid operations. However, current AI models often lack mechanisms to capture these interactions, limiting their ability to optimize building performance holistically. Addressing this challenge requires AI strategies capable

of dynamically balancing energy efficiency, renewable utilization, and occupant comfort, enabling HVAC systems to contribute effectively to sustainable and resilient zero-emission building operations.

5.2. Future Research Opportunities

The previous Section 5.1 identified and discussed several research challenges associated with the lack of AI-enabled HVAC system adoption. This section highlights key future research directions to advance AI-enabled building HVAC systems toward practical, scalable, and sustainable deployment.

- Security and privacy: Future studies in AI-enabled building HVAC systems need to emphasize addressing the concerns associated with the information security. The development of hybrid, advanced privacy-preserving AI methods, such as the integration of reinforcement learning with federated learning and secure multi-party computation, to ensure the security of occupant information and autonomous decision making, while enabling collaborative learning across diverse communities and building HVAC systems, represents a critical step. In this context, reinforcement learning and federated learning methods can be implemented through integrated blockchain frameworks with smart IoT devices [112,113], enabling the investigation of sustainability strategies and the optimization of edge intelligence for privacy-preserving solutions, effective resource allocation, and real-world adaptation (Figure 7 presents a representative conceptual depiction).
- Interoperability: Advancing interoperability continues to be a critical research area for AI-enabled building HVAC management systems. Future work should focus on the development of standardized communication protocols and open frameworks to enable seamless integration with building management systems, distributed energy resources, and IoT-based devices. Similarly, leveraging collaborative and open-source platforms (e.g., GitHub and Kaggle) can facilitate exchanging data, code sharing, and reproducible benchmarking of AI models, thereby accelerating research-driven innovation. The models can be implemented using Python with PyTorch and TensorFlow, ensuring consistency and reproducibility. Simultaneously, the adoption of modular AI architectures capable of adapting to heterogeneous hardware and software environments can further reinforce interoperability. Collectively, these directions will support the robust, generalizable, scalable, and efficient deployment of AI-driven smart HVAC systems, enabling diverse building clusters to operate as integrated, intelligent, and low-carbon systems. In parallel, ensuring data quality remains essential for achieving true interoperability. Sensor calibration errors, missing data, and noisy measurements can undermine AI model reliability and hinder seamless system integration. Therefore, incorporating standardized data preprocessing pipelines, fault detection algorithms, and robust learning methods will be critical to enhance interoperability across diverse devices and platforms.
- Generalizability and robustness: In complement to efforts on security, privacy, and interoperable deployment, future research should focus on methodological strategies that enable AI models to generalize effectively across diverse buildings, climate-adaptive conditions, and occupant behaviors and preferences. Key avenues include developing climate-adaptive monitoring approaches, designing AI-driven management techniques that flexibly and adaptively respond to occupant needs while ensuring thermal comfort and energy efficiency, and balancing computational costs and predictive complexity. By addressing these aspects, researchers can enhance the robustness and applicability of AI-enabled HVAC systems in real-world, heterogeneous environments.

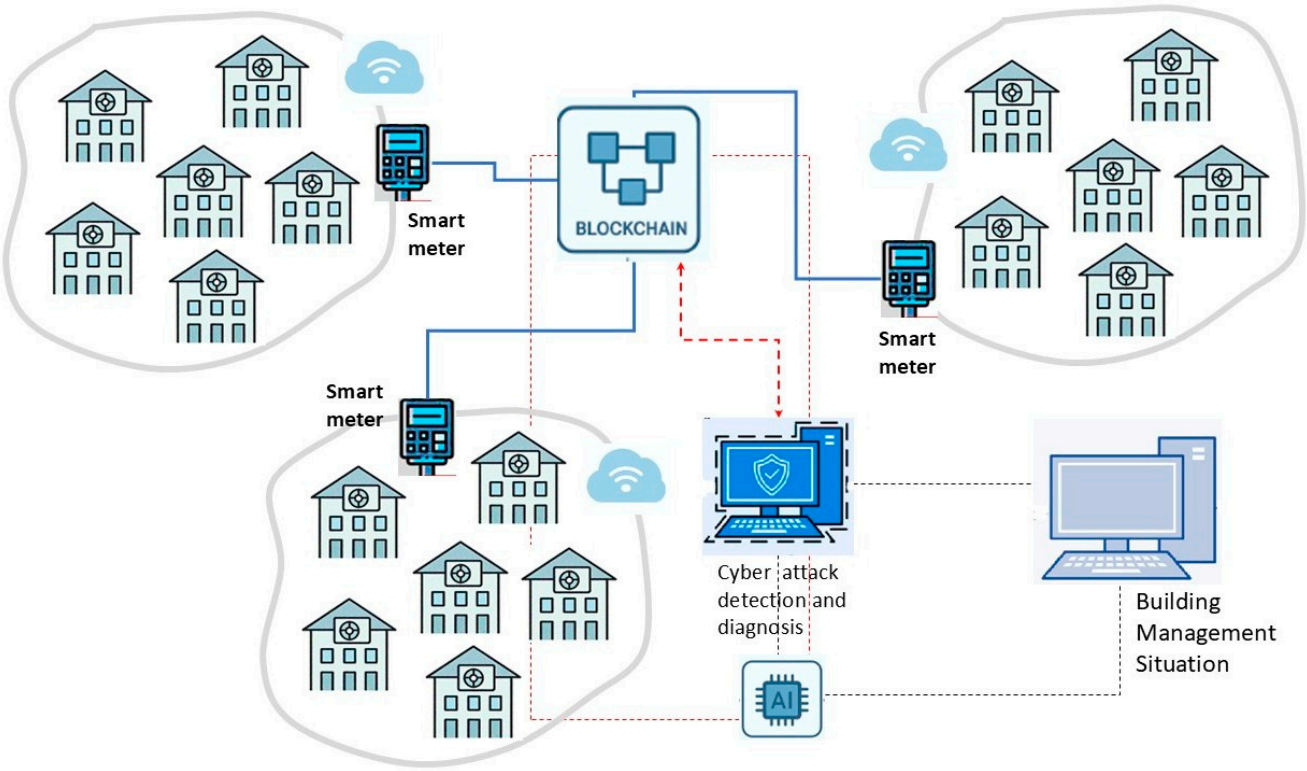


Figure 7. Conceptual depiction of a smart blockchain framework integrating advanced AI across diverse building clusters.

- Computational and infrastructure demands: Building on advances in security, interoperability, and model robustness, future research should address the substantial computational and infrastructure demands of AI-enabled HVAC systems. This includes designing lightweight AI models, implementing edge-computing strategies, and integrating cloud-assisted processing frameworks to balance performance, energy efficiency, and real-time responsiveness. Research should also consider resource-constrained or legacy buildings, ensuring that solutions are scalable, cost-effective, and maintain high operational reliability.
- Sustainability and lifecycle integration: Complementing the previous directions, future work should focus on aligning AI-enabled HVAC systems with broader sustainability goals. This involves developing strategies that optimize energy efficiency, renewable energy utilization, and occupant comfort throughout the building lifecycle. Researchers should explore frameworks that coordinate HVAC operations with distributed energy resources, storage systems, and smart grid interactions, thereby promoting holistic, low-carbon, and resilient building performance. In particular, adopting lighting AI models and edge-computing deployment can enhance computational efficiency, reduce the environmental footprint of digital operations, and enable real-time decision-making at the building level. Integrating such approaches ensures that AI-driven HVAC systems not only improve operational performance but also contribute meaningfully to sustainable and low-carbon building design.

For conciseness, future research directions highlight the need for integrated comprehensive solutions, combining robust AI methodologies, efficient computational frameworks, interoperability, and sustainability considerations. By pursuing these opportunities, future AI-enabled HVAC systems can achieve reliable, efficient, and low-carbon performance across diverse building contexts.

6. Conclusions

This paper systematically provided an overview of current research efforts in the domain of applying AI-enabled HVAC systems in residential, commercial, and educational buildings. The scope of a set of AI-enabled HVAC application models was reviewed in terms of AI method, HVAC type, objective, and key observations. Within the objective of each study, the application context of AI-enabled HVAC systems were analyzed across five aspects, including predictive maintenance, scheduling, adaptive optimization, renewable integration, and IoT-leveraged AI and HVAC systems. The review systematically highlighted both their potential and existing limitations. The key challenges were also identified and discussed, including security and privacy concerns, interoperability issues, limited generalizability and robustness, substantial computational and infrastructure demands, and the need to align HVAC operations with sustainability and building lifecycle objectives.

As seen from the systematic review, AI-enabled building HVAC systems have been attracting significant research attention. However, the relative lack of research efforts in certain areas can be attributed to the challenges that underscore the complexity of deploying AI-driven solutions across diverse building types, climates, and occupant behaviors. Current research efforts have made significant progress in developing advanced AI-driven HVAC frameworks, but they remain constrained by several challenges. These include security and privacy concerns, limited interoperability across hardware and software platforms, insufficient generalizability and robustness of models, high computational and infrastructure demands, and the need to align operational strategies with long-term sustainability and lifecycle objectives. Simultaneously, these challenges highlight the inherent complexity of deploying AI solutions across diverse building types, climatic contexts, and occupant behavior patterns. Specifically, no universal model or framework currently exists that can be seamlessly applied across all contexts; instead, application-specific and adaptable solutions are required.

The results of this systematic review indicate that several research areas warrant further attention. Future work should emphasize the development of privacy-preserving AI methods, interoperable and modular frameworks, robust and generalizable models, and computationally efficient architectures enabling real-time adaptability. Equally important is the integration of sustainability-oriented strategies to ensure AI-enabled HVAC systems contribute to low-carbon, resilient, and energy-efficient building operations. Promising future directions include big energy data analytics, adaptive control strategies, and lightweight edge-deployable AI architectures tailored for diverse building clusters. In parallel, improving data quality through standardized preprocessing pipelines, fault detection, and robust learning methods will be vital to ensure reliable and interoperable AI deployment across diverse building environments. By addressing these challenges and opportunities, AI-enabled HVAC systems can play a pivotal role in advancing sustainable urban development, supporting global energy efficiency targets, and contributing to broader decarbonization and climate mitigation goals.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
ML	Machine learning
DL	Deep learning
RL	Reinforcement learning
DRL	Deep reinforcement learning
DDPG	Deep deterministic policy gradient
DNN	Deep neural network
FNN	Feedforward neural network
ANN	Artificial neural network
KINN	Knowledge-infused neural network
RF	Random forest
XGB	eXtreme gradient boosting
LightGB	Light gradient boosting
RBF	Radial Basis Function
GB	Gradient boosting
AutCode	Autoencoders
DT	Decision trees
RidR	Ridge regression
BayR	Bayesian regression
PSO	Particle swarm optimisation
SVM	Support vector machines
SVR	Support vector regression
BPNN	Backpropagation neural network
LSTM	Long short-term memory
BiLSTM	Bidirectional long short-term memory
RNN	Recurrent neural network
CNN	Convolutional neural network
SOM	Self-organizing mapping
BPNN	Back propagation neural network
GA	Genetic algorithm
XLM	Extreme learning machine
KNN	K-Nearest Neighbor
LSA	Lightning search algorithm
DPN	Deep belief network
DELM	Deep extreme learning machine
BO	Bayesian optimization
DDPC	Data-driven predictive control
DPC	Differentiable predictive control
MPC	Model predictive control
GSHPS	Ground source heat pump system
nZEB	nearly zero energy building
AC	Air conditioning
HVAC	Heating, ventilation, and air Conditioning
VRF	Variable refrigerant flow
VAV	Variable air volume
ERV	Energy recovery ventilator

HP	Heat pump
ZCB	Zero-carbon building
AHU	Air handling unit
FCU	Fan coil unit
TRV	Thermostatic Radiator Valves
DR	Demand response
CCHP	Combined cooling, heating and power
PPG	Phasic policy gradient
PPO	Proximal policy optimization
DAS	Decoupled adversarial strategy
PMV	Predictive mean vote
HEMS	Household energy management system

Appendix A

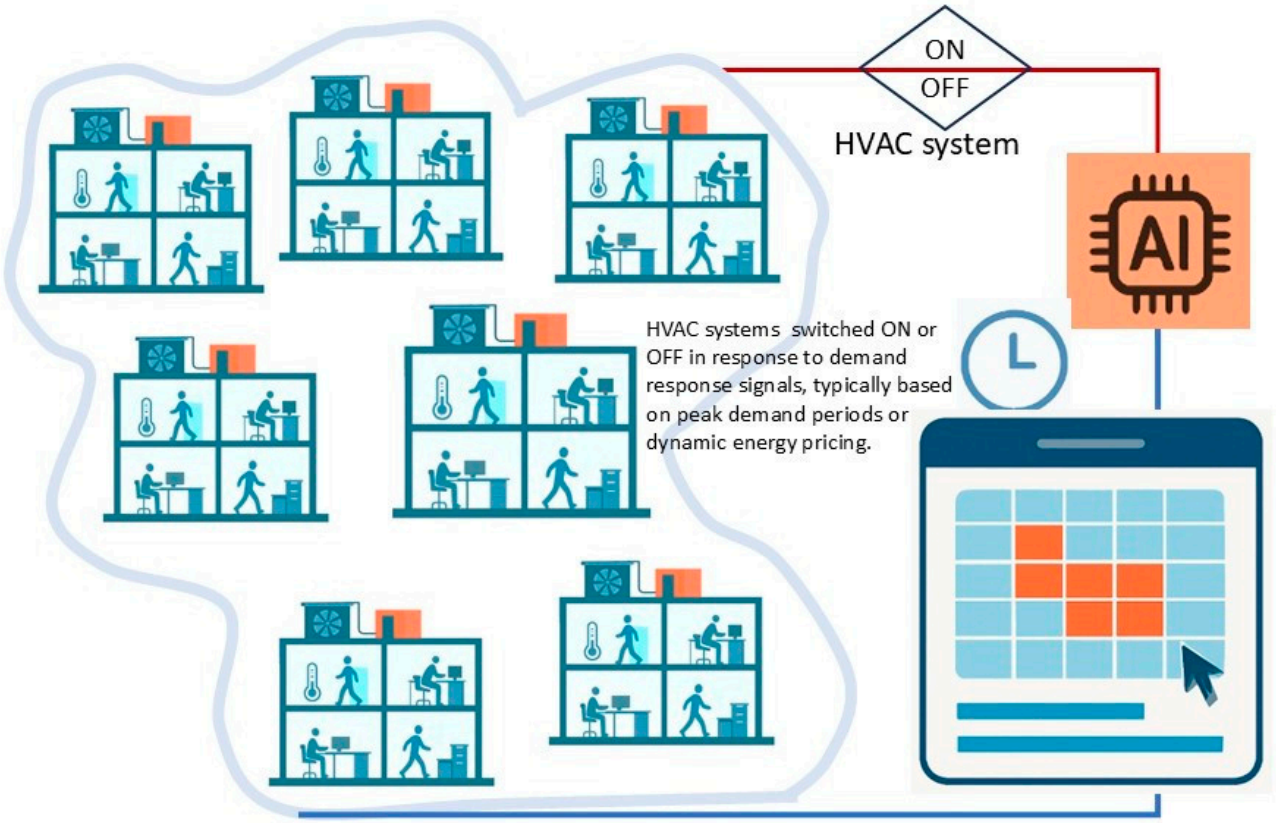


Figure A1. Conceptual depiction of AI-enabled HVAC system scheduling in the context of buildings.

Table A1. Comparison of HVAC scheduling and adaptive HVAC optimization strategies in buildings.

Aspect	HVAC Scheduling	Adaptive HVAC Optimization
Decision timing	Planned ahead (hour/day-ahead)	Real-time (continuous)
Primary focus	When and how long to operate	How to operate right now
Key inputs	Forecasted occupancy, prices, weather	Live sensor data, real-time comfort feedback
Control type	Open-loop or semi-automatic	Closed-loop, automated
Optimization horizon	Discrete intervals	Continuous
Typical objectives	Cost reduction, demand response	Multi-objective: comfort, IAQ, energy, emissions

Table A2. Overview of AI algorithms used in the reviewed literature for optimizing zero-emission building HVAC systems.

AI Algorithm	Category/Group	Key Characteristics	Advantages	Disadvantages/Limits
Decision trees, random forest, gradient boosting (XGBoost, LightGBM), ridge/Bayesian regression, K-nearest neighbor	Machine learning (tradition machine learning)	Supervised learning from historical data; interpretable models possible	Simple, interpretable, efficient on structured data; good baseline	Limited handling of temporal dependencies; performance drops with noisy/incomplete data
Deep neural networks (DNN), feedforward NN, artificial NN, Autoencoders, radial basis function NN	Deep learning	Multi-layer neural architectures; capture nonlinear relationships	Strong representation learning; effective for complex datasets	Require large data; risk of overfitting; high computational cost
Recurrent neural networks (RNN, LSTM, BiLSTM, GRU, Backpropagation NN)	Deep learning (advanced machine learning)	Sequence modeling, temporal dependencies	Effective for time-series HVAC load/comfort prediction	Computationally intensive; prone to vanishing/exploding gradients
CNN, deep belief network, extreme learning machine, deep extreme learning machine, self-organizing maps	Convolutional and specialized NNs (advanced machine learning)	Spatial/temporal feature extraction; unsupervised/self-organizing capabilities	Capture spatio-temporal features; fast training (ELM)	Less interpretable; limited robustness for irregular building data
RL, DRL, DDPG, data-driven predictive control, differentiable predictive control	Reinforcement learning	Learn optimal policies via interaction with environment	Suitable for real-time HVAC control; adaptive to changing conditions	Training instability; large data/simulation requirements
Particle swarm optimization, genetic algorithm, Bayesian optimization, lightning search algorithm, model predictive control	Optimization and hybrid methods	Search-based or model-based optimization; often hybridized with ML	Global search ability; strong in multi-objective HVAC optimization	Computationally expensive; slower convergence in large-scale systems
Knowledge-infused NN, hybrid ML–MPC frameworks	Knowledge-infused and hybrid AI	Combine domain knowledge with learning models	Improved interpretability; better generalization	Still emerging; complexity in integration

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