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# AI-driven HVAC control optimisation for enhancing energy efficiency and indoor environmental quality: A review of recent advances and emerging approaches

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A R T I C L E I N F O

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A B S T R A C T

Heating, ventilation, and air-conditioning (HVAC) systems are central to building decarbonisation, yet improving indoor environmental quality (IEQ) often increases energy demand. This paper presents a systematic literature review of AI-driven HVAC control optimization for jointly improving energy efficiency and indoor environmental quality across different building types and climatic contexts. Following a PRISMA-based screening process, the review synthesizes 143 recent peer-reviewed studies published between 2020 and 2025. The analysis revealed supervised learning as the dominant ML technique for prediction and surrogate modelling and is frequently embedded in model predictive control (MPC). Reinforcement learning and deep reinforcement learning are increasingly applied to multi-objective supervisory control of setpoints, airflow, dampers and HVAC components because they offer model-free adaptability. Hybrid and ensemble approaches are emerging to improve robustness and trade-offs between energy efficiency and IEQ. Across diverse building typologies and climates, the reviewed studies reported an average energy savings of 40% compared with baseline cases, with several studies achieving savings above 50% while maintaining excellent IEQ. Despite these promising results, real-world validation remains limited as only 8 of 130 studies progressed to field or testbed deployment, highlighting a concerning gap between simulation-based research and practical validation. This review provides a comprehensive, context-sensitive mapping of AI-driven HVAC applications for enhancing both energy efficiency and IEQ in buildings.

## 1. Introduction

Heating, Ventilation, and Air Conditioning (HVAC) systems are among the most energy-intensive components in residential, commercial, and industrial buildings, accounting for approximately 38% of global building energy consumption [1]. As the demand for energy efficiency intensifies in response to climate change, rising energy costs, and sustainability goals, optimising HVAC system performance has become a priority. HVAC systems are necessary and constant requirements for any habitable building; therefore, improving HVAC energy efficiency can drastically reduce a building's energy consumption regardless of its use [2].

IEQ is directly related to HVAC energy efficiency and the need to improve IEQ in buildings increases energy consumption and reduces HVAC system energy efficiency [3]. IEQ is a broad term that encompasses the overall condition of a building indoor condition, which affects the health, comfort, and productivity of its occupants. Its key components include IAQ, Thermal comfort, lighting, and acoustics. Maintaining IEQ at optimal levels is essential for improving occupants' health and productivity, yet it frequently conflicts with energy efficiency objectives. Traditional HVAC control approaches, including rule-based control, on-off control, PID control, and even conventional model predictive control in some practical settings, often struggle to handle nonlinear building dynamics, uncertain occupancy, weather variability, and multi-objective trade-offs between energy use and comfort. These limitations explain the growing interest in AI-driven control.

In recent years, AI/ML has emerged as a powerful potential tool for or addressing this challenge, offering capabilities such as intelligent

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control strategies, real-time energy consumption prediction, anomaly detection, and predictive maintenance. A growing body of literature explores the applications of AI/ML control algorithms for enhancing HVAC performance, with particular emphasis on reducing energy use while maintaining IEQ but despite considerable progress, several gaps persist.

Existing reviews provide important but partial foundations for understanding AI/ML applications in HVAC and building energy systems. Broad reviews tend to focus on general AI applications and practical implementation challenges, such as data quality, interpretability, and system integration, without offering a detailed synthesis of control-specific roles or energy-IEQ co-optimisation [4]. Other studies concentrate on building energy management systems, emphasising prediction accuracy and energy savings, while often giving limited attention to indoor environmental quality [5]. Method-specific reviews, particularly those centred on artificial neural networks, provide detailed technical comparisons but do not capture the broader landscape of emerging control paradigms such as reinforcement learning and hybrid approaches [6]. System-level reviews of smart and sustainable buildings typically treat HVAC control as one component within a wider sustainability framework, rather than as a dedicated optimisation problem [7]. Therefore, although these reviews are valuable, they collectively leave a clear gap for a systematic literature review that specifically examines AI-driven HVAC control optimization by control role, energy and IEQ co-optimization, building-type and climate related patterns, generalisability, and deployment readiness (Table 1).

Compared with earlier reviews, this study makes four main contributions. First, it focuses specifically on AI-driven HVAC control optimization, rather than combining control with broad AI applications such as fault diagnosis, equipment design, or general building analytics. Second, it distinguishes AI methods by their functional role in control, including supervised-learning-assisted control, reinforcement-learning-based control, deep-reinforcement-learning-based control, and hybrid AI-driven control. Third, it synthesizes evidence across control objectives, building types, climatic conditions, and generalisability. Fourth, it examines persistent practical barriers, including data quality, transferability, interpretability, simulation-to-reality gaps, and deployment constraints. This study establishes a foundational framework for future innovation in energy-efficient HVAC system design and aims to answer the following questions.

1. Which AI-driven control approaches are most commonly applied to specific objectives such as energy reduction, thermal comfort control, indoor air quality control, and multi-objective IEQ-energy optimization?
2. How do building type and climate zone, influence the reported performance and applicability of AI-driven HVAC control strategies?
3. What are the main barriers to AI/ML models generalisability and real-world deployment, including data scarcity, transfer learning needs, and simulation-to-reality gaps?
4. What research directions are most critical for robust, scalable, and field-deployable AI-driven HVAC control?

## 2. Methods

We conducted this systematic review to consolidate and evaluate recent literature on the application of ML to HVAC system optimisation, with a focus on energy efficiency and IEQ. Eligibility criteria were defined based on inclusion and exclusion parameters, including those specific to IEQ.

We included only peer-reviewed journal articles published in english and excluded conference papers, preprints, and grey literature. The publication period was limited to studies published between 2020 and 2025 to ensure the selection of recent developments in the field. Also, we included only studies in the area of AI/ML-based HVAC control optimisation with a focus on energy efficiency or IEQ or both, and excluded

**Table 1**
Research gaps from other relevant studies.

| References | Main focus of the review | Research gaps/limitations | How these SLR address these gaps |
|---|---|---|---|
| Aghili et al. [4] | Reviews AI for HVAC energy management, covering both control and maintenance and emphasizing practical HVAC applicability rather than only abstract ML theory. It also notes ongoing challenges related to data quality, interpretability, infrastructure compatibility, long-term effectiveness, and climatic diversity. | The review remains a general overview of AI in HVAC optimization, with emphasis on methodologies, trends, and practical implementation rather than a fine-grained synthesis of control-specific roles, energy/IEQ co-optimization, and cross-context comparison across building types and climate zones. | The present SLR narrows the scope to AI-driven HVAC control optimization and explicitly synthesizes evidence by control role (e.g., supervised-learning-assisted, RL-based, DRL-based, and hybrid control), while also discussing building type, climate zone, generalisability, transferability, and deployment readiness. |
| Ali et al. [5] | Reviews AI applications in building energy management systems (BEMS), focusing on energy savings potential, accuracy/error rates, and differences across building types. | The review is centered mainly on BEMS-level energy savings and model reliability, with IEQ receiving relatively little attention compared with energy prediction and HVAC optimization. | The present SLR extends beyond energy savings alone by explicitly addressing IEQ together with energy efficiency. It also shifts the synthesis from generic BEMS applications toward control-oriented HVAC optimization. |
| Michailidis et al. [6] | Provides an in-depth review of artificial neural network (ANN) applications in BEMS, covering HVAC, domestic hot water, lighting, and renewables. Its novelty lies in detailed comparison of ANN architectures, training schemes, network depth, computational demand, statistical metrics, BEMS type, and building testbed characteristics. | Because the review is intentionally centered on ANNs, it does not provide a broader synthesis across other ML control paradigms such as RL, DRL, and hybrid AI control. Its scope is also broader across BEMS domains, which leaves less room for a dedicated synthesis of HVAC control optimization. | The present SLR broadens the method taxonomy beyond ANNs to include supervised learning, reinforcement learning, deep reinforcement learning, and hybrid control approaches, while narrowing the application scope specifically to HVAC control optimization for energy efficiency and IEQ. |
| Bibri et al. [7] | Conducts a broad systematic review of AI and AI-powered digital twins across smart, green, and zero-energy buildings, with emphasis on environmental sustainability, cross-system integration, and holistic built-environment outcomes. | Its scope is intentionally cross-system and cross-typology, spanning building lifecycle stages and sustainability indicators. As a result, it does not provide a dedicated synthesis of AI-driven HVAC control optimization. | The present SLR complements this broader sustainability review by focusing specifically on HVAC control optimization, offering a deeper synthesis of control methods, energy/IEQ co-optimization, building-type and climate-related performance patterns, and real-world deployment challenges relevant to HVAC systems. |

review papers to prevent indirect citation.

We conducted a systematic search across the following four databases: Scopus, Web of Science, ScienceDirect, and Google Scholar. We selected articles for their extensive coverage in engineering and computer science disciplines. These databases were selected based on their academic credibility and relevance to multidisciplinary research in HVAC and AI.

An electronic search was performed in June and July of 2025 using a combination of keywords and Boolean operators. The search string was slightly adapted for each database while maintaining a consistent structure and terminology. An example of the search strategy used is as follows: "Artificial Intelligence" or "machine learning" OR "artificial intelligence" OR "deep learning" OR "reinforcement learning" AND "HVAC" OR "heating, ventilation, air conditioning" AND "optimisation" OR "control" OR "energy efficiency" OR "indoor environmental quality".

The review adheres strictly to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure methodological transparency and reproducibility [8]. The PRISMA 2020 framework guided the multi-step selection process. Initially, 255 studies were retrieved. After removing duplicates and screening titles and abstracts against the eligibility criteria, 143 articles were selected for full-text review and inclusion. The PRISMA flow diagram in Fig. 1 illustrates the complete study selection workflow, including the number of records screened, excluded, and retained.

The review is organised in three complementary layers: Sections 3 synthesize the studies by AI/ML control techniques for energy efficiency and IEQ co-optimisation, Section 4 discusses optimisation objective, including energy efficiency, IEQ, demand response, and multi-objective optimisation, whereas Section 6 provides a comparative analysis of the performance of control models/algorithms applied in the reviewed studies for energy efficiency and IEQ across building types and climatic conditions and further addresses generalisability and deployment challenges these models/algorithms.

### 2.1. Research contribution by geography

The studies included in this review span multiple geographical regions, with China emerging as the most prolific contributor by a significant margin, as shown in Fig. 2. The United States similarly accounts for a considerable share of publications, with numerous studies originating in Massachusetts, thereby establishing itself as the second principal hub. A third prominent centre of activity is Australia, including Perth and various multi-city Australian studies. Within Europe, contributions are dispersed. However, notable medium-sized clusters manifest in Germany, Italy, and Spain, complemented by additional research from Belgium, Romania, the Netherlands, France, and a collaborative effort spanning China and Germany. Beyond China, notable scholarly input from East Asia is evident in South Korea, Japan, India, Malaysia, Bangladesh, and Pakistan. In the Middle East and North Africa, significant studies emerge from Iran, Saudi Arabia, Kuwait, Qatar, Jordan, Iraq, and Morocco. North America, excluding the United States, has contributions from Canada. Finland, Sweden and Denmark represent Northern Europe.

Africa, apart from Morocco, and Latin America are conspicuously absent, and Eastern Europe is minimally represented. This concentration suggests that the existing findings may be most applicable to high-income, temperate or subtropical urban environments. A broader representation of underrepresented regions can enhance future research on this subject to evaluate generalisability across diverse climatic conditions, infrastructure development, and policy frameworks.

## 3. AI/ML HVAC control techniques for IEQ and energy efficiency optimisation

Machine Learning (ML), a subfield of artificial intelligence (AI), is gaining relevance in HVAC system optimisation in this age of AI boost [9]. Supervised Learning, Reinforcement Learning, and Deep Reinforcement Learning are the dominant ML techniques in the studies

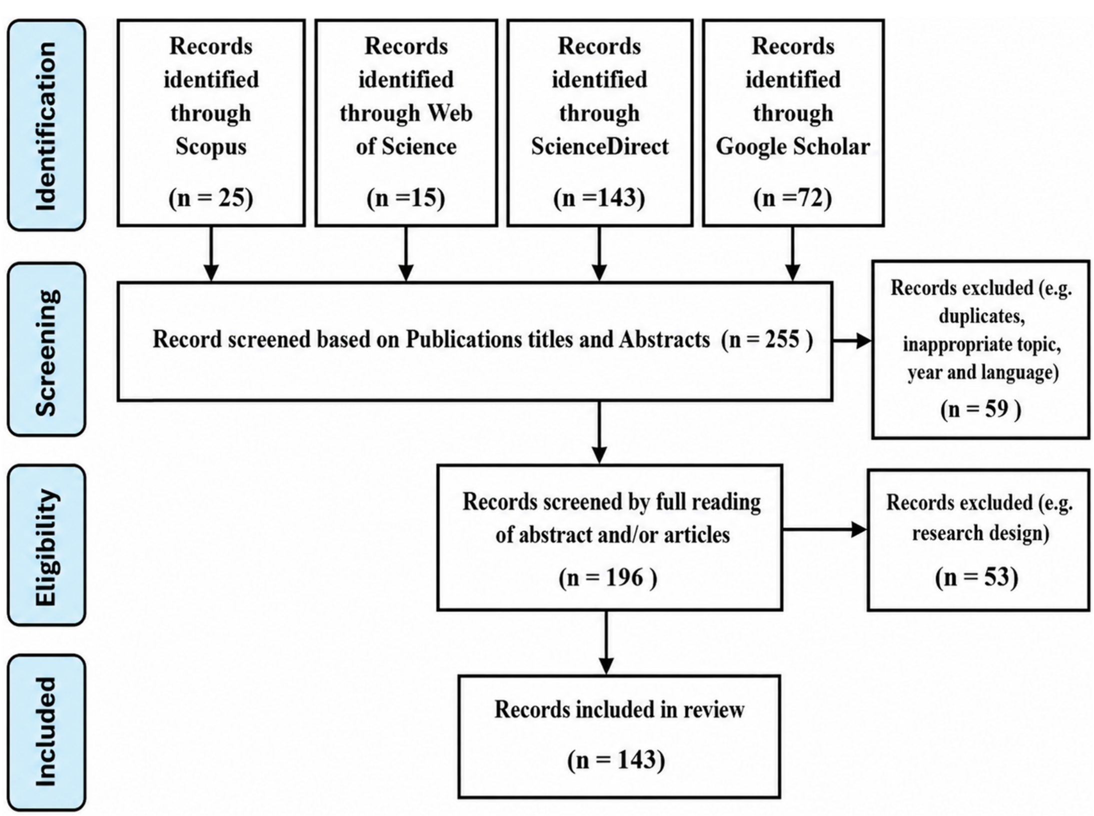


**Fig. 1.** PRISMA flow diagram for articles' selection.

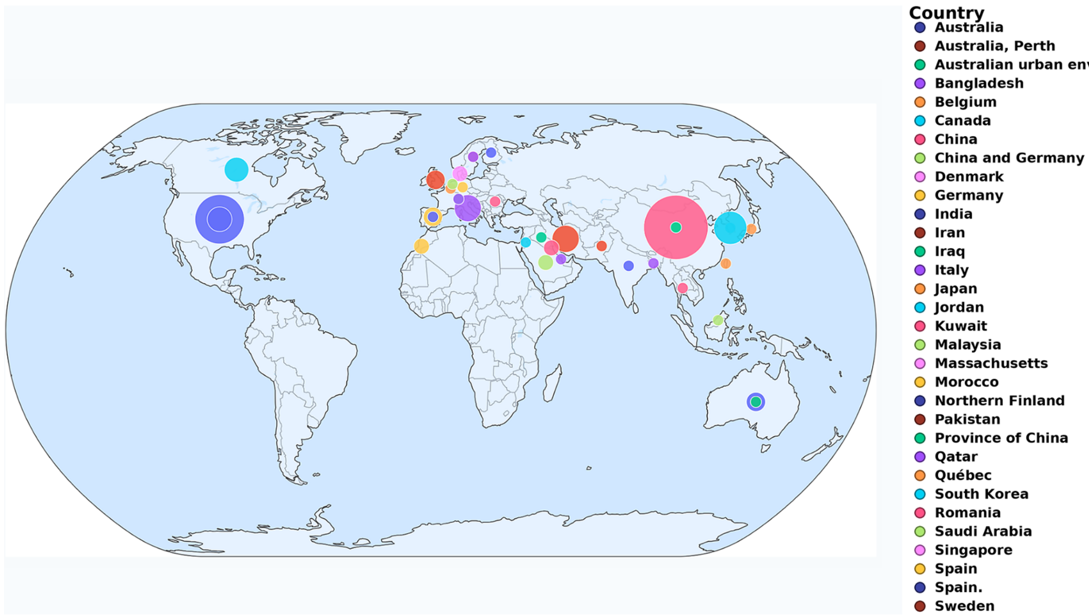


**Fig. 2.** Publications contribution by countries.

**Table 2**
Key studies applying SL-based control for IEQ and energy efficiency optimisation.

| Ref. | Location & Climate | Building Type | Model/Algorithm | Main Contribution | Key findings | Limitations of Study |
|---|---|---|---|---|---|---|
| [22] | Hebei, China (Temperate Continental) | Commercial (hospital ORs) | Linear model and its OVs | Reduced ventilation airflow and fan power in hospital ORs. | Ventilation reduction from 7963.73 m3/h to 5912.47 m3/h. 36% reduction in fan power consumption. | Limited to hospital OR conditions. Uncertain model transferability to other Vent. systems |
| [23] | Kuwait hot desert climate | Commercial (office building) | Deep Neural Network | Improved energy use and comfort with interpretable DNN control. | 31.27% energy reduction, average ATV is 0.5 °C compared with HAVOK-MPC's 1.13 °C. | Needs wider real-building validation of prediction model accuracy. |
| [24] | Singapore (tropical rainforest) | Institutional (Office and Lecture theatre) | Artificial Neural Network (ANN) | Achieved large cooling savings with ANN-based VAV control. | 58.5% savings in the office. 36.7% savings in the lecture hall. 0.07 PMV in the lecture hall (-0.5, 0.5 during all class time). | Limited to specific office and lecture-hall spaces in tropical climate, reducing generalisability. |
| [25] | Tianjin, China (Temperate, continental monsoon) | Commercial (An Office space) | Convolutional Neural Network (CNN) | Reduced FCU energy while maintaining comfort temperature. | 18.18% HVAC reduction compared with rule-based control. Temperatures within the comfort range of 24-26 °C | Single office case study. Model not generalisable. |
| [26] | Indiana, USA (Humid continental) | Institutional (university classroom) | Support Vector Machine (SVM) | Reduced fan energy while maintaining $CO_2$-based IAQ. | 51.4% HVAC fan energy consumption by Successfully maintains IAQ ($CO_2$ levels) | Single classroom; $CO_2$-focused IAQ evaluation. |
| [26] | Kuwait (hot desert climate) | Residential (single-family home) | Linear Regression, ANN | Reduced cooling energy and PMV discomfort in housing. | Decreased the PMV discomfort duration by over 60%. 20% cooling energy reduction | Limited to a single-family home and hot desert climate. Other applications uncertain. |
| [27] | Islamabad, Pakistan. (Humid subtropical) | Commercial (single office room) | Transformer Neural Networks | Applied transformer model for energy-saving HVAC prediction. | 50% energy Savings. 0% of occupants reporting discomfort (60 minutes prediction) | Tested in a single office room with limited spatial diversity. |
| [28] | Seoul, South Korea. (Humid continental) | Institutional (School building) | Integrated Neural Net. | Coordinated heating, cooling, and ventilation in a school. | PMV (μ: -0.1018, σ: 0.3214). $CO_2$ below 700 ppm. 8.9% (heating) and 6% (cooling) savings | School-specific case study. Limited evidence of transferability. |
| [29] | Kajang, Malaysia (Tropical climate) | Institutional (27-year-old, four-story academic) | Generalised Linear Model | Supported AC energy management after building renovation. | 20% energy savings after the renovation Increased load reduction from 12% to 18% after renovations. | limited ability to represent complex nonlinear HVAC dynamics. |
| [30] | Singapore (Tropical rainforest climate) | Commercial (Office) | Recurrent Neural Net. | Reduced cooling energy while maintaining PMV comfort. | 31.6% reduction in cooling energy consumption. PMV range between (-0.5, 0.5). | Single tropical climate office case. May require modification for other systems. |
| [31] | Rabat, Morocco. (Mediterranean climate) | Commercial (Laboratory) | LSTM | Used LSTM for ventilation energy reduction and IAQ prediction. | 16.44% energy reduction. 98.7% LSTM model accuracy. | Laboratory-specific validation. limited real-building diversity and deployment. |
| [32] | Nanchang, China. (Humid subtropical) | Institutional (library) | CNN | Improved occupancy-based control, energy use, PPD, and $CO_2$. | 99.3% occupancy Detection precision. 52.1% energy savings. PPD dropped from 14.3% to 7.2%. $CO_2$ reduced by 55%. | Performance under different occupancy patterns and HVAC configurations remains uncertain. |

reviewed. The key applications of these ML techniques are for HVAC system optimisation, aiming to improve energy savings, which, in turn, reduce greenhouse gas emissions in the building sector [10]. ML techniques often deploy advanced control, prediction, and/or estimation architectures to handle the complexity of modern or retrofitted buildings [11,12]. However, the effectiveness of ML techniques depends, among other things and most importantly, on the. The quality and availability of data determine its ability to handle the multidimensional, complex relationships posed by advanced HVAC systems [13].

### *3.1. Supervised-learning-based HVAC control*

Supervised learning (SL) is a fundamental ML technique that utilises fully labelled datasets in training the algorithms. In this instance, input features are paired with corresponding desired outputs to learn a mapping function that predicts outputs for subsequent new or unseen data [14]. HVAC systems often leverage this feature for prediction tasks. SL models for HVAC control optimisation can be utilised for operational prediction or serve as core predictive models within sophisticated control frameworks such as Model Predictive Control (MPC) [15]. In supervised learning MPC framework, the ML model typically serves as the predictive component, estimating future indoor temperature, HVAC load, occupancy-related demand, or IEQ states over the control horizon. The optimizer then determines the control sequence subject to operational and comfort constraints. Compared with conventional MPC, which relies on explicit physics-based or first principles models, supervised-learning-assisted MPC can reduce modelling effort and improve adaptability to complex system behaviour [16]. Developing high-performance SL models requires intricate data handling, parameter tuning and evaluation protocols. The models' accuracy depends heavily on the quantity and quality of the data [17].

Compared with other ML techniques, SL offers some advantages in the application of HVAC systems. SL generally demonstrates superior stability and reliability, especially when applied to real-time control architecture with lower computational requirements [18,19]. SL methods, particularly those utilising Deep Learning architectures such as ANNs, are the best alternative for short-term load prediction (STLF) but their suitability vary according to data richness, control horizon, and the complexity of the target dynamics [20,21].

Overall, the supervised learning-based studies synthesised in Table 2 show that SL models are mainly used for prediction, estimation, and control support in HVAC optimisation. Their key contributions include reducing fan power, cooling energy, and HVAC operational demand while maintaining thermal comfort or $CO_2$-based IAQ. Models such as ANN, DNN, CNN, RNN, LSTM, SVM, and transformer networks demonstrated strong performance in forecasting, occupancy-informed control, and energy-efficient HVAC operation. However, most studies were validated in single buildings, specific climates, or controlled test spaces, which limits their generalisability. In addition, several studies focused on narrow IEQ indicators, mainly thermal comfort or $CO_2$, with limited consideration of broader IEQ parameters and long-term field deployment.

### *3.2. Reinforcement-learning-based HVAC Control*

Reinforcement learning is a promising approach for HVAC systems control optimisation [33,34]. Reinforcement-learning-based HVAC control learns a decision policy through repeated interaction with the building/HVAC environment, where actions are selected based on observed states and updated according to reward feedback linked to energy, comfort, or IAQ objectives [9,35]. RL application in a building is to primarily develop advanced supervisory level control strategies aimed at achieving multiple, often conflicting, objectives, such as minimising energy consumption while simultaneously maintaining thermal comfort and/or IAQ [36,37].

RL problems are typically formulated as a Markov Decision Process (MDP), which includes a set of states (S), a set of actions (A), a reward function (R), and a set of transition probabilities [38,39]. In HVAC control optimisation applications, the 'state' often comprises environmental variables such as indoor/outdoor temperature, humidity, and $CO_2$ concentration. 'Actions' are the control signals sent to the HVAC system, such as adjusting temperature setpoints or fan speeds. The 'reward' function is designed to balance multiple objectives, such as minimising energy consumption while penalising deviations from comfort ranges [38,40,41].

Their adaptive and learning qualities define the superiority of RL techniques, the capacity to offer multi-objective optimisation and their low runtime computational cost [42–44]. These enable RL algorithms to attain superior energy efficiency and tighter temperature regulation in buildings compared with other ML applications. However, RL techniques have high computational requirements, including substantial upfront training time and the need for hundreds of episodes to learn an effective policy [45]. RL can also exhibit a high Simulation-to-Reality Gap because many RL controllers are trained in simulated environments, and discrepancies between the simulation and the actual building can challenge the controller's performance upon deployment [46,47]. There are other concerns, such as difficulties in scaling and the interpretability of the underlying decision-making logic due to the models' black-box nature [48,49].

The reinforcement-learning-based studies synthesised in Table 3 demonstrate the growing role of RL in adaptive and multi-objective HVAC control. Their main contribution is the ability to optimise sequential control decisions, such as cooling operation, setpoint control, ventilation, and central plant management, while balancing energy use and comfort. Several RL models achieved considerable energy savings and improved PMV, PPD, temperature stability, or $CO_2$ levels compared with rule-based or conventional control strategies. Nevertheless, the reviewed RL studies also reveal important limitations, including simulation dependence, algorithmic complexity, limited scalability, and uncertain robustness under real-world operating conditions. Many studies were also restricted to specific building types or climates, making cross-building transferability a key unresolved issue.

### *3.3. Deep-reinforcement-learning-based HVAC control*

Deep-reinforcement-learning-based HVAC control extends RL by using deep neural networks to approximate value or policy functions, allowing control in higher-dimensional and continuous state-action spaces. Traditional HVAC control strategies, such as Rule-Based Control (RBC) or conventional Proportional-Integral-Derivative (PID) controllers, are often inefficient and can potentially compromise occupant comfort because they lack dynamic adaptability [9,36]. However, DRL soars above these limitations with its model-free approach by learning optimal control policies through continuous interaction with the building environment and providing dynamic adaptability for complex and non-linear HVAC systems while addressing the trade-off between energy consumption, occupant comfort, and IAQ without needing an explicit system model [58–60].

A significant obstacle for DRL is sample inefficiency during deployment [61]. DRL algorithms often require a vast number of interactions with the environment (samples) to converge to a good policy [62,63]. Training a DRL-based HVAC controller can take dozens of months or more to achieve the desired performance, which is not feasible for direct training during real building operation [64–66]. This extended training time contrasts sharply with the speed of simpler traditional RL algorithms in small-scale, discrete problems [67,68].

The DRL-based studies synthesised in Table 4 extend conventional RL by addressing more complex HVAC control problems involving high-dimensional states, dynamic occupancy, and multi-objective energy-IEQ optimisation. Their contributions include improved control of heating, cooling, ventilation, temperature violations, $CO_2$ concentration, and operational cost. Methods such as SAC, PPO, DQN, GRU-RL, Double Q-

**Table 3**
Key studies applying RL-based control for IEQ and energy efficiency optimisation.

| Ref. | Location & Climate | Building Type | Model/Algorithm | Main Contribution | Key findings | Limitations of Study |
|---|---|---|---|---|---|---|
| [50] | USA, Tennessee (Humid subtropical) | A single-family home | Deep Q Neural Network | Reduced cooling cost and eliminated comfort violations. | 43.89% cost energy reduction. Comfort violations drop to zero | Primarily simulation-based. Real-time field validation is needed. |
| [15] | Guangzhou, China (Humid subtropical) | Institutional (A university building) | Hierarchical soft actor-critic, DDQN | Improved central plant energy efficiency and comfort. | ITC time went up by 0.30% to 56.56%. Energy Eff: 22.11% (Year1), 24.97% (Y2) | Complex algorithm. requires evidence of scalability in diverse real buildings. |
| [51] | Turin, Italy (Humid subtropical climate) | | DDPG, Deep Q-Network (DQN). | Achieved high energy savings and comfort improvement. | 65% energy reduction, thermal comfort increase (up to 25% increase). | Performance depends on training quality and building-specific assumptions |
| [40] | Oklahoma City, USA (Humid subtropical) | Commercial (A 5-Zone building) | Proximal Policy Optimisation (PPO) | Balanced energy savings and PMV comfort using PPO. | PMV values ranged from -0.9 to +0.9. 22% maximum energy reduction. | Model not generalisable beyond studied configuration. |
| [52] | Basra city, Iraq (Hot desert climate) | Residential (multi-unit residential buildings) | Cooperative Multi-Agent RL. | Coordinated chillers and AHU fans using multi-agent RL. | 44% energy savings, occupants' thermal comfort went up by an average of 20.5% | multi-agent coordination complexity may hinder deployment. |
| [53] | Meknès, Morocco. (Continental climate) | Residential | Q-Learning algorithm | Reduced energy, discomfort, and $CO_2$ using Q-learning. | 26.3% energy savings, thermal discomfort from 6.38 to 1.38 Kh/zone. $CO_2$ (48%) | Model may struggle with high-dimensional or continuous HVAC control problems. |
| [54] | Tehran, Iran (Hot desert climate) | Residential | Q-learning (DQN) | Improved EUI, PMV, and PPD using Q-learning/DQN. | 25% reduction in EUI. PMV to 0.25 from 0.80. PPD reduced to 10% from 40%. | Hot-climate residential focus only. Limited climate transferability |
| [55] | Taiwan (Humid subtropical climate) | Institutional (University classrooms) | Deep Q-Learning | Reduced classroom energy use and $CO_2$ levels. | 43% energy savings The average $CO_2$ was reduced by about 24%. | IAQ assessment was $CO_2$-based and may not represent broader IEQ performance. Not generalisable |
| [45] | Saudi Arabia (Hot & dry desert climate) | Smart Building | Q-learning | Outperformed PID in energy and temperature control. | 55% in energy savings, Maintains ±0.5 °C temp. deviation compared with PID ±1.2. | Model performance in conventional buildings remains uncertain. |
| [56] | Taipei, Taiwan (humid subtropical) | Commercial (Office Room) | PPO algorithm | Improved FCU energy cost and PMV consistency. | The model achieved 29.13% energy cost savings and 83.33% PMV consistency. | Scalability to larger multi-zone buildings was suggested but not fully demonstrated. |
| [57] | Seoul, South Korea (Dry-winter humid continental) | Residential (multi-story apartment buildings) | Proximal Policy Optimisation (PPO) | Reduced power use and improved temperature stability. | 63% reduction in power consumption, maintained temp. within ±0.7 °C, compared with ±1.5 °C | Occupant diversity and long-term operation were not fully addressed. Not generalisable. |

**Table 4**
Key studies applying DRL-based control for IEQ and energy efficiency optimisation.

| Ref. | Location & Climate | Building Type | Model/ Algorithm | Main Contribution | Key findings | Limitations of Study |
|---|---|---|---|---|---|---|
| (Si [59] | Dübendorf, Switzerland (Temperate climate) | Commercial building (Offices and Lab) | Soft-Actor Critic (SAC) | Reduced energy and temperature violations with SAC. | 15% to 50% energy reduction, decrease in temp. violations by 25% | Single-building heating valve case. Broader seasonal and system-level testing is needed |
| [38] | Shanghai, China (Humid subtropical climate) | Institutional (university classroom) | LSTM, PPO | Improved PMV, $CO_2$, and energy using LSTM-PPO for adaptive HVAC control. | 15% reduction in PMV, 13% energy savings, $CO_2$ level was 579.43 ppm | Limited classroom validation. Real-world deployment and long term robustness remain uncertain. |
| [62] | Shenyang, China (humid continental) | Commercial (seven-floor office building) | Deep Q-Network (DQN) | Applied DQN to heat-pump and AHU operation, for heating and cooling energy reductions. | 9.38% heating and 24.26% cooling energy reduction. | DQN may be limited by discrete action representation and building-specific training. |
| [58] | Denver, USA (Cold semi-arid climate) | Commercial (Office building) | (GRU)-RL algorithm | Improved comfort and reduced operating costs with GRU-RL. | ITC increased by 88.4%. 20% heating and 17.5% cooling costs reduction | Model is based on an idealised four-pipe FCU system. Limited generalisability. |
| [69] | Seoul, South Korea (Temperate climate) | Institutional (A kindergarten) | Double Q-learning | Reduced HRV energy while maintaining $CO_2$ below 1000 ppm. | $CO_2$ concentration below 1000 ppm, 58% energy savings | IAQ evaluation focused mainly on $CO_2$. Requires broader pollutant and field validation. Limited generalisability. |
| [46] | Bangholme, Australia (Temperate climate) | Institutional (Three classrooms) | LSTM, DDQN | Improved classroom temperature, $CO_2$, and energy performance. | $CO_2$ concentration below 800 ppm, 9.5-14.6% temp. and, 12.2-17.4% $CO_2$, 10.9-30.4% energy savings. | Not generalisable without further testing across buildings, climates, and operating schedules. |

learning, LSTM-PPO, and LSTM-DDQN showed promising performance in both energy reduction and IEQ maintenance. However, these studies remain limited by small validation contexts, such as single buildings, individual classrooms, or idealised HVAC systems. In addition, DRL approaches often require extensive training, careful reward design, and further field testing before they can be considered reliable for large-scale deployment.

### 3.4. Hybrid and ensemble algorithms for HVAC control

The application of hybrid and ensemble ML algorithms for HVAC control optimisation and energy efficiency improvement is a significant trend [70]. Hybrid AI-driven control combines predictive models, optimization routines, or learning-based policies to improve robustness, flexibility, and multi-objective control performance [71]. Hybrid and ensemble ML models are utilised to enhance predictability and enable advanced control strategies that balance conflicting objectives of primarily minimising energy consumption while maximising thermal comfort and IAQ [72]. This is to address the lack of adaptability of traditional control methods to dynamic, nonlinear building operations. These algorithms are very effective for predicting critical variables required for efficient control, such as energy consumption, heating and cooling loads (CL/HL), and predicting IEQ metrics like Predicted Mean Vote (PMV), and particulate matter levels which are essential for predictive modeling [73–75].

These advanced methods combine predictions from multiple algorithms to achieve better performance and robustness than single, traditional ML techniques. Hybrid and ensemble algorithms also have superior predictive accuracy, greater robustness, and improved generalisability due to their dynamism and ability to handle the complex, nonlinear nature of HVAC systems [17]. Despite their strengths, these advanced algorithms present several challenges in the context of HVAC control optimisation and real-world deployment, including training time and computational cost, challenges in MPC integration, model complexity and interpretability [48,65].

The hybrid and ensemble studies synthesised in Table 5 show an emerging trend toward combining predictive models with adaptive control algorithms to improve HVAC performance. These approaches contribute by integrating the forecasting strength of supervised learning with the decision-making capability of RL or DRL, leading to improved thermal comfort, reduced AC use, lower ventilation energy, and better energy performance compared with rule-based control. However, the reviewed studies are still limited in number and are often highly system-specific, such as mixed-mode offices, elevator cabins, heat pump systems, or small office buildings. Their complexity, dependence on high quality data, and limited field validation remain major barriers to wider practical application.

### *3.5. Emerging trends and developments in AI-driven HVAC control*

Across the reviewed studies, the current trend in AI-driven HVAC control shows a clear progression from prediction-oriented models toward adaptive, multi-objective, and hybrid control strategies. Supervised learning remains widely used for forecasting energy demand, occupancy, thermal comfort, and IAQ variables, often as a support layer for model predictive control [26]. However, reinforcement learning and deep reinforcement learning are increasingly being adopted because they can learn dynamic control policies and address trade-offs between energy consumption, thermal comfort, and IAQ. More recently, hybrid and ensemble approaches have emerged to combine the predictive accuracy of supervised models with the adaptive decision-making capability of RL-based controllers [77]. This trend indicates that the field is moving beyond isolated energy saving models toward integrated, data-driven control frameworks that aim to balance energy efficiency, occupant comfort, indoor air quality, robustness, and deployment readiness.

## 4. Optimisation objectives in AI/ML-driven HVAC control

### *4.1. AI/ML for energy-efficient HVAC operation*

The application of ML techniques in HVAC systems often has a dual purpose, to improve IEQ (most often thermal comfort or IAQ) and reduce energy consumption [79]. ML models can be widely used to predict energy consumption and key environmental variables, providing foresight for optimisation strategies. This is done through data-driven methods by extracting hidden relationships and patterns directly from large volumes of historical data [20]. Supervised learning models are most commonly used for energy load prediction because they offer remarkable capabilities for handling nonlinear problems [80]. SL models are frequently favoured over other ML approaches, particularly RL, for the specific task of energy load prediction due to their inherent design for regression tasks, their efficiency and stability in training, and their proven high accuracy in modelling complex building dynamics [70].

SL models are very effective for predicting cooling loads. From studies reviewed [24,81], and [30] achieved the highest reduction in cooling energy consumption of 58.5%, 31.27% and 31.6% respectively. These studies employed SL techniques, specifically Artificial Neural Networks, Deep Neural Networks, and Recurrent Neural Networks. The Extra Trees Regressor (ETR) method has demonstrated the highest prediction accuracy for HVAC and lighting energy consumption in some studies, yielding an $R^2$ of 0.9943 [82]. The Decision Tree model has also shown superior effectiveness in optimising AC systems in legacy buildings, achieving up to a 20% reduction in energy consumption [29].

However, to boost prediction accuracy and robustness, models are often combined. For example, CNN-LSTM networks combine feature extraction and time-series learning to accurately predict energy load. Sarker et al. developed an Attention-integrated LSTM (Attention-LSTM) model for accurate, short-term (10-minute) energy prediction in AC units, achieving a Mean Absolute Percentage Error (MAPE) of 3.4310% [80]. Ensemble techniques, such as Gradient Boosting Machines (GBM) or Voting Hybrid Regression (VHR), improve lighting, heating, and cooling load prediction accuracy, reduce overfitting, and enhance model generalisation for energy HVAC system optimisation and energy consumption reduction [82,83].

**Table 5**
Key studies applying hybrid and ensemble control models for IEQ and energy efficiency optimisation.

| Ref. | Location & Climate | Building Type | Model/Algorithm | Main Contribution | Key findings | Limitations of Study |
|---|---|---|---|---|---|---|
| [43] | São Paulo, Brazil (Humid subtropical climate) | Commercial (Offices) | RL + SL (DQN and XGBoost) | Combined XGBoost and DQN for occupant-centric HVAC/ window control. | TC duration increased by 24%. AC usage decreased by 24.7%. | Not generalisable because performance depends on available occupant behaviour and building-specific data. |
| [76] | China (Humid subtropical monsoon climate) | Commercial (elevator cabins) | Unsupervised learning | Applied unsupervised learning to elevator ventilation control for energy and infection risk reduction. | 59% energy savings. Infection probability below 1.2% | Highly system-specific application. Lack airflow limit transferability to general HVAC systems. limited generalisability. |
| [77] | Tianjin, China (Humid continental climate) | Commercial (Office building) | RL+ Deep RL (Duelling Deep Q-network) | Combined RL and duelling DDQN for FCU and ground-source heat-pump control. | Energy savings from 8% to 40%, Thermal comfort is kept within a defined range. | System complexity and specific HVAC configuration may limit deployment without further field validation. |
| [78] | Seoul, South Korea (Dry-winter humid continental) | Commercial (small office building) | RL + SL (GRU and DQN) | Integrated GRU and DQN for heat-pump control, achieving high energy savings. | 58.79% energy savings compared with a rule-based baseline model. | Small office case study. model transferability and long-term operational reliability remain uncertain. |

### 4.2. AI/ML-aided indoor environmental quality optimisation

The studies reviewed mainly addressed thermal comfort and IAQ as components of IEQ. The application of ML in Lighting and acoustics optimisation is underrepresented, and none of the selected studies addressed these components of IEQ, as illustrated in Fig. 3. Finding the Balance between IEQ and energy efficiency is a crucial part of advanced HVAC systems in buildings. In this case, machine techniques become vital because traditional control methods often result in compromising occupant comfort due to their lack of dynamic adaptability in the quest to improve energy savings of HVAC systems [38]. ML algorithms are widely used to model and predict thermal comfort indices, often serving as the predictive layer in advanced control systems such as Model Predictive Control (MPC) or Deep Reinforcement Learning (DRL) [84].

These algorithms are applied to accurately optimise thermal comfort by predicting subjective metrics, such as the Predicted Mean Vote (PMV) and Thermal Sensation Votes (TSV), based on environmental and personal factors [85]. Boutahri et al. performed a study predicting PMV values. The result indicated that Random Forest (RF) and EXtreme Gradient Boosting (XGBoost) algorithms demonstrated superior performance, achieving accuracies of 96.7% and 9.64% respectively, compared with the Support Vector Machine (SVM) algorithm, which had an accuracy of 81.1% [2].

ML algorithms are also effective for developing personalised thermal comfort models, moving beyond generalised models such as Fanger's PMV. For example, a study by Almadhor et al. predicting personalised thermal sensation votes (TSVs) using a Digital Twin approach integrated with an Attention-based Long Short-Term Memory (LSTM) model achieved a test accuracy of 83.8% in classifying comfort into "Uncomfortably Cold," "Neutral," and "Uncomfortably Warm" [86]. ML techniques can also leverage complex inputs, such as physiological signals. An experimental study conducted by Ren et al. utilised physiological parameters like electrocardiogram (ECG), electroencephalogram (EEG), and skin temperature to develop a thermal comfort prediction model using the Random Forest (RF) algorithm. The system achieved an overall accuracy of 89.3%. After balancing the data using the SMOTETomek method, the accuracy reached 97.3% [87].

IAQ is also an essential component of IEQ, for which ML techniques are efficiently applied to enable the HVAC system to dynamically meet IAQ standards of a building while significantly conserving energy [88, 89]. To keep the concentration of pollutants such as $CO_2$, PM 2.5 and VOCs under acceptable levels, HVAC systems must provide ventilation rates between 5 and 10 Kh/zonL/s per person [90]. This demands the air handling unit fans, which are the major energy-consuming components of the HVAC system, to run continuously and at higher intensity. ML techniques are used to accurately predict pollutant concentrations and the occupancy patterns of a building, ensuring the correct ventilation rate is achieved and IAQ is maintained at acceptable levels [91,92]. Taheri et al. developed a dynamic indoor pollutant regulation model using ML algorithms [16]. In this context, six state-of-the-art SL algorithms, including Support Vector Machine, AdaBoost, Random Forest, Gradient Boosting, Logistic Regression, and Multilayer Perceptron, were tuned and compared for modulating the ventilation rate in real time in a campus classroom. The Multilayer Perceptron outperformed the others by reducing HVAC fan energy consumption by 51.4% while providing necessary ventilation and maintaining IAQ within ASHRAE standards [16]. ML algorithms can predict not only a building's indoor temperature but also relative humidity, which is essential for improving occupants' overall comfort. Kaligambe et al. reported that the XGBoost algorithm accurately estimated temperature, humidity, and $CO_2$ concentration across various case studies, with average root mean squared errors (RMSEs) of 0.3 deg, 2.6%, and 26.25 ppm, respectively [93].

Mixed-mode ventilation (MMV) is another area where ML techniques can be applied to optimise IEQ. RL algorithm can optimise mixed-mode ventilation by flexibly switching between Natural Ventilation and air-conditioning based on outdoor and indoor conditions [48,94,95]. Integrating the window opening area as a continuous control variable allows the system to open the window to an optimal area [96,97]. It helps to reduce heat gain from introducing outdoor air when the exterior is hot, while simultaneously ensuring sufficient outdoor air for good IAQ [98]. An ML application for MMV is primarily proposed for co-optimising multiple objectives, including minimising energy consumption, maintaining thermal comfort, and enhancing IAQ, with a focus on $CO_2$ and particulate matter levels. For example, an RL-based Explainable AI framework developed by Dai et al. was able to achieve a 52% reduction in cooling energy while successfully maintaining good thermal comfort and IAQ performance when compared with existing baseline strategies [48].

In IEQ-oriented HVAC applications, AI/ML methods can also serve as surrogate or reduced-order alternatives to CFD-based analysis when real-time control support is required. This is particularly relevant for airflow distribution, contaminant transport, and indoor $CO_2$ estimation,

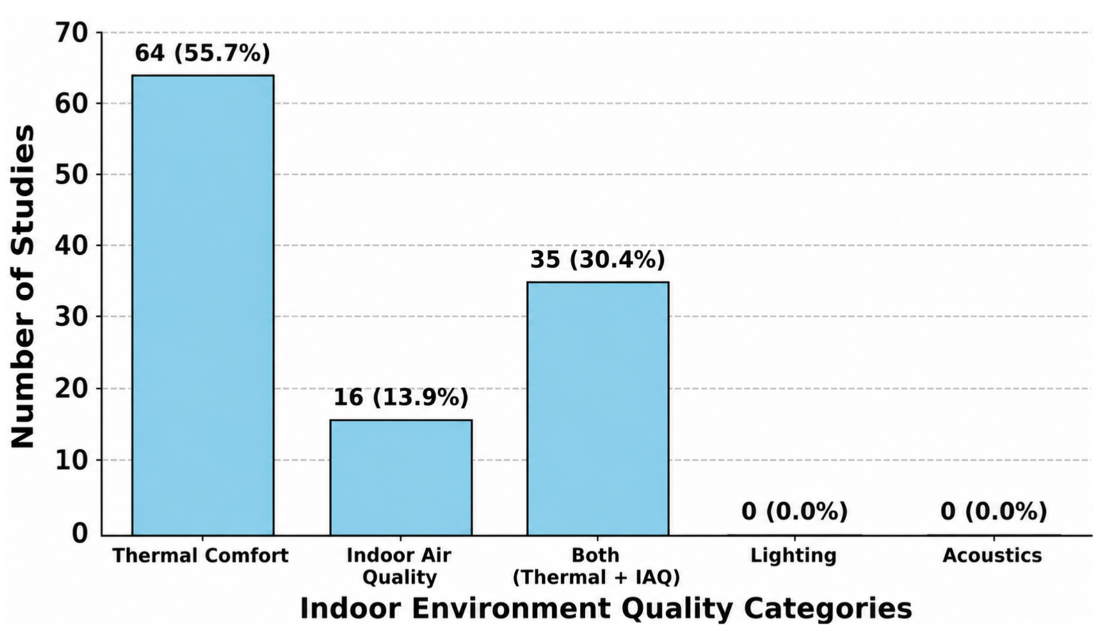


**Fig. 3.** The components of indoor environmental quality addressed by studies.

where full CFD simulation is often too computationally intensive for online control [99]. Supervised and deep-learning models can therefore be used to approximate CFD-informed relationships and support faster control-oriented prediction, virtual sensing, and scenario evaluation [100].

### 4.3. AI/ML-enabled demand response

The integration of HVAC systems with advanced ML techniques is a crucial area of research focused on optimising energy consumption, enhancing thermal comfort, and enabling effective participation in Demand Response (DR) programs [9]. Traditional control methods, such as on-off and Proportional-Integral-Derivative (PID) controls, usually rely on fixed temperature set points or predefined rules. They often experience operational inefficiencies due to their limited adaptability to dynamic changes like occupancy, weather or energy shifting during peak load periods to improve energy efficiency without compromising indoor environmental quality in buildings. DR implementation relies on the HVAC system's ability to adjust power use through control strategies such as set-point control (widen or tighten temperature deadbands) or direct load control (load shedding/shutdown) [40]. DRL techniques, such as Deep Q-Learning (DQL), Deep Deterministic Policy Gradient (DDPG), and Soft Actor-Critic (SAC), have been successfully applied by Kumkam et al., Du et al., and Kim & Kwon respectively, for demand response. A study by Kumkam et al. comparing DQL with MPC found that DQL significantly outperformed MPC, achieving energy reductions of 3.29% to 4.62% compared with rule-based and on-off controls, respectively, over a year of testing [9]. Du et al. applied a DDPG-based control strategy for a multi-zone residential HVAC system to reduce energy consumption cost by 15% and comfort violation by up to 98% compared with a rule-based strategy [101–103].

Hybrid RL Approaches, combining RL with predictive ML models, can also enhance HVAC DR performance. For example, Hou et al. developed a CCD-LSTM-DDQN framework that used LSTM to estimate occupancy and forecast HVAC performance. This technique is then incorporated into the Duelling Deep Q-Networks (DDQN) control agent to minimise HVAC operation time during unoccupied periods, contributing to energy savings and compliance with IEQ levels [46,104,105]. Q-Learning was also integrated with an Input Convex Long Short-Term Memory (ICLSTM)-based MPC framework to improve performance by testing alternative control actions via exploration-exploitation [106,107].

Accurate load prediction is foundational for advanced HVAC control. It enables optimisation strategies to anticipate energy consumption and performance [20]. Artificial Neural Networks and Multi-Layer Perceptrons (MLPs) are widely used. For example, Alaraj et al. used a Feedforward Neural Network (FNN) to predict one-year-ahead HVAC electricity consumption, achieving 33% annual energy savings through optimisation based on predicted occupancy [108]. Regression and Ensemble Methods such as Support Vector Regression (SVR) and Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost/XGBM) are commonly employed for load prediction and thermal comfort prediction [2,79]. The Gradient Tree Boosting (GTB) model was shown to be highly accurate for predicting building cooling loads, with an average accuracy of 99.36% reported by [70].

### 4.4. Multi-objective optimisation of energy, thermal comfort, and IAQ

Multi-Objective Optimisation (MOO) frameworks are essential in modern building management, particularly for HVAC systems, where control decisions must simultaneously maximise energy efficiency and IEQ [36,109]. MOO strategies address the inherent conflicts among these objectives by identifying optimal solutions that balance competing demands [45].

- *Energy Efficiency vs. Thermal Comfort Trade-offs:* The fundamental challenge of advanced HVAC control is the trade-off between minimising energy consumption and maximising occupant thermal comfort [110,111]. Predictive control frameworks, most commonly those that leverage ML techniques, are widely employed to dynamically manage this conflict [25]. Thermal comfort is often quantitatively evaluated using the PMV and the Predicted Percentage of Dissatisfied (PPD) [112,113]. PMV is based on a heat balance model and is widely used as a thermal comfort control factor, particularly in fully regulated spaces, despite some limitations in representing actual thermal comfort [114]. The optimisation objective is typically formulated to minimise energy usage or cost while ensuring the PMV remains within a comfortable range of -0.5 to +0.5 [115]. MPC is widely used for this task by predicting a building's future thermal behaviour using dynamic models to balance energy use and thermal comfort thresholds [78]. However, the effectiveness of MPC depends heavily on the accuracy of its underlying predictive model [116].

Also, model-free RL algorithms, such as Deep Q-Learning (DQL), have gained attention as alternatives to MPC for dynamic control [78]. RL agents learn optimal control strategies via a trial-and-error approach to maximise a comprehensive reward function that weights energy consumption and thermal comfort [9]. However, identical reward settings can lead to different behaviours depending on the control framework, highlighting the need for systematically fine-tuning reward weights to optimise the trade-off [117].

- *Indoor Air Quality + Thermal Comfort + Energy Efficiency Optimisation*: The most common IAQ parameters monitored include $CO_2$*, particulate matter (PM 2.5* and PM 10), Total Volatile Organic Compounds (TVOC), and formaldehyde CH2O [110,118]. High concentrations of $CO_2$ can cause drowsiness and respiratory demands, and high concentrations of TVOCs may cause headaches and dizziness [88,114]. There are conflicting results in a single control decision aimed at improving IAQ and Thermal comfort. Increasing outdoor air intake lowers indoor $CO_2$ levels but may increase the heating or cooling load, affecting energy consumption and causing a period of thermal discomfort [119–121]. An accurate, real-time prediction of these pollutants is essential for adequate demand-controlled ventilation [122,123].

ML algorithms, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), and hybrid models (CNN-LSTMs), are highly effective for predicting multivariate environmental parameters due to their ability to approximate complex nonlinear relationships [124]. An example is the PM2.5 EPSO-CNN-LSTM model framework, specifically designed by Nguyen et al. for accurate IAQ prediction, managing indicators such as temperature, humidity, $CO_2$, *TVOC, and PM* 2.5 levels efficiently [125].

Integrated optimisation frameworks are also effective in this area. Elhami et al. designed a three-objective optimisation framework for an educational building. This framework achieved 99.74% prediction accuracy and successfully reduced discomfort hours by 63.1%, lowered $CO_2$ concentrations by 9.61%, and increased energy efficiency by 13.44%. This performance demonstrates a significant trade-off among energy efficiency, thermal comfort, and IAQ [126–128].

- *Fairness in Comfort*: In multi-occupant spaces, fairness-aware optimisation approaches are crucial for shared HVAC control [129]. Multi-Agent Reinforcement Learning (MARL) can be utilised for multi-zone thermal control problems [109,130]. In these systems, agents can pursue zone-specific objectives, such as prioritising energy efficiency or thermal comfort within individual areas, rather than optimising a single global goal [109,131]. Zhang et al. evaluated a Multi-Agent RL approach by employing a Centralised Training with Decentralised Execution (CTDE) paradigm for equitable cooling load allocation during demand response. This approach demonstrated better coordination, ensuring equitable sacrifices in control performance without disproportionately burdening specific thermal zones. It resulted in a significantly lower standard deviation of supply air temperatures of 0.08 °C across agents, compared with the 0.21 °C achieved with decentralised execution, confirming a more balanced outcome [119,132].

## 5. AI/ML application, data and digital infrastructure challenges

A significant challenge in ML HVAC applications is sample inefficiency, which is familiar with model-free DRL algorithms, leading to lengthy training times to achieve acceptable performance, often requiring dozens of months or more [66]. It affects the feasibility of direct training during deployment [65]. There is also a high likelihood of poorer control performance by RL controllers during the initial deployment learning stage, potentially leading to occupants' discomfort [133]. In predictive modelling used in techniques like MPC, model accuracy is crucial but can be compromised by changes in building types, occupancy schedules, or load profiles [134]. Additionally, model-free approaches like classic Q-learning face dimensional catastrophe and computational complexity when dealing with large or continuous state and action spaces typical of real-world HVAC systems [62]. Many high-performing ML models, especially those based on deep neural networks (DNNs), are criticised for their "black-box" nature, making it difficult for human operators to understand the underlying decision-making process [10,135]. This lack of interpretability can hinder stakeholder trust and may conflict with legal requirements for transparent control strategies [136]. Overall, most advanced ML-based control approaches remain confined to academic research due to significant challenges in practical deployment and ensuring the operational reliability of AI-driven strategies in real-world scenarios [13].

### 5.1. Data scarcity, federated learning and transfer learning

ML and Deep Learning (DL) models require large amounts of high quality data for training to achieve accurate predictions and robust generalisability [44,137,138]. However, acquiring sufficient and representative datasets can be difficult in real-world applications for several reasons. In developing accurate predictive models, such as those used for MPC, extensive datasets are required, which are often costly and time-consuming to acquire [31]. Due to this huddle, most studies rely on small, case-specific datasets, which restrict the generalisability of models across diverse building types, regions, or climatic conditions [17]. For new buildings, insufficient historical data may be collected, hindering the application of SL-based modelling [139]. At the same time, the performance of prediction models relies on fixed training datasets. Hence, insufficient or unevenly distributed samples can ultimately affect prediction accuracy [140].

Also, the use of localised data often necessitates retraining or transfer learning when applying models to new contexts. For instance, a study by Giri et al. on ventilation mode prediction identified a limitation. Data was obtained from only one healthcare facility, suggesting that incorporating data from diverse international facilities would increase the model's accuracy and generalisability [141]. For studies on human activities, such as thermal comfort services, sufficient data may be unavailable due to privacy concerns [11]. Data confidentiality is a significant hurdle, especially in sensitive industries such as semiconductor manufacturing facilities (SMFs), where sharing HVAC data could reveal sensitive production information [10,142]. It limits the availability of critical operational data needed for optimisation.

Federated Learning (FL) has emerged as a critical solution, particularly for multi-building scenarios that require privacy preservation, such as healthcare facilities. FL is a decentralised approach that allows multiple devices or clients to train a shared ML framework without requiring them to interchange or centralise their raw data. This capability significantly enhances privacy, which is crucial in sectors that handle sensitive information. FL reduces data transfer costs and the associated risks related to centralised storage [143]. FL can be incorporated into IoT frameworks for IAQ and HVAC control optimisation, particularly to manage environmental data that is often non-independently and identically distributed (non-IID) and sensitive across distributed buildings. For example, Ramadan et al. developed a Hierarchical Adaptive Federated Aggregation (HAFA) algorithm within an IoT framework for IAQ monitoring across multiple hospitals. The framework demonstrated enhanced scalability and robustness while maintaining data safety, even with non-IID data [143]. For these reasons, many researchers suggest introducing FL techniques in future studies to protect the privacy of HVAC system data during training. The long-term goal is to expand the framework to cover multi-building scenarios, enabling collaborative IAQ management across smart cities [122].

Transfer learning is increasingly relevant in AI-driven HVAC control because it enables knowledge gained from data-rich source buildings to be reused in new but similar target buildings with limited data availability [17]. Its main benefits include improved data efficiency, shorter training time, reduced computational and data collection cost, and better performance in buildings where long-term historical data are unavailable [120]. However, its effectiveness depends strongly on the similarity between source and target domains, since differences in building characteristics, weather, occupancy, or HVAC configuration can reduce transfer performance. In addition, transferred models often still require site-specific fine-tuning, especially when local uncertainties or different sensing and zoning structures are present [66]. Recent developments suggest that transfer learning can support more scalable HVAC applications, particularly when combined with reinforcement learning, active learning, or decentralized control frameworks, and its potential now extends beyond energy prediction to include fault detection, thermal comfort personalization, and cross-seasonal control [65,120].

### 5.2. Data quality and standardisation issues

The need for high-quality data and unified protocols represents a critical challenge in developing and deploying advanced control strategies, such as AI and ML, for HVAC systems [13]. A significant research gap exists in creating a cohesive approach to handle the operational data generated by diverse building systems [10]. There is a crucial need for a unified, practical framework, with supporting strategies, to enable the reliable deployment of ML-optimised HVAC controls at the field level [144]. The lack of standardisation across different HVAC systems and facilities makes it challenging to compare or integrate data [10].

Some common data quality issues identified in studies reviewed stem from inconsistencies and measurement issues. In some cases, Data acquired from various sensors often involves differing sampling strategies. For example, some features may be sampled periodically, perhaps on a 10-minute basis [145]. In contrast, others are measured only on a state-change basis, leading to time misalignment and feature value mismatches in the raw dataset [28,66]. Also, sensors may be prone to failure, be installed in the wrong location, be miscalibrated, or yield questionable readings. A lack of routine accuracy calibration means sensor readings that exhibit "drift" over the long term [146]. To ensure high quality data input for training data, comprehensive preprocessing may be necessary. The preprocessing includes cleaning raw data to eliminate errors, addressing inconsistencies, detecting outliers using statistical thresholds or range checks, imputing missing data via linear or spline interpolation, and applying signal smoothening [29,147].

## 6. Comparative synthesis of AI-driven HVAC control algorithm performance

### 6.1. Energy efficiency outcomes across control algorithms

ML algorithms applied to HVAC control optimisation in the studies reviewed demonstrated significant potential to achieve substantial energy savings or cost reductions across various building types and climatic conditions. The energy savings were primarily realised by enabling predictive or optimal control strategies that leverage building thermal inertia, dynamically adjusting setpoints based on real-time and forecasted conditions, or reducing energy waste during unoccupied or low-demand periods. The reported energy and or IEQ savings values shown by Figs. 4–9 in this chapter represents study-specific outcomes rather than as an absolute ranking of AI/ML control models/algorithms. Most of the studies reviewed differ substantially in their baseline controllers, building types, climatic conditions, HVAC system boundaries, control objectives, simulation or field-validation settings, and thermal comfort or IAQ constraints. The studies reviewed compare one AI-driven controller with an MPC, a rule-based control, PID, on/off controller, or other AI control algorithms.

This distinction is important because the same reported percentage of energy savings may have different implications depending on the baseline and application context. For example, a RL-based controller compared with a simple rule-based controller may show large savings, whereas the same controller compared with a well-tuned MPC or optimized supervisory controller may show a smaller improvement. Similarly, studies that prioritise IAQ or thermal comfort may report lower energy savings because the control objective intentionally penalises comfort violations, high $CO_2$ concentration, or inadequate ventilation. Consequently, the plotted results show evidence of where and how AI/ML methods have been applied successfully, and not demonstrating one algorithm family is universally superior across all HVAC control situations.

Only two reviewed studies by Chen et al. and Zhang et al. have the most similarities in terms of baseline controllers, building types, climatic conditions, control objectives and thermal comfort or IAQ constraints. Both studies examined MPC-based natural ventilation using automated/operable windows in smart commercial buildings in Cambridge Massachusetts winter conditions. The control objective was to reduce $CO_2$ concentration, maintain thermal comfort, and avoid extra heating-energy penalty. Thus, both studies can be compared directly on $CO_2$ compliance, cold-discomfort hours or temperature drop, and heating-energy reduction [73,148].

Studies that reported high savings, as shown in Fig. 4, focused on cooling systems, which account for a large share of energy consumption, or on optimising variable components such as ventilation fans/dampers. Models such as Adaptive GMM and ANN were used to anticipate future energy needs, enabling proactive control, such as pre-heating or pre-cooling during low-cost periods, thereby significantly shifting energy demand and minimising waste.

DRL methods, particularly those dealing with continuous actions like PPO variants, often outperform discrete methods like DQN by finding optimal values rather than being limited to a few discrete setpoints. Figs. 5–7 show the reported energy-saving outcomes by applied models from the reviewed studies based on building typology. Supervised learning-based models like WDQN and Adaptive GMM reported almost 60% energy savings in commercial buildings' HVAC applications in commercial buildings as against a RBC [76,78].

Studies that reported the lowest energy savings, minimal comparative improvements, or even net negative performance were often due to inherent algorithmic limitations, difficulties in scaling, or a primary focus on other objectives other than energy minimisation. Some studies successfully applied Neural Network models designed primarily for occupant thermal comfort or IAQ control and these yielded lower energy-savings percentages of 1% to 12% as against a RBC, because they prioritised maintaining comfort bounds over aggressive energy reduction [19,111,113].

### 6.2. IEQ outcomes across control algorithms

The reviewed literature reported significant advancements in enhancing thermal comfort and IAQ through AI-based HVAC control methodologies as shown in Fig. 8. These methodologies have achieved measurable improvements in energy efficiency, occupant satisfaction, and air quality, underscoring their potential applications in AI-driven

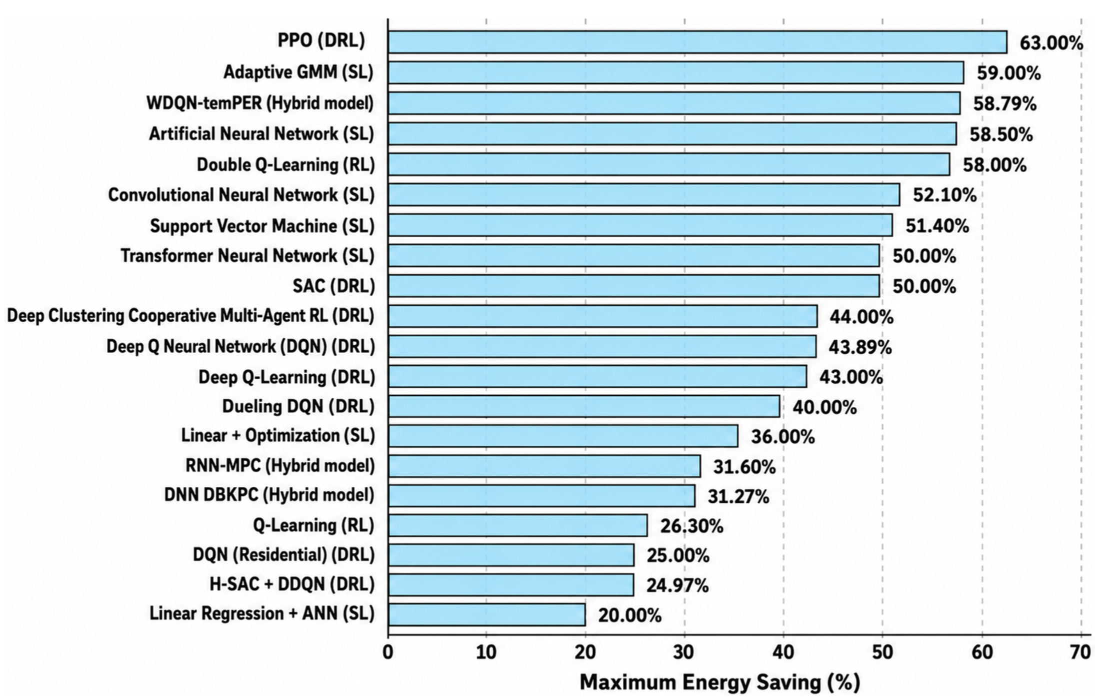


**Fig. 4.** Reported outcomes from reviewed studies on AI/ML-based control models for energy-saving.

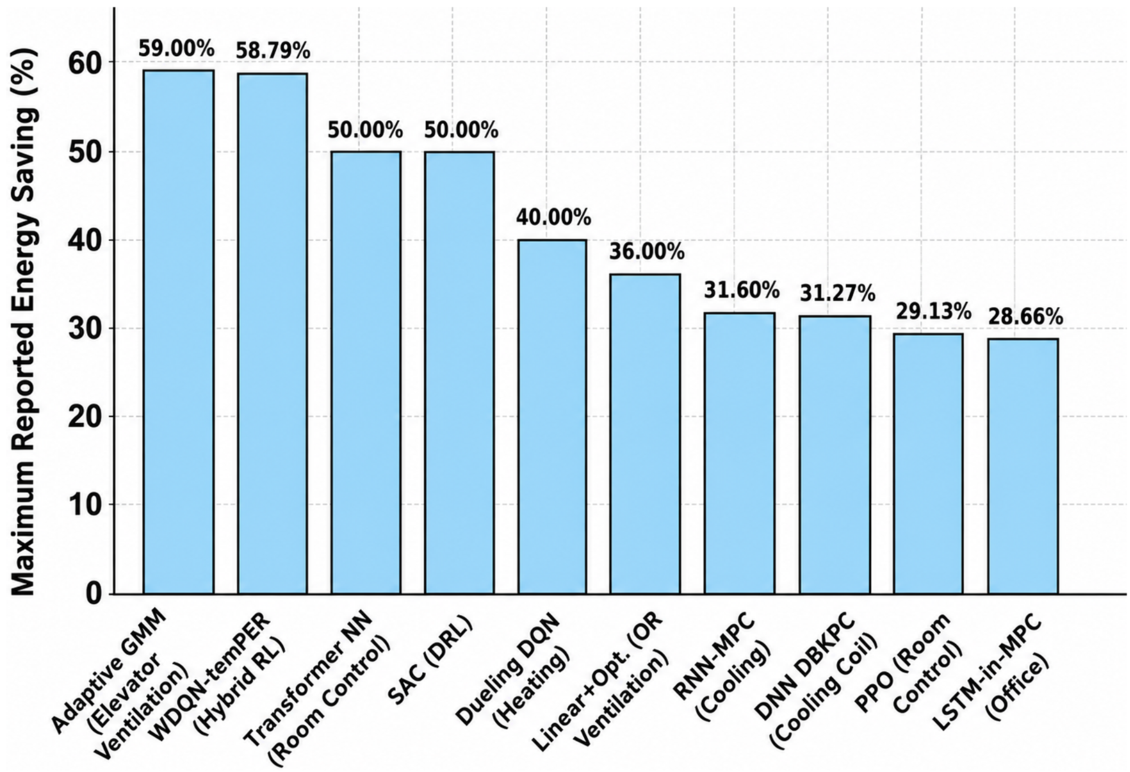


**Fig. 5.** Reported energy-saving outcomes of AI/ ML-based control models applied to commercial buildings.

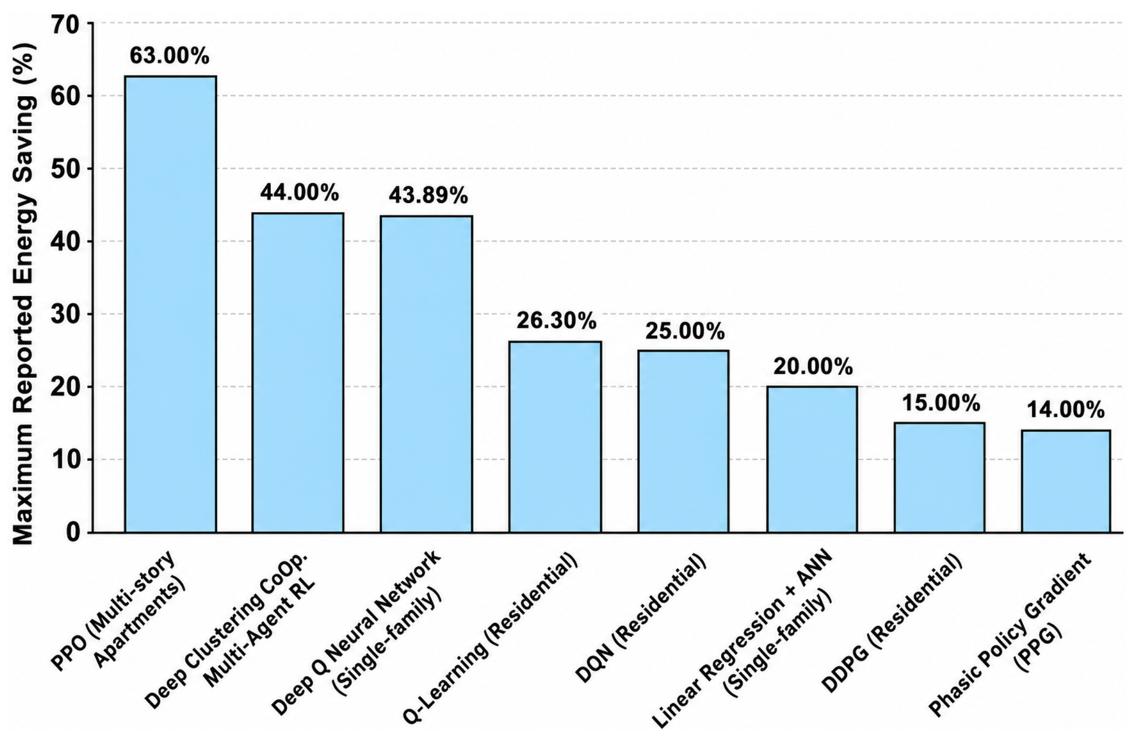


**Fig. 6.** Reported energy-saving outcomes of ML/AI control models applied to residential buildings.

mixed-mode ventilation systems.

A study applied a Convolutional Neural Networks (CNNs) algorithm dedicated to optimising thermal comfort and it reported an exceptionally high performance, approaching 100% improvement in indoor comfort conditions compared with a RBC [149].

In applications centred on IAQ, Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and FL frameworks reported robust predictive and control proficiencies. Studies that applied these algorithms reported $CO_2$ concentration control accuracies ranging from 78% to 97%, with IAQ improvement indices (notably reductions in pollutant or $CO_2$ peaks) averaging approximately 85% to 90% as against different baselines [2,88,143]. These studies adeptly discerned temporal patterns

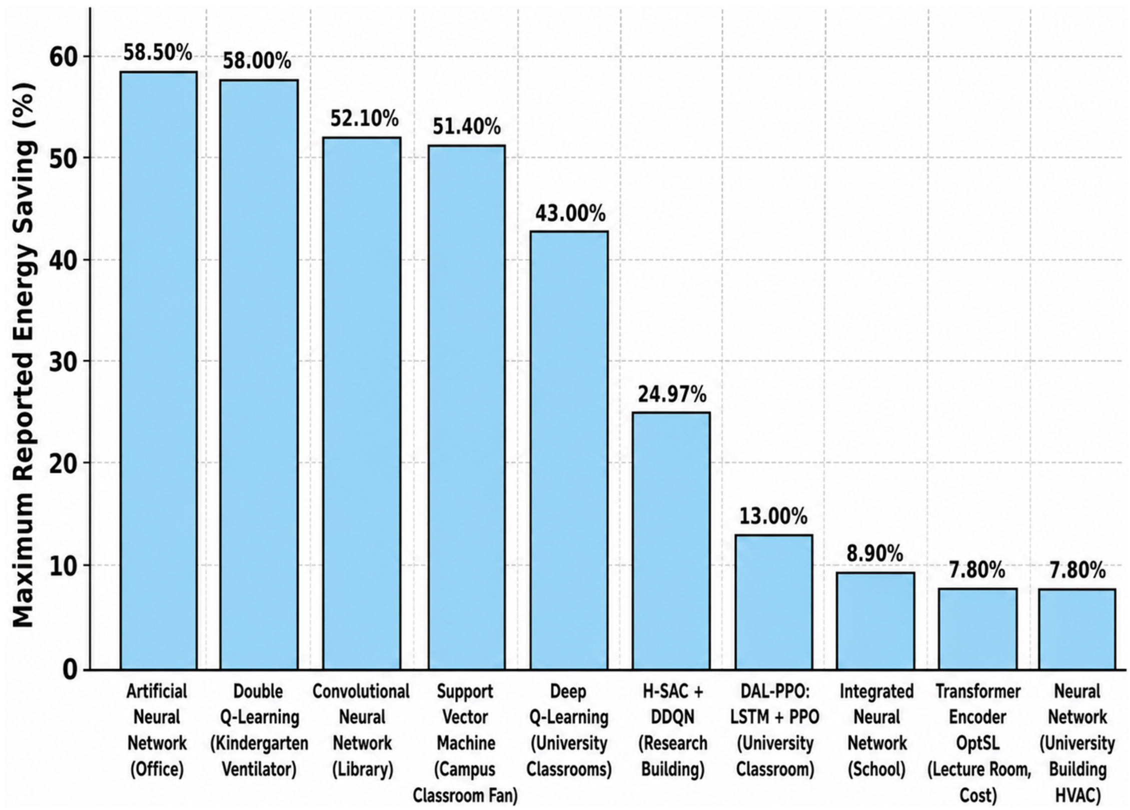


**Fig. 7.** Reported energy-saving outcomes of ML/AI control models applied to institutional buildings.

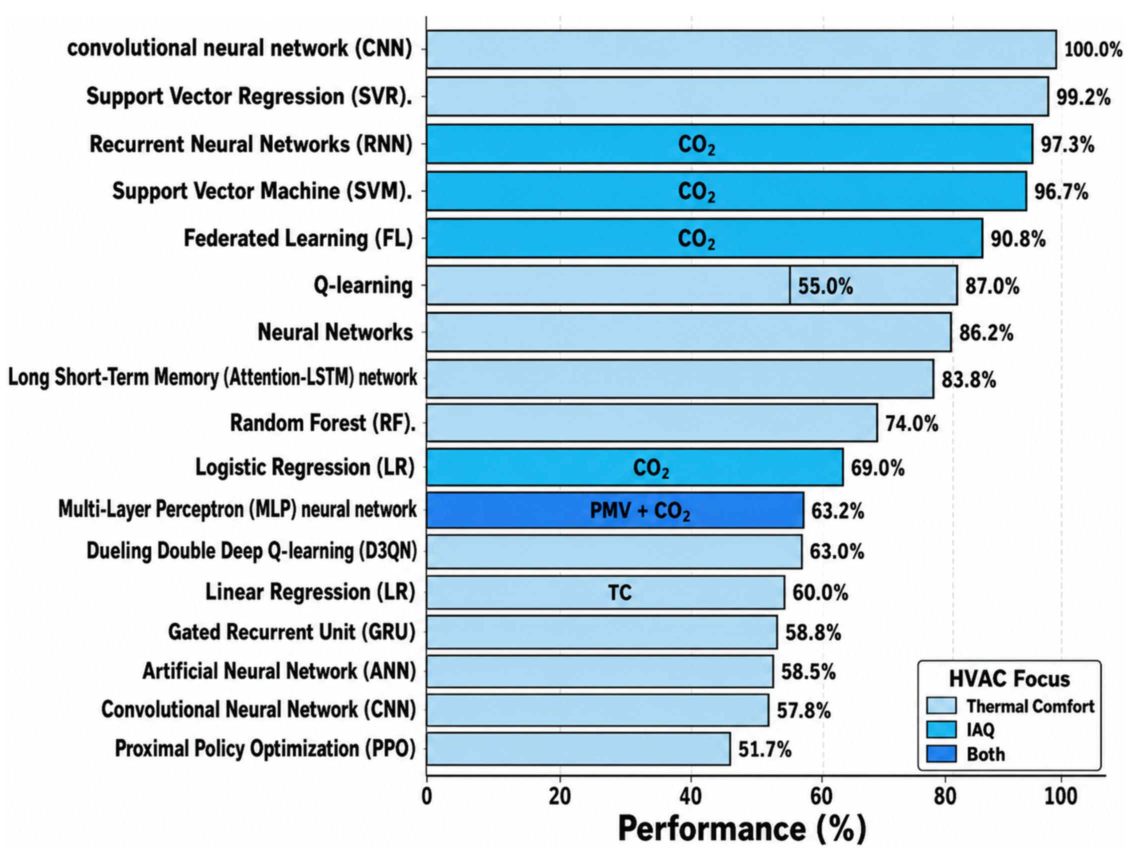


**Fig. 8.** Reported outcomes from studies on AI/ML control models for thermal comfort or IAQ optimisation.

 

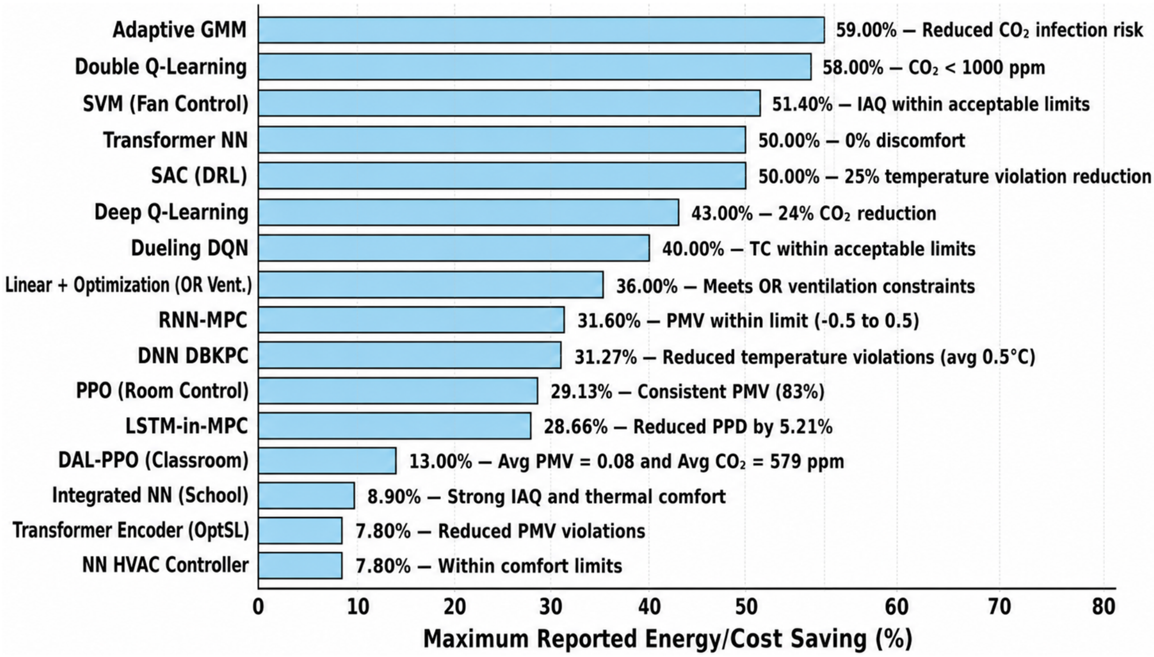


**Fig. 9.** Reported outcomes from studies on AI/ML control models for energy and IEQ co-optimisation.

in indoor pollutant concentrations and adjusted ventilation rates, thereby mitigating excessive energy consumption associated with ventilation while maintaining healthy air quality standards.

Some ML algorithms/models performed well at optimising thermal comfort, IAQ, or both, while others optimised energy efficiency. However, these algorithms/models did not necessarily do well in balancing indoor environmental quality and energy efficiency optimisation, as shown in Fig. 9. These minimal improvements could also be due to the relative strength of their baseline control methods or other case specific constraints.

### 6.3. Building typology and climate-related patterns

The reviewed studies show that the reported performance of AI-driven HVAC control is strongly shaped by both building context and climatic conditions. Rather than indicating a universally superior control method, the evidence suggests that model suitability depends on the dominant load characteristics, HVAC configuration, and operational priorities within each building and climate setting. As shown by Fig. 10, commercial buildings appeared most frequently in the reviewed literature, with many high-performing applications targeting cooling-intensive systems, ventilation control, or multi-zone operation. In these cases, stronger results were often associated with control approaches that could respond flexibly to varying occupancy, weather, and indoor air quality requirements. Residential buildings follow and were more commonly linked to simpler comfort-oriented or setpoint-based control strategies.

Climate significantly influences the efficacy of various ML controllers

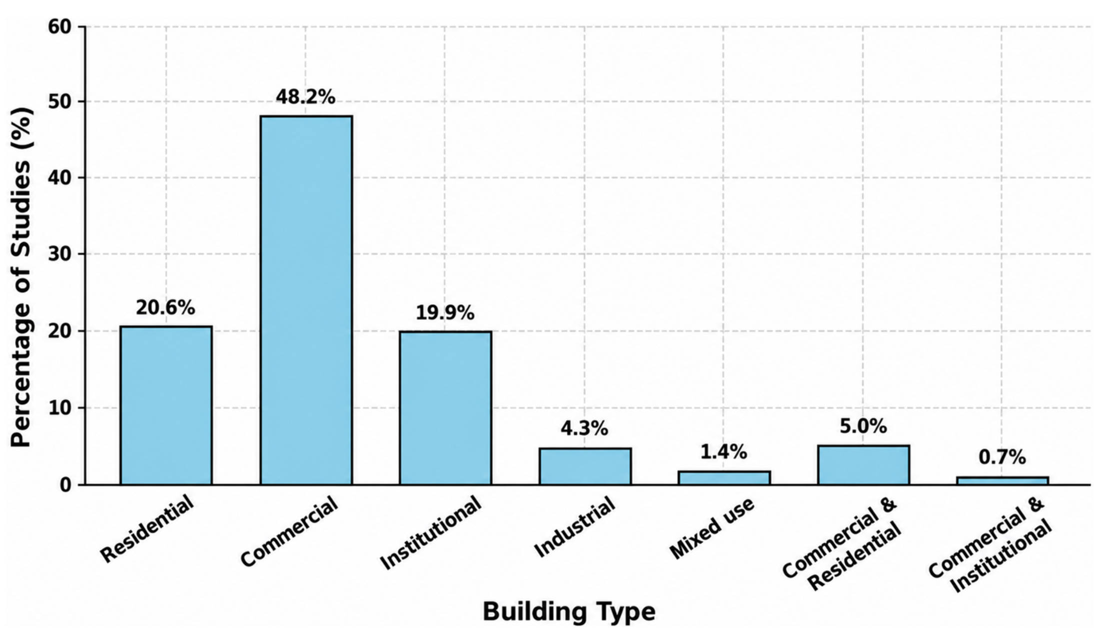


**Fig. 10.** AI/ML-based HVAC control applications by building types from reviewed studies.

in achieving optimal energy savings for HVAC systems. Climate classifications in this study are reported using the Köppen system, where, for example, Cfa/Cwa denote humid subtropical climates, Cfb/Dfb denote temperate oceanic and humid continental climates, Csa/Csb denote Mediterranean climates, and Af/Am denote tropical rainforest and tropical monsoon climates.

Based on the reported energy-saving and IEQ optimisation outcomes across the reviewed studies, we developed a climate-algorithm matrix, presented in Fig. 11. The matrix accounts for variations in outdoor conditions, building types, control objectives, and performance baselines. It highlights distinct performance clusters of AI-based HVAC control algorithms across the climate zones most frequently represented in the reviewed literature.

In humid-subtropical climates, buildings are subject to prolonged, humid cooling periods necessitating frequent economiser and dehumidification interventions. Within this context, studies that applied hybrid predictive models combined with reinforcement learning (RL) methodologies reported higher performance. XGB-DQN and Transformer-based frameworks consistently reported approximately 24-65% reductions in cooling energy cost while enhancing occupant comfort, attributable to precise short-term load prediction from Transformers or XGBoost, synergised with discrete and continuous action optimisation techniques such as DQN, PPO, or SAC that capitalise on the inherent variability. In temperate oceanic and continental climates (Cfb/Dfb), energy demands are moderate and closely tied to weather patterns, thus favouring smooth-action and sample-efficient RL approaches like SAC and model-based DQN adaptations. Studies that applied this method recorded double-digit energy savings with minimal comfort infringements compared with Hierarchical and Option-Based Baselines, which resulted in their respective high and medium ratings in the matrix [15,27].

Mediterranean climates (Csa/Csb) are conducive to continuous-action RL methodologies. However, DDPG and its stabilised derivatives surpass tabular or discrete RL approaches in terms of energy efficiency and comfort levels. In contrast, A study applied mixed-integer linear programming (MILP) recorded high performance during summer months by achieving substantial cooling savings through ventilation scheduling constrained by IAQ considerations as against a conditional control system [150].

Overall, the evidence indicates that the same algorithm family can perform differently across climates and building types because HVAC control effectiveness depends not only on the learning method itself, but also on the interaction among climate severity, sensible versus latent loads, system type, occupancy pattern, and IEQ objectives. For this reason, controller selection should not be based on algorithm popularity alone. Instead, AI-driven HVAC control strategies should be matched to the building type, climatic context, and dominant operational objective.

### 6.4. Models’ generalisability

Across the studies reviewed, supervised learning methodologies exhibit the greatest asserted applicability, as illustrated in Fig. 12. Its models were more implementable across a variety of building typologies and HVAC configurations. However, in practice, these assertions are constrained by the available data and contextual factors. Numerous models were developed in singular-zone environments or within specific climatic regions, accompanied by caveats regarding generalisation.

When supervised models demonstrate successful transferability, it is typically due to the incorporation of physics-informed variables, such as thermal loads and occupancy proxies, into the feature set, alongside a methodological pipeline that encompasses rigorous validation, such as cross-building folds, and straightforward adaptation steps, such as fine-tuning or recalibration. Interpretable frameworks are underscored as more amenable to transfer, as practitioners can effectively identify drift and re-specify features.

Reinforcement Learning and Deep Reinforcement Learning are

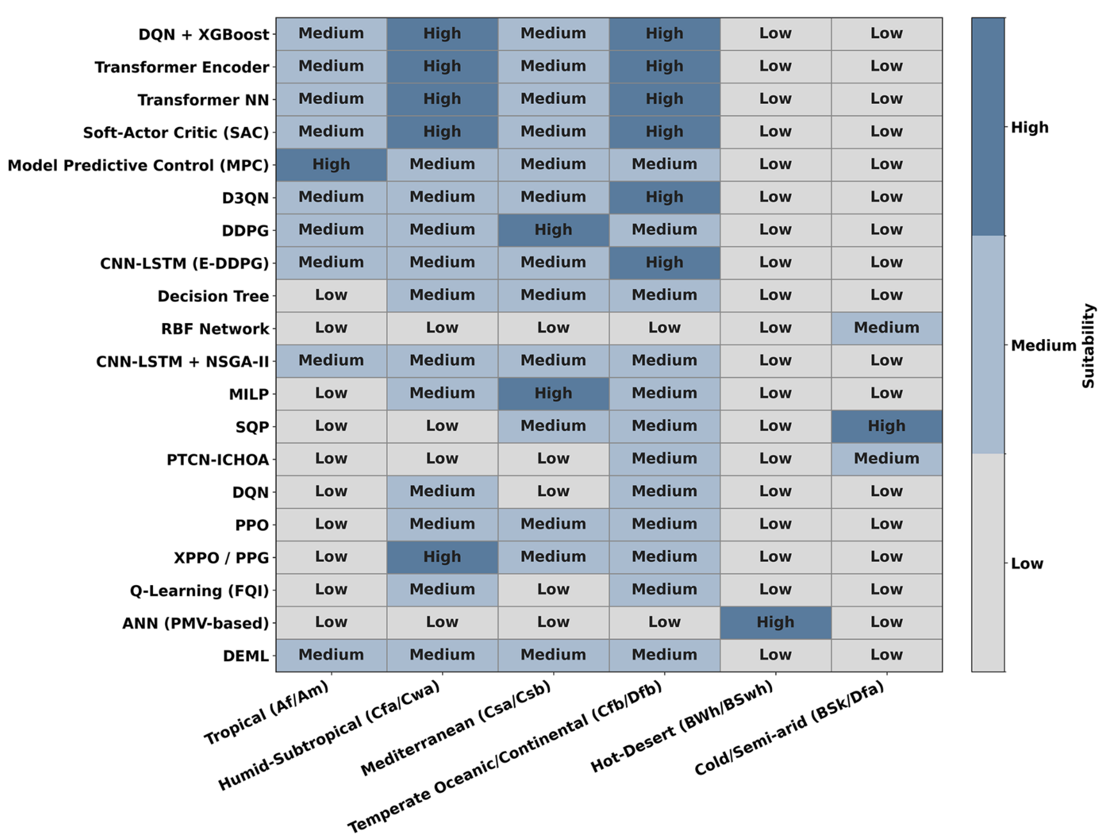


**Fig. 11.** Performance of most applied AI/ML models/algorithms from reviewed studies by climate.

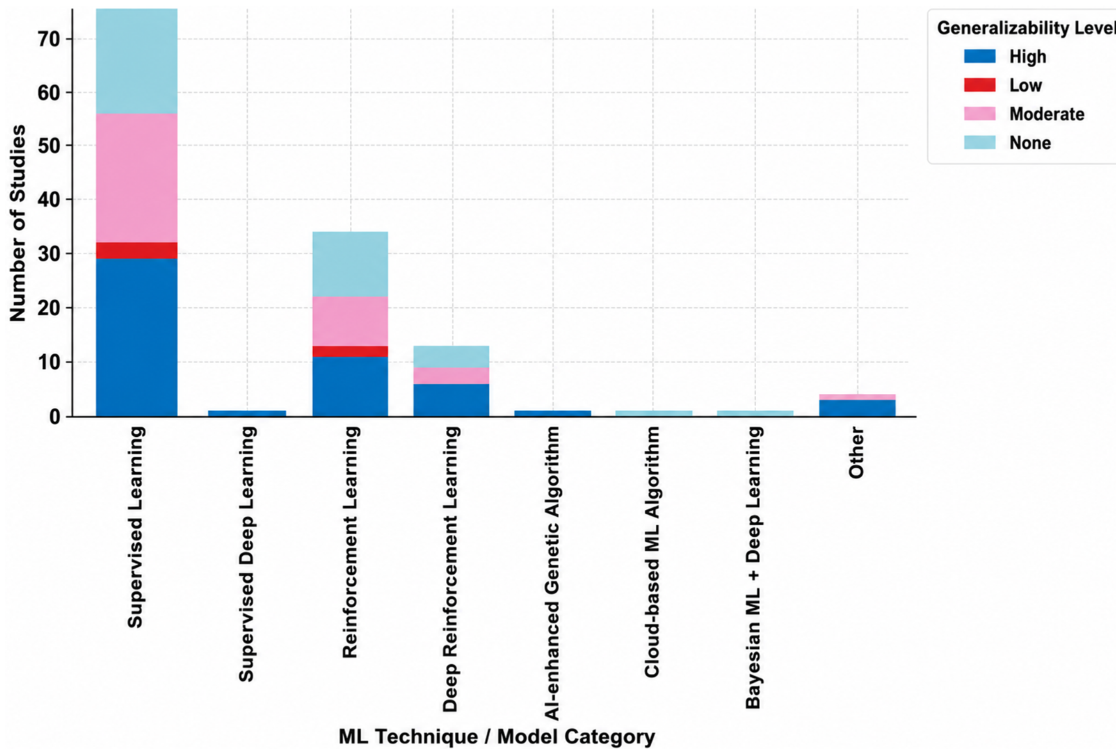


**Fig. 12.** Generalisability of AI/ML-based HVAC control techniques.

consistently justified by their model-free adaptability, which enables them to acquire control directly through interaction. It facilitates transferability across varied environments. Empirical evidence suggests that generalisation is contingent upon the design of state/action and the degree of exposure to variability throughout the training process, such as shiftable versus non-shiftable loads, and diverse occupancy patterns.

Policies derived from Deep Reinforcement Learning demonstrate enhanced generalisation when trained with domain randomisation, such as varying dynamics, weather conditions, and comfort preferences. Generalisability is also improved when the deployment phase includes safe exploration strategies and constraint management. In the absence of these considerations, policies risk overfitting to the simulation environment's idiosyncrasies and may underperform in real-world systems.

In summary, supervised Learning achieves generalisation through the utilisation of high-quality features and recalibration. Deep learning demands diverse training data and thorough regularisation [100]. At the same time, Reinforcement Learning and Deep Reinforcement Learning derive maximal benefit from training data rich in variability and from deployment strategies that prioritise safety.

### 6.5. Model deployment and challenges

The rate of implementation of ML models for the optimisation of HVAC systems in scholarly literature remains a significant obstacle, driven by multiple factors [54]. The majority of ML methodologies applied to HVAC systems remain confined to simulation environments, as their practical application is hindered by considerations of safety, generalisation, data availability, cost, and infrastructural constraints [77]. Model-free RL strategies require extensive trial-and-error training, which demands vast interactions. Moreover, initial explorations often involve testing extreme actions, thereby risking energy inefficiency, occupant discomfort, or undue stress on equipment during implementation [51]. Predominantly, calibrated simulators fail to accurately capture the complexities of real-world scenarios, such as sensor inaccuracies, actuator backlash, equipment wear, fluctuating schedules, and nonstationary occupant behaviour. Consequently, controllers that may appear robust in a digital twin context can underperform or exhibit unpredictable behaviours upon actual deployment [120,149].

Model-based approaches encounter distinct impediments: predictive models that are sufficiently accurate for MPC are often costly, tailored to individual buildings, and require considerable time for development and maintenance, thereby constraining scalability [41]. Data-driven methodologies necessitate extensive, high-quality datasets alongside standardised logging practices. Newly constructed or inadequately metered buildings typically lack historical data, and data sharing is often blocked by inconsistent schemes or confidentiality [70].

Operationally, black-box policies erode trust, complicate validation and compliance, and hinder diagnosis when issues arise [17]. These challenges have limited most AI-driven HVAC control optimisation studies to simulated environments, with few moving to real-world deployment or subsequent testing under authentic conditions. Only 8 of the 130 studies validated simulation results through deployment or

**Table 6**
A summary of studies with deployed ML models.

| Study | ML Model | Deployment/Testing |
|---|---|---|
| [49]Guo et al., 2025 | Deep Q-Network (DQN) controller | A test building |
| [130] Miao et al., 2024 | MADDPG-MSN | Real word aircondition testing |
| [26] Park et al., 2024 | linear regression, regression trees, and artificial neural networks | Full-scale experimental house |
| [24] S. Yang et al., 2020 | Dynamic Artificial Neural Network | Two single-zone Testbeds, an office and a lecture theatre |
| [22] Z. Liu et al., 2024 | Extra Trees (ET) and Multi-Layer Perceptron (MLP) | Deployed in an Operating Room |
| [13] Z. Liu et al., 2024 | AI-enhanced Genetic Algorithm | BAS Testbed Validation |
| [59] Silvestri et al., 2024 | Soft-Actor Critic (SAC) DRL controller | An office building |
| [53] Boutahri & Tilioua, 2025 | RL agent (Q-learning algorithm) | 5-member family Residence (BOPTEST) |

testbed testing, as shown in Table 6, representing a mere 6% deployment rate for the studies reviewed.

## 7. Conclusion

The reviewed literature indicates that no single AI-based HVAC control technique can be identified as universally most effective for co-optimising indoor environmental quality and HVAC energy efficiency across all applications. Instead, effectiveness depends on the control role of the model, the objective being prioritised, and the operational context. Supervised learning remains the most widely applied approach, particularly for prediction, virtual sensing, and support within model predictive control frameworks, while reinforcement learning and deep reinforcement learning are increasingly used where dynamic and multi-objective control is required. The reviewed studies further suggest that hybrid and ensemble approaches are especially promising for co-optimisation because they combine the predictive strengths of supervised models with the adaptive decision-making capacity of learning-based control, thereby supporting more robust balancing of energy efficiency, thermal comfort, and indoor air quality. The studies reviewed reported an average energy savings of 40%, with several studies exceeding 50% while maintaining excellent IEQ. These reported energy savings and IEQ figures are not directly comparable across all cases due to differences in system boundaries, baselines, and performance metrics.

With respect to generalisability, the reviewed studies show that supervised learning models tend to offer stronger practical transfer potential when they are built on robust features, validated carefully, and supported by recalibration or fine-tuning. By contrast, reinforcement learning and deep reinforcement learning are often presented as adaptable because they learn control policies directly from interaction, but their generalisability depends strongly on training diversity, state-action design, and the use of safety-aware deployment strategies. In this sense, the review suggests that the most effective models for co-optimisation are not simply those with the highest reported savings, but those whose control logic, data requirements, and adaptation pathways make them more reliable across varying buildings and operating conditions.

The performance of AI-driven HVAC control is strongly influenced by both building type and climatic context. The reviewed studies do not support a universal relationship between algorithm choice and performance but rather, outcomes vary according to occupancy behaviour, HVAC system configuration, control objective, and local environmental conditions. Commercial and institutional buildings appear most frequently in the literature and often provide the clearest evidence of AI-driven performance gains, especially in applications involving cooling control, ventilation management, and multi-zone operation. Residential applications are less represented and are more often associated with simpler setpoint regulation or comfort-oriented control tasks. This suggests that reported performance is partly shaped by the complexity, sensing availability, and operational flexibility of the building type under study.

Climatic conditions also affect the suitability and reported effectiveness of different control approaches. The reviewed studies show that cooling-dominated and humidity-sensitive climates often favour adaptive or hybrid strategies capable of responding to variable loads and indoor air quality constraints, whereas in temperate, continental, or more prediction-sensitive contexts, strong performance is often linked to stable predictive control support and careful tuning to local conditions. These patterns indicate that ML-driven HVAC control should be evaluated relative to the dominant load characteristics and comfort constraints of the target environment, rather than interpreted as an intrinsic property of the algorithm alone. In this study, climate and building type therefore emerge as key contextual variables that shape both achievable performance and the practical applicability of ML-based control strategies.

The study identifies several recurring methodological challenges that continue to limit the maturity of ML-driven HVAC control optimisation research. First, many studies rely on small, case-specific datasets and simulation-based evaluation, which constrains generalisability and makes cross-study comparison difficult. Second, the lack of uniform benchmarks, common evaluation metrics, and consistent baselines reduce the reliability of broad claims about algorithm superiority. Third, advanced models, particularly deep learning and model-free reinforcement learning approaches, often face challenges related to data demand, computational burden, sample inefficiency, and limited interpretability. These issues are especially important in HVAC control, where poor early-stage performance, unsafe exploration, and low transparency can directly affect occupant comfort and operational trust.

### 7.1. Future research directions

The main research gaps identified by the review include limited field validation, insufficient treatment of transferability across buildings and climates, underrepresentation of diverse building contexts, and weak integration of deployment-oriented considerations such as recalibration, constraint handling, and safety-aware implementation. Future research should therefore move beyond simulation-only demonstrations and focus more explicitly on robust transfer, practical deployment workflows, and context-sensitive validation across varied building types and climatic settings. Greater attention is also needed for harmonised benchmarking, interpretable control frameworks, and methods that can jointly support energy efficiency and indoor environmental quality without sacrificing real-world reliability. Addressing the challenges of these processes will give a clear path for researchers to convert promising lab-scale results into robust, generalisable, and deployable AI-driven HVAC solutions that deliver both energy and IEQ benefits in diverse real-world settings.

## CRediT authorship contribution statement

**Christopher Otoo:** Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Tao Lu:** Conceptualization, Validation, Visualization, Writing – review & editing. **Xiaoshu Lü:** Conceptualization, Funding acquisition, Supervision, Validation, Visualization, Writing – review & editing. **Haneda Katsuyuki:** Validation, Visualization, Writing – review & editing. **Yanping Yuan:** Validation, Visualization, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Data availability

No data was used for the research described in the article.

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