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Systematic Review

A Systematic Review on the Use of AI for Energy Efficiency and Indoor Environmental Quality in Buildings

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Abstract: Global warming, climate change and the energy crisis are trending topics around the world, especially within the energy sector. The rising cost of energy, greenhouse gas (GHG) emissions and global temperatures stem from the over-reliance on fossil fuel as the major energy resource. These challenges have highlighted the need for alternative energy resources and urgent intervention strategies like energy consumption reduction and improving energy efficiency. The heating, ventilation, and air-conditioning (HVAC) system in a building accounts for about 70% of energy consumption, and a decision to reduce energy consumption may impact the indoor environmental quality (IEQ) of the building. It is important to adequately balance the tradeoff between IEQ and energy management. Artificial intelligence (AI)-based solutions are being explored for improving building energy performance without compromising IEQ. This paper systematically reviews recent studies on AI and machine learning (ML) for building energy management and IEQ by exploring common use areas, the methods or algorithms applied and the results obtained. The overall purpose of this research is to add to the existing body of work and to highlight energy-related AI applications in buildings and the related gaps. The result shows five common application areas: thermal comfort and indoor air quality (IAQ) control; energy management and energy consumption prediction; indoor temperature prediction; anomaly detection; and HVAC controls. Gaps involving policy, real-life scenario applications, and insufficient study of the visual and acoustic comfort areas are also identified. Very few studies take into consideration the need to follow IEQ standards in the selection process and positioning of sensors in AI applications for IEQ in buildings. This study reveals a need for more systematically summarized research.

Keywords: buildings; thermal comfort; energy management; energy consumption; indoor environmental quality; artificial intelligence; machine learning

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1. Introduction

The need to improve indoor environmental quality (IEQ) in buildings influences the energy demand and directly impacts energy consumption [1]. Heating, ventilation, and air-conditioning (HVAC) systems are used to help maintain IEQ in buildings, and they account for about 70% of energy consumption in buildings [2,3]. The building sector accounts for about 40% of the world's total energy consumption [4]. The building and construction sector is also responsible for about 39% of carbon dioxide (CO_2) emissions globally [5,6]. With the challenges of climate change and global warming, it is imperative to find sustainable solutions that will reduce the emission of greenhouse gases (GHGs). The integration of renewable energy sources (RESs), energy management techniques and energy efficiency in buildings are important steps toward a greener future. Several energy management methods for buildings developed earlier have performed below expectations in practice [7]. This is due to the complex and dynamic relationship between energy management, energy efficiency and IEQ [8]. Researchers have explored the use of building management systems (BMSs) and building energy management systems (BEMSs) to help improve building performance [9]. BMSs are typically used to automate procedures for electrical or mechanical equipment connected in a building. These systems can involve large-scale monitoring and control of HVAC systems, closed-circuit television, doors, etc., with the aim of effectively and efficiently performing each task [9]. BEMSs are designed to monitor the building state and control HVAC systems to ensure the efficient use of energy and to maintain occupants' comfort. BEMSs gather information from systems to help execute adequate control strategies [8]. One common challenge with BEMSs is the gathering of large amounts of data, which need to be understood and accurately interpreted by building managers for the right reaction to be made for building management. The work of processing this rapidly growing body of information from the BEMS and taking adequate actions to maintain building operations is critical. This highlights the need for a more efficient method of managing energy and maintaining IEQ by exploring entirely novel solutions or by combining BEMSs with other methods. This study will review the use of artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) in energy management, energy efficiency, and IEQ in buildings. Firstly, according to Britannica [10], AI is the ability of digital computers or systems to perform intellectual tasks consistent with humans, which may include reasoning, generalizing, learning, etc. Secondly, ML is the process of training a digital computer with relevant data to achieve AI [10]. ML employs algorithms to learn patterns in historical data for predictive or forecasting purposes [11]. ML involves learning without being programmed and learning the underlying features of data using deep-learning networks. We have supervised and unsupervised learning algorithms in ML [12]. When a model is built with a set of data with both known input data and desired output data it is called supervised learning, while in unsupervised learning, only input data are used to find structures in a dataset. We also have deep learning, which is another class of ML. It includes multi-layer perceptron (MLP), convolutional neural network (CNN), recurrent neural network (RNN), etc. Figure 1 is an ML tree highlighting the different branches and subbranches of ML for better insight.

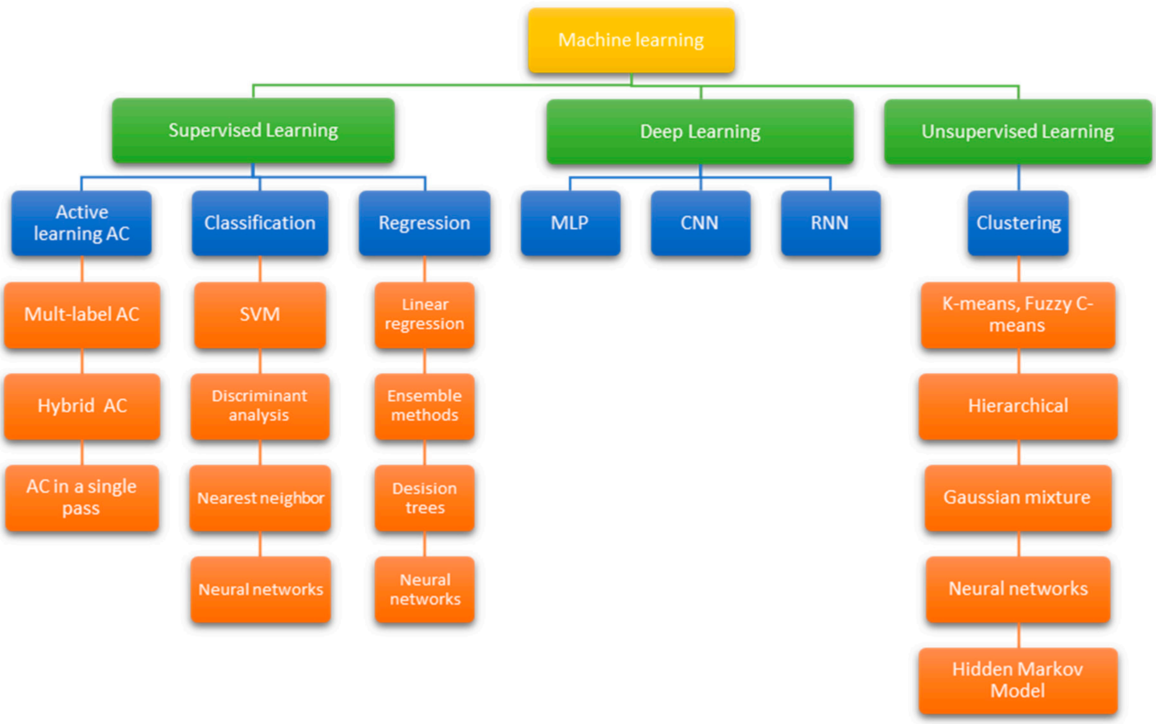

Figure 1. Machine learning tree [13–15].

There are several applications of AI and ML for improving or proffering new solutions for existing challenges in different industries. In structural engineering, ML methods have been used for damage identification, performance optimization, reliability assessment, etc., as observed in the review conducted by [16]. Also, unsupervised ML has been explored to address issues related to the long-term settlement analysis of shield tunnels in the drilling of tunnels. Shen et al. [17] proposed the use of a new time-series algorithm, shape-based distance K-medoids (SBD-K-medoids), for clustering. The algorithm was tested and validated, and when compared to existing benchmark algorithms, the SBD-K-medoids algorithm produced about the same level of clustering precision as the benchmarks and at a statistically faster rate. The proposed algorithm was used in a case study to prove its validity and value for engineering practice. In the field of civil engineering, Lu et al. [18] explored several articles on AI use for (1) predicting the durability of self-consolidating concrete using neuro-fuzzy-based algorithms; (2) predicting the 28-day compressive strength of a normal and a high-strength self-compacting concrete; (3) improving the selection process of contractors using fuzzy logic; and (4) assessment of slope failure using an ANN, etc. In the oil and gas industry, Agwu et al. [19] explored several articles where ANNs, fussy logic, support vector machines (SVMs), hybrid intelligent systems (HISs), genetic algorithms (GAs), case-based reasoning (CBR) and the particle swarm algorithm (PSA) were explored in drilling fluids engineering and the prediction of problems in wells. Pan and Zhang [20] also explored AI use in the construction engineering and management (CEM) industry by reviewing articles from 1997 to 2020. Several use areas were identified, such as information fusion where SVMs, ANNs, and reinforcement learning were used for structural health monitoring. In computer visioning, deep learning and CNN were used for structural health monitoring. Also, in natural language reports for safety report analysis and intelligent optimization using single/multi-objective optimization for construction project scheduling. In this present study, we will review the use of AI technology in buildings to improve energy management and IEQ. Over the years, several reviews and studies have been carried out on improving energy management and IEQ in buildings using different methods [21–25]. Recent strides in technology have led to increasing interest in the use of AI, ML, and related technology to achieve better and more reliable results.

Figure 2 highlights the current work in the field of AI applications in buildings for energy management, energy efficiency and IEQ. On the right side, the capabilities of AI tools are highlighted as the following:

(1) Data collection—using sensors, data on temperature, relative humidity, air quality, energy consumption, etc., can be collected.
(2) Data processing—using algorithms, the collected data can be processed for relevant information.
(3) Predictive analytics—trends, consumptions and forecasts can be predicted.
(4) Optimization—building design optimization [26] and energy use optimization.
(5) Fault detection and diagnosis—algorithms can be used for fault detection and diagnosis [27].
(6) Anomaly detection—for unusual energy consumption or energy generation detection [28].
(7) Control management—HVAC controls management, switch control and monitoring.
(8) Integration with BEM—can be seamlessly integrated with BEMSs, BMSs, etc. [29].

Each of these capabilities are harnessed together with sensors and BEMSs to achieve the following:

- Thermal comfort and IAQ control.
- Energy management and consumption prediction.
- Anomaly detection.
- Indoor temperature prediction.
- HVAC controls in buildings.

This study will investigate the state of the art in the application of AI and ML in buildings from the use area perspective. The algorithms in each application will be discussed and their applicability to real-life scenarios highlighted. The following research questions have been proposed to serve as a research guide: R1—In what areas are AI-based solutions applied for energy management in buildings? R2—What is the most suitable AI method for energy management in buildings? R3—What application areas are yet to be explored? R4—Are these methods applicable in real-life scenarios? R5—What are the challenges to their applications in real life? Using these questions, the authors will present their findings in the following format: Section 1—Introduction, Section 2—Materials and Methods, Section 3—Results, Section 4—Discussion, and Section 5—Conclusions.

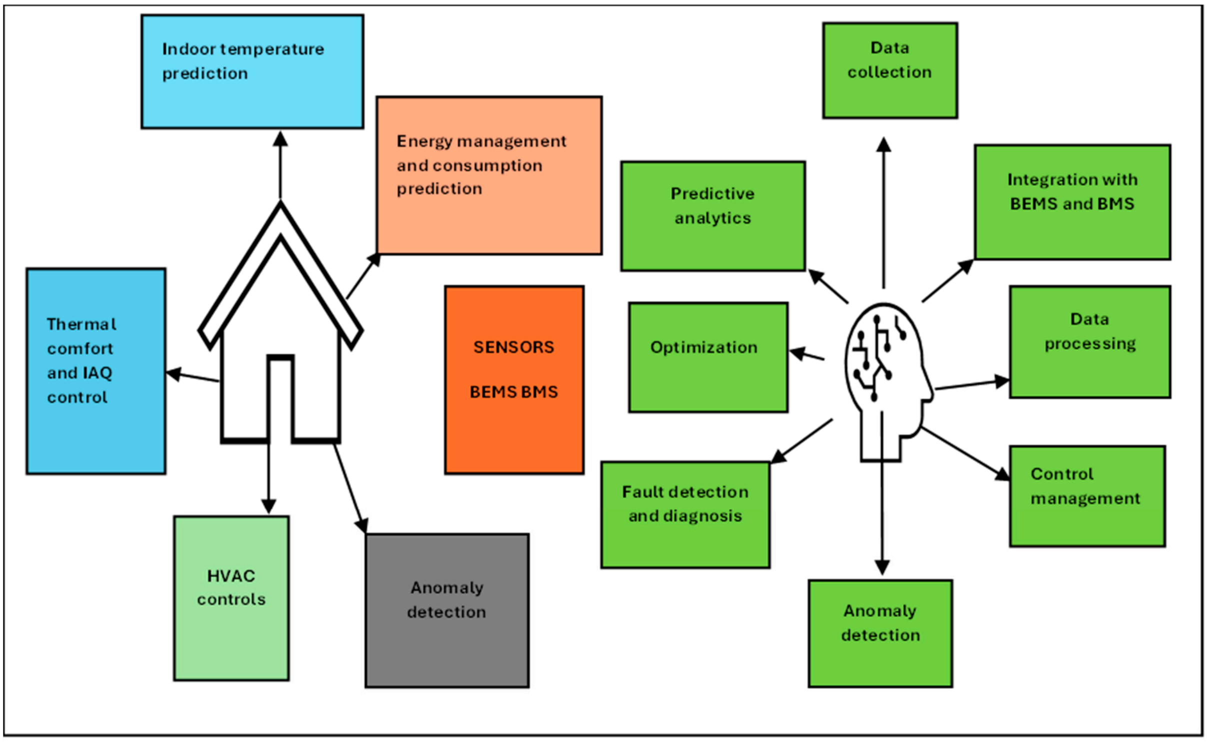

Figure 2. Current AI application areas in buildings [30].

2. Materials and Methods

A comprehensive search strategy that helped retrieve relevant publications was used. The general goal was to first retrieve all the studies within the last 10 years related to AI and energy in buildings. The following databases were searched using carefully selected keywords based on the predetermined search strategy: ScienceDirect, Scopus, Google Scholar, PubMed, b-on, and Semantic Scholar. The keywords artificial intelligence, machine learning, energy efficiency, energy management, energy consumption, and indoor environmental quality were used in the "Harzing publish or perish 8" software program. The Harzing publish or perish application is a software program used to retrieve academic citations and analyze the scholarly impact developed by Professor Anne-Wil Harzing [31]. The results are displayed on the screen, and they can be analyzed and saved in different formats.

A 10-year timeframe limit was applied; that is, publications between 2013 and 2023, with very few exceptions where the article was highly relevant to the subject of interest. The search for articles began on the 15 May 2023, while searches of PubMed, b-on and Semantic Scholar ended on 29 June 2023. The last search date of ScienceDirect, Google Scholar, and Scopus was 17 July 2023. Figure 3 presents the PRISMA diagram highlighting the screening process used.

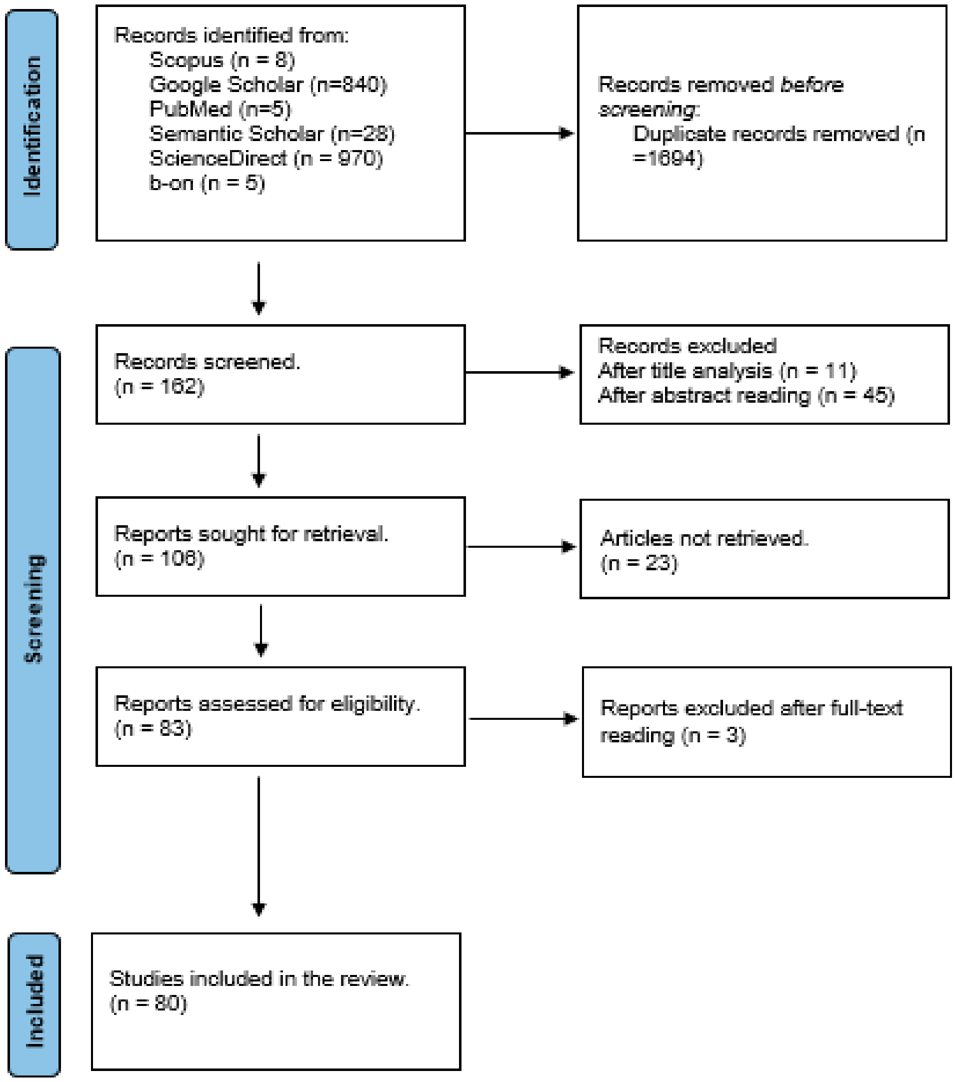

Figure 3. PRISMA diagram.

The PRISMA diagram (see Supplementary Materials) serves as a comprehensive visual representation of the meticulous steps involved in conducting this systematic review. Initially, a broad search across multiple databases yielded a total of 1856 records, which were meticulously screened to eliminate duplicates, resulting in 162 unique records for further evaluation. These records were rigorously scrutinized based on their titles and abstracts, and 56 studies were excluded at this stage due to lack of relevance. Subsequently, the full texts of 106 reports were thoroughly assessed to determine their eligibility for inclusion, with 80 studies meeting the predefined criteria and being incorporated into the final review. Despite the thoroughness of the screening process, 82 records were ultimately excluded during various stages, highlighting the stringent criteria applied to ensure the integrity and reliability of the included studies. Furthermore, from the 80 relevant papers accepted, there were 19 review papers, 17 papers on thermal comfort and IAQ control-related studies, 29 papers related to energy management and energy consumption prediction, 3 papers on anomaly detection, 3 papers on predicting the indoor temperature and 9 papers on HVAC controls. Figure 3 highlights the inclusion and exclusion process used to arrive at the most relevant and suitable studies. Using a combination of the five research questions (R1–R5) and the proposed keywords as guides, a search was performed of the Scopus, Google Scholar, PubMed, Semantic Scholar, ScienceDirect and b-on databases. Scopus returned 8 results, Google Scholar returned 840 results, PubMed returned 5 results, Semantic Scholar returned 28 results, and ScienceDirect and b-on returned 975 results. After screening for duplications and using the initial preliminary exclusion criteria, the results were streamlined to 162 articles. Further thorough scrutiny resulted in a final sample of 80 relevant articles, as shown in Figure 3. The search criteria of keyword relevance, publication date, relevance to the research questions and number of citations were used as the inclusion criteria. All the articles that did not apply AI to buildings were excluded. Articles older than the 10-year time frame were excluded, except if they met other criteria, including a minimum of 100 citations (n = 3). Articles that met the other criteria except the number of citations were summarized but not discussed in-depth (n = 8). Articles that met all the selection criteria were discussed and summarized in depth.

Figure 4 was generated using a VOSviewer version 1.6.19. A VOSviewer is a software tool used to construct and display bibliometric relationships between several variables [32]. The most obvious variables have the highest number of connections and the largest circles. Figure 4 presents a visualization of key cluster words from the returned results. The three cluster words "efficiency", "artificial intelligence", and "building" have the highest links and connections. Moreover, "indoor air quality" and "indoor environmental quality" are the next set of words with the highest number of connections. This provides an immediate idea of the research focus from the studies collected. Below, Table 1 presents a breakdown of the most linked cluster words.

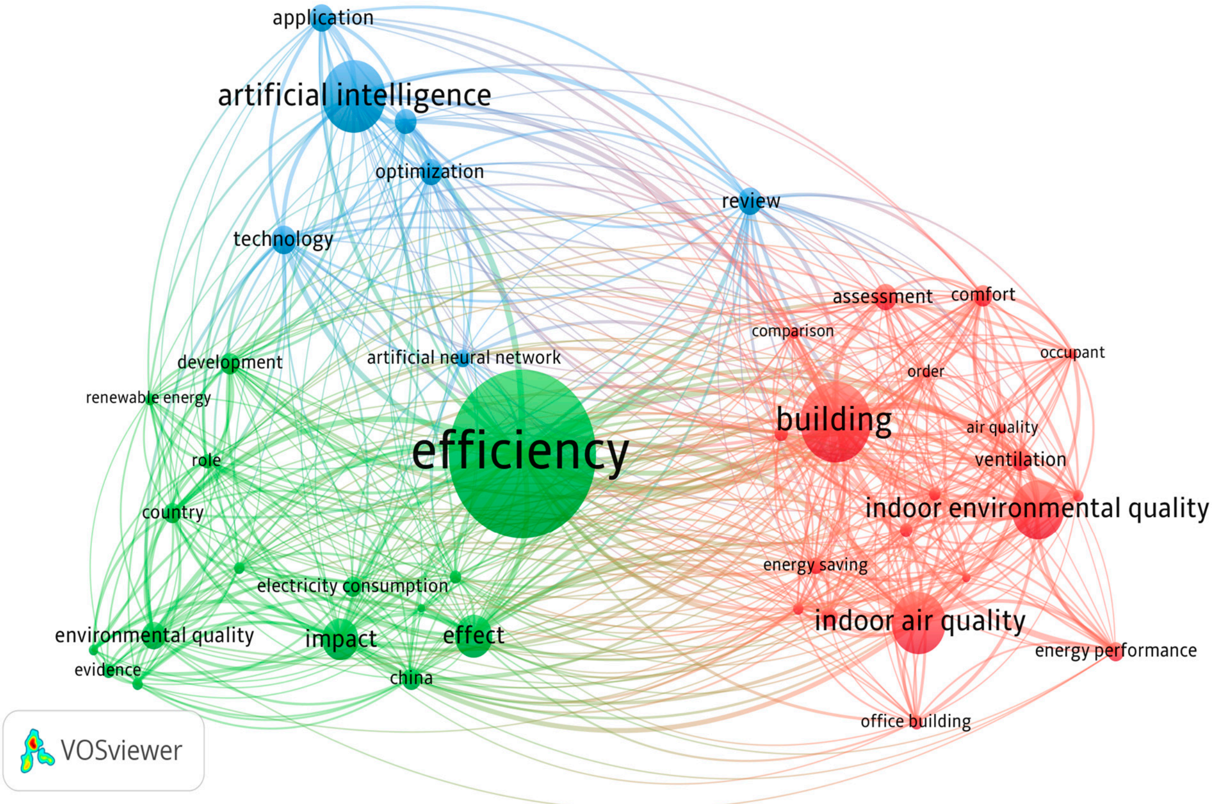

Figure 4. Network visualization of key cluster words.

Table 1. Breakdown of the three most returned cluster words.

Item/Words	Links	Total Link Strength	Occurrences	Cluster
Efficiency	42	344	246	2
Artificial intelligence	27	122	99	3
Building	37	292	112	1
Total 43	527	1711		3

3. Results

3.1. Analysis of Relevant Reviews

In recent times, several authors have conducted reviews on the use of AI-based solutions in buildings with different focus points, including addressing energy efficiency issues, thermal comfort issues and the methods applied in the different studies. Yan et al. [33] conducted a thorough review of AI-based applications in building energy efficiency, with a focus on zero-energy buildings while considering occupants' influence. This review highlighted AI use in the following areas. (i) In indoor comfort areas—where IoT technology is applied to sensors and controls while AI methods are used to maintain thermal comfort. (ii) In energy efficiency optimization—as a prediction tool in the application of renewable energy sources (RESs) in buildings, solar photovoltaic (PV) performance optimization, tilt angle determination, HVAC controls, etc. (iii) In forecasting needs—energy consumption forecasting, energy pattern profiling and future load demands. They identified several AI algorithms, like the artificial neural network (ANN), support vector machine (SVM), convolutional neural network (CNN) and artificial bee colony (ABC), in different use areas. The authors also identified the need for changes in regulations and laws with the progressive use of AI solutions. Mehmood et al. [34] explored the history of AI, the decision-making techniques of AI tools and the supplementary use of big data in AI-based techniques for energy management, energy efficiency and IEQ in buildings. In another review, Tien et al. [35] presented a summary of the literature on ML and deep learning (DL) used in built environments. This study focused on the frameworks, the methodology, and the performance of the techniques used. They pointed out the difficulty in selecting the right ML/DL models for specific challenges, highlighting the lack of use cases for other IEQ parameters except thermal comfort. Broday et al. [36] assessed the use of the IoT for IEQ in buildings in 91 articles. They pointed out that sensors are a critical part of the IoT, and these sensors should be made highly sensitive, low cost, and consistent with metrological performance standards. They argued that in many cases, AI and ML experts do not adequately factor in standard measurement methods, suitable sensor choice and placement in the building. This amounts to the collection of bad or incomplete measurements, resulting in the wrong use of AI and ML. Farzaneh et al. [37] grouped the decision tree (DT), fuzzy logic (FL), particle swarm optimization (PSO), nearest neighbor (NN), principal component analysis (PCA) and hybrid models as the most used ML models for energy efficiency. They identified opportunity areas for AI in renewable energy forecasting, energy accessibility, and energy efficiency in smart buildings. Ngarambe et al. [38] focused on AI as a tool for intelligent predictions in the area of thermal comfort in buildings. They suggested the use of the extended predicted mean vote (ePMV) and adaptive PMV (aPMV) in place of the PMV since the PMV was developed under a steady-state chamber and does not consider non-adults and unhealthy individuals. They believed that comfort models should be integrated with control schemes to optimally use energy and balance thermal comfort. They pointed out that most articles focused on the predictive accuracy of their models without details on how these models can be used in building control systems. A systematic review of AI-assisted techniques for thermal comfort and energy efficiency conducted by Merabet et al. [39] assessed the output of the techniques, the method of implementation and the effectiveness in improving energy efficiency while maintaining thermal comfort. They reviewed articles published between 1993 and 2020. They identified about 20 AI techniques that were developed for energy efficiency and thermal comfort. These solutions achieved energy savings of about 21.81–44.36%, and thermal comfort improvement between 21.67 and 85.77%. They also identified the areas of focus and limitations of each publication [40]. In this review, the authors grouped the studies according to autonomous cycles of data analysis tasks in other to allow them to accurately evaluate the state of each research work and to appreciate the challenges and opportunities currently faced. Aguilar et al. highlighted different approaches and strategies for using AI in building energy management, including how and when to use these approaches in smart buildings [40]. Kuzior et al. [41] compared the use areas of blockchain and AI in the energy industry. They found blockchain's prominence in wholesale electricity distribution, peer-to-peer energy trading and electricity data management, while AI tools were used for energy management and energy efficiency in buildings. They noted the paucity of studies linking blockchain to energy efficiency in buildings. For anomaly detection concerning energy consumption, Himeur et al. [42] presented various ML methods in use, the data privacy challenges, the feature extract and the detection level in each study. This review identified various challenges and defined anomalous consumption, the importance of privacy preservation, and platform reproducibility, etc. [43]. Khalil et al. presented statistical analysis models and data-driven models used for building energy forecasting. They categorized their studies based on the building type, location, data components, models, temporal granularity, performance indicators and the approach used. Cheng et al. [44] conducted a 20-year review of the application of AI-based controls for HVAC systems. They showed that studies applied AI-based controls for HVAC in four areas; (i) medium- to large-scale utilities for commercial buildings; (ii) air conditioners and chillers for residential buildings; (iii) composite buildings for air conditioning; and (iv) specific buildings like greenhouses. Case studies were carried out where AI-assisted HVAC controls were analyzed compared to typical HVAC controls, and they concluded that the normalized Harris index presented in their research can be used effectively to analyze the performance of AI-assisted HVAC controls, especially in cases of non-linear control systems. In building energy forecasting, ref. [45] presented previous studies on forecasting energy consumption by highlighting different methods and their advantages and disadvantages. They discussed the use of single methods like the SVM and ANN, hybrid methods (a combination of conventional and AI methods), and the combination of two AI methods. A key takeaway is that although conventional methods are easier to use and implement in real buildings due to the non-linear factors, they may not produce the best performance in forecasting. Wang et al. [46], in a similar fashion, discussed the advantages and limitations of using single or ensemble models for energy prediction in buildings. Zhao et al. [47] also presented several prediction methods and their challenges. They highlighted the difficulty of adapting engineering methods to reality, the inaccuracy of statistical methods, the need for large historical data and the importance for more studies of gray methods. Zhang et al. [48] focused on the use of ML to predict occupancy behaviors and patterns in the areas of energy systems, energy efficiency and IEQ. They provided insights into the workflow of the ML-based prediction models for occupancy by identifying three basic prediction models: the white-box model, ML models and hybrid models. They opined that occupancy patterns and behavior can be used both for energy minimization and for influencing IEQ parameters. Brito et al. [49] concluded that AI/ML models deliver better results than conventional methods. Ramokone et al. [50], in their review, focused on the model type, the forecasting accuracy of the model, and the area of application. They highlighted the absence of reliable and simple instruments to instantaneously solve the energy and environmental balance problems in buildings. They also identified the energy consumption drivers and their implications for building performance. Other reviews on AI applications were based on their design and integration into building energy management systems (BEMSs). Sha et al. [51] focused on using computational intelligence to solve HVAC design optimization problems with use case examples. Mason et al. [52] also focused on using reinforcement learning (RL) for autonomous BEMSs. Kadir et al. [53] reviewed studies where data-driven models were developed for building energy consumption, considering the ML algorithm, the data properties and processing methods employed, and the measure of performance used for evaluation.

Although these studies have analyzed the use of AI in buildings from multiple perspectives, the internal indicators and comparisons to other decision-making support approaches have not been fully studied for building retrofit. There is still a lack of systematic summaries of the internal details between the different methods used for decision-making, application areas and the reasons. This is more advantageous in early decision-making support for building retrofit compared to other approaches. Table 2 highlights each review article discussed, the building type and the application area.

Table 2. Comparison of relevant reviews on the use of AI, ML, and IoT in buildings for energy management, energy efficiency and IEQ.

Ref	Year	Research Approach									Building Type	Focus/Limitation
		Algorithm		Thermal Comfort/IAQ	Energy Efficiency/ Management	Controls	Anomaly Detection	Forecasting/ Prediction	Lighting	Acoustic		
		AI	IoT									
[33]	2021	×	✓	✓	✓	✓	×	✓	×	×	ZEB	Focus on implementation of ZEB with consideration of occupancy
[34]	2019	✓	×	✓	✓	×	×	✓	×	×	Commercial and residential buildings	Highlights the importance of combining AI and big data in building energy solutions
[35]	2022	✓	×	✓	✓	✓	×	✓	×	×	Traditional building, smart building, intelligent building	Focus on the framework, methodology and performance, also on occupancy
[36]	2022	✓	✓	✓	✓	✓	×	×	×	×	Smart building	Focus on IoT, use of IoT to improve indoor comfort, sensor types
[37]	2021	✓	×	×	✓	×	×	✓	×	×	Smart building	Application of AI, big data through BEMS and DRP concepts
[38]	2020	✓	×	✓	✓	✓	×	✓	×	×	General building stock	The study highlights the theoretical benefits of ML for thermal comfort prediction
[39]	2021	✓	×	✓	✓	✓	×	×	×	×	Traditional buildings and smart buildings	Assess output and implementation of AI-based techniques for building controls
[40]	2021	✓	×	✓	✓	✓	×	✓	×	×	Smart building	Studies grouped based on the concept of autonomous cycles of data analysis tasks
[41]	2022	×	×	×	✓	×	×	×	×	×	Unspecified building type	Bibliometric analysis of possible use areas of blockchain and AI in the energy industry
[42]	2021	✓	✓	×	✓	×	✓	×	×	×	General building type	Focus on anomaly detection in building energy consumption
[43]	2022	✓	✓	×	✓	×	×	✓	×	×	Domestic, education, commercial, office	Focus on analyzing data-driven approaches for forecasting building energy consumption
[44]	2019	✓	×	✓	✓	✓	×	✓	×	×	Residential, commercial, and composite buildings	Presented NHI to be used to analyze the performance of AI-assisted HVAC controls
[45]	2017	✓	×	×	✓	×	×	✓	×	×	No specified building type	Analyzed different forecasting methods, AI and conventional methods for building energy consumption
[46]	2017	✓	×	×	✓	×	×	✓	×	×	Different building types	Focus on the principles, applications, advantages, and limitations of AI-based prediction methods for future energy use in buildings; the importance of the building type was emphasized
[47]	2012	✓	×	×	✓	×	×	✓	×	×	Unspecified building type	Highlights factors influencing building energy performance, comparing engineering, statistical and AI methods for energy predicting energy use
[48]	2022	✓	✓	✓	✓	×	×	✓	×	×	Office and academic buildings	Review on ML methods for occupancy behavior and patterns
[49]	2022	✓	×	×	✓	×	×	✓	×	×	Unspecified building type	Focus on finding the most suitable energy prediction model using ML in buildings

Table 2. *Cont.*

Ref	Year	Research Approach									Building Type	Focus/Limitation
		Algorithm		Thermal Comfort/IAQ	Energy Efficiency/ Management	Controls	Anomaly Detection	Forecasting/ Prediction	Lighting	Acoustic		
		AI	IoT									
[50]	2021	✓	×	×	✓	×	×	✓	×	×	Residential buildings	Focused on the model type used, the forecasting accuracy of the model, and the area of application; identifying drivers of consumption, including occupancy, and their implications for the energy performance of the building
[51]	2019	✓	×	✓	✓	×	×	×	×	×	Unspecified building type	Using computational intelligence (CI) for HVAC system optimization design
[52]	2019	✓	✓	×	✓	✓	×	×	✓	×	Smart building	Focus on the use of RL to develop autonomous building energy management systems
[53]	2018	✓	×	×	✓	×	×	✓	×	×	Commercial, educational, and residential buildings	Review of studies that developed data-driven building energy consumption prediction models, focusing on the scopes of prediction, the data properties and preprocessing methods used, ML algorithms the performance evaluation method applied
This Study	2023	✓	✓	✓	✓	✓	✓	✓	×	×	Smart buildings, residential, commercial, and educational buildings	Application of AI and ML from the perspective of the use area, highlighting the algorithms in each application for building energy and their applicability to real-life scenarios

Note: ✓ denotes inclusion and × exclusion.

3.2. Application Areas

Based on the comprehensive study of recent related articles and publications, AI/ML models are used in several studies with different techniques broadly used for energy management, energy efficiency and energy saving. Also, for learning and predicting accurate patterns or behaviors to improve IEQ in the building. Several use areas have been identified in this study: (1) for thermal comfort and IAQ control; (2) for energy management and energy consumption prediction; (3) for anomaly detection; (4) for predicting indoor temperature; and (5) for HVAC controls. We can observe in Figure 5 a pie chart of the application areas identified in this study and the percentage distribution of relevant articles analyzed for each application area. The energy management and prediction area accounts for the largest slice of the pie, with 47.5% of articles focused on this area. This highlights more interest in managing and predicting energy consumption. Anomaly detection and predicting indoor temperature have the fewest studies, cumulatively accounting for about 10% of the total application areas. This highlights the need for more studies in these areas. Figure 5 also offers a snapshot of the application areas with high, medium, or low severity in terms of the lack of available studies. The specific colors serve as severity indicators. The green shades indicate low severity, blue indicates medium severity, while the different shades of red indicate high severity. Appendix A presents all the application areas covered in each analyzed study and the algorithms used.

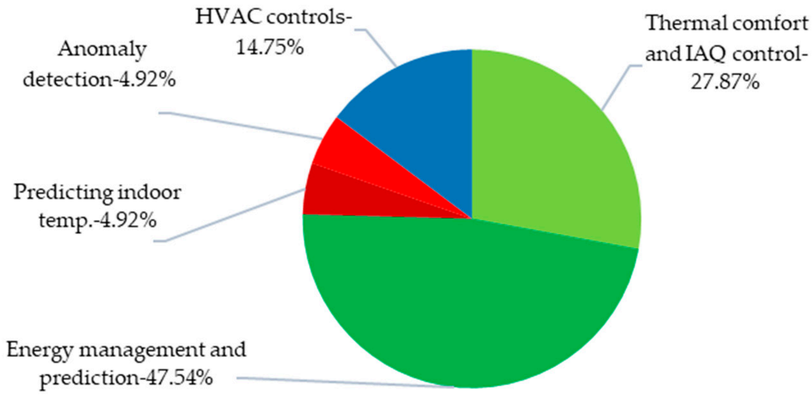

Figure 5. Application area by percentage distribution.

3.2.1. For Thermal Comfort and IAQ Control

AI-based solutions have been applied to several thermal comfort control or indoor climate-related problems in a building environment using different methods. In 2010, Moon et al. [54] used ANNs to enhance thermal conditions within residential buildings using a thermal control logic framework, a predictive and an adaptive logic, combined with a hardware system. Again, Moon et al. [55] compared the outcome of a non-adaptive fuzzy-based control, adaptive neuro-fuzzy inference system (ANFIS)-based control, and adaptive ANN-based control for thermal comfort control in buildings. Using a simulation, each method was tested on a typical two-storey residential building in the US. The results showed that the two adaptive models outperformed the fuzzy model with an increased thermal comfort period and lower deviation from the set point, although no considerable difference was noticed in all three methods in terms of energy savings. Moon et al. [56] again proposed the development of an ANN-based thermal control logic for double-skin envelopes in the winter, where the control logic was to help predetermine how the heating system works and the opening conditions of the building envelope using a set of predicted future indoor temperature values. After parametric optimization and testing, the control logic and model were found to be very effective. In predicting thermal behavior, Mustafaraj et al. [57] used an ANN-based non-linear autoregressive model with external inputs (NNARX), a non-linear autoregressive moving average model with external input (NNARMAX) and a non-linear output error model (NNOE) in a commercial building, an open-plan office. The goal was to predict the thermal behavior of the room, the room temperature and relative humidity, using external and indoor climate data from three seasons (autumn, summer, and winter) to train and validate the models. They employed the use of an optimal brain surgeon algorithm to prune unnecessary signals, errors, etc. The results showed that the NNARMAX, NNARX and NNOE demonstrated good predictions, although the NNOE performed the least well of the three models. Yu et al. [58] developed a control algorithm for an air-conditioning system for the optimization of thermal comfort, IAQ and energy savings using deep Q-learning in RL. The goal was for the control agent to balance IAQ and thermal comfort with energy savings in the classroom. Tzuc et al. [59] comparatively applied three AI techniques, multilayer perceptron (MLP) and radial basis function (RBF), and a group method of data handling to model and predict the temperature in a building in a tropical climate. They reported that the MLP technique delivered the highest accuracy in terms of the estimation. Ahn et al. [60] employed the use of AI to solve the challenge of the impact of human common sense or anti-logic on the use of controls that lead to a deterioration in energy efficiency in buildings. They integrated an energy supply model based on AI, an ANN model and a PMV model for the HVAC system of the building. They wanted to achieve adequate heating and cooling air in the building that would not compromise thermal comfort and energy efficiency. The result was a 17.4% and 25.7% energy consumption reduction, plus 2.5% and 10.2% improved thermal comfort levels for office and residential buildings, respectively. Several studies used decision trees (DTs), and random forest (RF) techniques to develop predictive models to predict thermal sensation votes. Wang et al. [61], Lu et al. [62] and Chaudhuri et al. [63] all carried out studies on predicting the thermal sensation vote by developing RF models. The results, with varying accuracy levels, all proved better than the traditional PMV model, even though they were all applied in different areas: aged-care homes [61], educational buildings [62] and human physiological parameters and gender [63]. Bin et al. [64] used a different technique to develop their predictive model to predict the PMV by employing an SVM algorithm. They adopted a non-linear least squares support vector machine (LS-SVM) optimized by PSO and a particle swarm optimization (PSO) algorithm to predict the PMV index. They compared the results of both algorithms with a grid search. The result showed that the optimized LS-SVM is more accurate and effective. Megri et al. [65] also used SVM in developing a model for predicting thermal comfort in buildings. Valladares et al. [66] focused on tropical and subtropical regions and applied a deep reinforcement learning (DRL) technique for the controls in maintaining thermal comfort and air quality while consuming less energy from air conditioners and ventilating fans. Table 3 presents each study on the use of AI for thermal comfort and IAQ control, the algorithms used and the building types.

In 2016, Moon et al. [67] tried to determine the optimal application for the setback temperature to enhance indoor thermal comfort and energy efficiency using an ANN. An ANN model and a control algorithm were developed and tested using transient simulation (TRNSYS 16.1) and matrix laboratory (MATLAB version 14) software. For air quality prediction, Majdi et al. [68] applied a novel method using a neural network of the radial base function, with the inputs being temperature, air humidity and CO_2, while the output was volatile organic compounds (VOCs) in the air. The model was trained for 138 days and tested for 3 days using 1104 samples and 24 samples, respectively. The outcome showed a 3% error after testing with different radii of the Gaussian function. For indoor comfort, Wahid et al. 2019 [69] used a hybrid of the firefly algorithm (FA) and genetic algorithm (GA) for comfort optimization with minimum energy consumption in smart buildings with data from sensors, power control systems, actuators, and users. Kolokotsa et al. [70], in their study, used a bilinear model-based predictive controller together with a BEMS to manage the energy cost and IEQ in a laboratory building at the University of Crete, Greece. They aimed at predicting the IEQ conditions and finding the most appropriate action to take in reaching the set points while minimizing energy. They employed a monitoring system of four sensors and a control system of BEM actuators. The results obtained showed satisfaction in selecting the best solution based on energy consumption, but more work is required on IEQ conditions as variations were observed between the predicted and real values of CO_2 in the laboratory used.

Table 3. Application area: For thermal comfort and IAQ control.

Reference	Year	Algorithm	Application Area		
			Thermal Comfort	Energy Efficiency/ Management	Building Type
[54]	2010	ANN	✓	✓	Residential buildings, using a thermal control framework
[55]	2011	Adaptive ANFIS, non-adaptive ANFIS, ANN	✓	✓	Two-storey residential building for thermal comfort control
[56]	2013	ANN	✓	✓	Thermal comfort control for double-skin envelope in winter
[57]	2010	ANN, NNARX, NNARMAX, NNOE	✓	✓	Commercial building, open-plan office
[58]	2021	Deep Q-learning in RL	✓	✓	Educational buildings, control agent to balance thermal comfort and IAQ in classroom
[59]	2020	MLP, RBF	✓	✓	Educational building, tropical climate, a university laboratory
[60]	2017	ANN, PMV	✓	✓	Office and residential buildings
[61]	2019	RF	✓	✓	Aged-care home
[62]	2019	RF, SVM	✓	✓	Educational building
[63]	218	RF	✓	✓	Focus on thermal sensation human physiology and gender
[64]	2010	SVM	✓	✓	-
[65]	2016	SVM	✓	✓	Office environment
[66]	2019	DRL	✓	✓	Educational building (classroom and laboratory)
[67]	2016	ANN, TRNSYS	✓	✓	-
[68]	2022	NN of the radial base function	✓	✓	Smart homes
[69]	2019	Hybrid FA and GA	✓	✓	Smart buildings
[70]	2009	Bilinear model-based predictive control	✓	✓	Educational building (university laboratory)

Note: ✓ denotes inclusion.

3.2.2. For Energy Management and Energy Consumption Prediction

In the area of energy management and consumption predictions, several models have been proposed and tested. A recent study by Khan et al. [71] proposed a hybrid AI-based framework to accurately predict both energy consumption and energy generation in a building. The hybrid framework consists of convolutional long short-term memory (convL-STM) to learn descriptive patterns from the building's previous power data, a bidirectional gated recurrent unit (BDGRU) to extract temporal aspects and an MLP for forecasting. They used energy data from household consumption and photovoltaic generation after refining the data to train the model. The results obtained showed a reduction in the error as compared to a state-of-the-art technique in use, 0.012 and 0.045, respectively, in terms of the mean square error (MSE). Xiang et al. [72] also proposed using an AI-based energy management model in green buildings to improve IEQ and minimize energy consumption while preserving its "greenness". They used LSTM models to enhance energy consumption using the temperature and air-quality sensors in the green building to collect data, recording a 94.3% higher performance and lower energy ratio of 15.7%. A prediction ratio of 97.1%, with an accuracy ratio of 97.4% and an energy management level of 95.7%, was achieved. Frassanito et al. [73] presented a human–machine synergy as a solution for improving energy efficiency in an Italian hospital. The combination of a cloud-based ML algorithm and the IoT was used to modify the HVAC control features. This accounted for a 20% total reduction in energy consumption without compromising indoor comfort. Kaur et al. [74] proposed, designed and developed a smart home (SH) model using AI and the IoT to monitor all the input and output, including energy, electricity supply, water, and occupants. Gao [75] used PSO and restricted Boltzmann machines to optimize energy efficiency in residential buildings, presenting three optimization options: back-propagation neural network (BPNN) optimized by improved PSO, BPNN optimized by basic PSO and a non-optimized BPNN. The experimental results obtained showed that the BPNN optimized by improved PSO is significantly better than the BPNN optimized by basic PSO and the non-optimized BPNN. Sayed et al. [76] introduced an approach by utilizing AI, the IoT and recommendation systems to improve residential energy efficiency. Their framework used AI, micro-moment concepts and IoT sensors to influence users' habits through a routine and reward system. Users receive notification advice through a home management app on energy-saving actions. A mini-pilot program was conducted using about 10 users to confirm the effectiveness of their approach. In a bid to address the challenge of using model-based predictive control (MPC) as an advanced control strategy, Cotrufo et al. [77] proposed a novel approach by developing an AI-based MPC using commonly available variables. They applied this approach to a building in Varennes, Quebec, for the reduction of natural gas use for the heating season. A 23.9% reduction in natural gas consumption and a 6.3% reduction in building heating consumption were reported. In 2021, Ma et al. [78] designed an improved ML model to accurately predict energy consumption in a green building using box plots and data-driven systems for collecting data and preprocessing energy consumption. Using a gradient descent algorithm and a cross-validation approach to construct a type-2 fuzzy wavelet neural network (T2-FWNN) system with high accuracy, Abiyev et al., 2023 [79] predicted the energy demand in residential buildings. Using MATLAB to execute their research, Vijayan P. [80] used linear regression (LR), SVM, free tree (FR), the ensemble model and ANN models for energy forecasting. A process for selecting the most suitable model for specific areas using data from the Kaggle data center and experimental data was also used to create regression models of appliances' energy use in low-energy buildings. No decisive conclusion was reached on the most suitable model. Nainwal et al. [81] compared results using a multilinear regression (MLR) algorithm and ANN for predicting energy consumption in residential buildings. Consumption data from six dwelling units were used to train and test the algorithms and the results showed that the ANN performed better than the MLR. [82] Another comparative study using three AI techniques for energy consumption estimation was conducted, using MLP, RBF and SVM on the Weka 3.6 software and data from the years 1990–2000 for 15 manufacturing industries in Canada for training, testing and simulation. The results showed that MLP delivered the best result of the three AI techniques, the next was SVM and RBF. Again, Jozi et al. [83] also presented a study where five algorithms were used to forecast energy consumption in an office building in Porto, Portugal. The ANN, SVM, hybrid fuzzy inference systems (HyFIS), Wang and Mendel's fuzzy (WM) rule learning method and a genetic fuzzy system for rule learning based on MOGUL (modular online growth and use of language—GFS.FR.MOGUL). They used two forecasting strategies and three consumption types—HVAC, Light and Sockets. The ANN, SVM, HyFIS and WM presented better results in the first strategy, while GFS.FR.MOGUL did not show improved results between strategies. SVM is said to have performed better based on the second strategy. Chegari et al. [84] applied a combination of ANNs and metaheuristic algorithms for the multi-objective optimization of building performance and indoor thermal comfort of a building in the Marrakech region of Morocco. The appropriate multi-objective optimization algorithm was selected based on its comparative performance in line with the objectives to be achieved: multi-objective particle swarm optimization (MOPSO) algorithm. The conclusion is that the building performance optimization (BPO) technique is very useful for solving tough design problems in building optimization as the annual thermal energy demand and annual weighted average of degree hours showed significant improvement potential, given the optimization results. Table 4 presents all the studies analyzed for the energy management and energy consumption prediction area.

Table 4. Application area: Energy management and energy consumption prediction.

Reference	Year	Algorithm	Application Area		
			Energy Efficiency/ Management	Forecasting/ Prediction	Building Type
[71]	2021	convLSTM, BDGRU	✓	✓	NZEB, to predict consumption and generation
[72]	2022	LSTM	✓	×	Green buildings, energy management, improve indoor climate
[73]	2019	IoT, cloud-based ML	✓	×	Human–machine synergy for hospital building to reduce consumption costs without compromising IAQ
[74]	2021	AI and IoT	✓	×	Smart homes, to monitor input and output inkling supply and consumption
[75]	2022	PSO and BPNN (optimized and non-optimized)	✓	×	Energy efficiency optimization in residential buildings
[76]	2022	IoT and AI-based framework	✓	×	Residential energy, to improve energy efficiency
[77]	2019	AI-based MPC	✓	✓	Institutional building, reduction of natural gas use, GHG emissions, and energy management
[78]	2021	ML	✓	✓	Green buildings, predict energy consumption
[79]	2023	T2-FWNN	✓	✓	Residential buildings, predict energy demand
[80]	2022	LR, SVM, FR and ANN	✓	✓	Low-energy building, forecast consumption and appliance energy use
[81]	2022	MLR, ANN	✓	✓	Residential building, energy consumption prediction
[82]	2016	MLP, RBF and SVM	✓	×	Industrial buildings, energy consumption estimation
[83]	2019	ANN, SVM, HyFIS and WM, GFS.FR.MOGUL	✓	✓	Office building, forecast energy consumption
[84]	2021	ANN, MOPSO, BPO	✓	×	Residential building, multi-objective optimization of building performance
[85]	2017	GBRT, ML (RF, extra-tree)	✓	×	Identify optimal design for heating and cooling loads in a building
[86]	2021	ANN	✓	✓	Commercial buildings (shopping center), predict energy consumption
[87]	2019	SVR		✓	Residential building, forecast energy consumption
[88]	2015	LSSVM, DSORCGA, RCGA	✓	✓	Predict daily building energy consumption
[89]	2018	ANN, GA, MPC	✓	×	Office building, optimization tool

Table 4. *Cont.*

Reference	Year	Algorithm	Application Area		
			Energy Efficiency/ Management	Forecasting/ Prediction	Building Type
[90]	2023	AI	✓	×	Industrial building, managing energy savings
[91]	2020	RF, M5P, RT	✓	✓	Multiple buildings, predict energy consumption
[92]	2019	Optimized ANN, TRNSYS	✓	✓	Non-residential building, evaluate heating demand
[93]	2017	ANN	✓	×	Residential buildings, characterize heating demand based on ratings and actual
[94]	2019	ANN	✓	✓	Residential building, prediction of heating and cooling loads
[95]	2019	ML (tree-based, lazy learning), MLP, SVR	✓	✓	Residential building, prediction of energy loads
[96]	2021	AANN, SVR	✓	✓	Residential building, energy prediction
[97]	2018	FL, IoT	✓	×	Residential, home energy management
[98]	2021	Elitist NSGA II, SVR	✓	×	Smart home, energy demand planning
[99]	2021	Gradient boosting and SVM	✓	✓	Smart home, prediction of solar radiation production

Note: ✓ denotes inclusion and × exclusion.

Papadopoulos et al. [85] used a gradient-boosted regression tree (GBRT) compared with other ML techniques (RF, extra-tree) to approximate building performance simulation models and to identify the optimal design in terms of the heating and cooling loads. The results showed that GBRT outperformed RF and extremely randomized trees in terms of the prediction accuracy. Pinanggih et al. [86] predicted energy consumption in a Cirebon city shopping center in Indonesia with an ANN algorithm processed on MATLAB. They also used a second method, the exponential smoothing method, and compared the results. The results obtained for 7 days using the ANN had an accuracy of 97.92%, while the second method returned a result of 97.65%. Ma et al. [87] applied support vector regression (SVR) for forecasting building energy consumption in a building in southern China. In their approach, they used multiple parameters, such as weather data, and economic factors as input data. They also used k-fold cross-validation with a radial-basis function kernel-based searching method to evaluate the performance of the SVR. Jung et al., in [88], used a novel least squares support vector machine (LSSVM) by designing a hybrid direct search optimization (DSO) and real-coded genetic algorithm (RCGA) to effectively predict daily building energy consumption. The DSORCGA was used to select suitably fitting free parameters, speeding up the computational speed by optimizing the free LSSVM parameters. Reynolds et al. [89], on the other hand, designed a building optimization solution using the combination of an ANN, GA and MPC and using weather, occupancy, and indoor temperature as inputs. Their strategy acted as either a predictive control or an optimization tool for energy consumption reduction or energy cost reduction, in this case by successfully shifting the loads to cheaper price periods. Zhao [90], in his study, applied AI to intelligently manage industrial building energy savings. Pham et al. [91] applied the RF model in predicting energy consumption for multiple buildings on a short-term basis (hourly). The RF model was trained and tested using five different datasets from one year of energy consumption data of the buildings. They used four different evaluation scenarios with respect to the length of the learning data to evaluate the RF. Their results showed that RF offered a closer correlation with the "actual" during the test period than M5P and random tree (RT), and it is effective in predicting hourly energy consumption. Ciulla et al. [92] applied an optimized AI algorithm in the evaluation of the heating energy demand in non-residential buildings across Europe. They took into consideration the climatic conditions of European countries and developed dynamic simulation models for these countries, where each model was characterized by 13 parameters to create a reliable database. The shape factors of the buildings were also considered. The collected data were used to train the ANN architecture. The best four ANN models were selected, trained, and validated after the optimization phase. The accuracy of the ANN was evaluated accordingly. Magalhaes et al. [93] also developed an ANN model to characterize the relationship between the heating energy demand based on energy ratings, actual heating energy use and indoor temperature for different heating patterns in residential buildings. They used data from the simulation of different building stocks with different occupations and heating patterns to develop their ANN model. The results showed $R^2 > 0.93$, a good estimation of both the heating pattern and indoor temperature. Khalil et al. [94] designed and developed an ANN for the prediction of the heating and cooling loads in buildings using the roof area, surface area, overall height, relative compactness, glazing area and distribution and wall area as input variables, while the cooling and heating loads were the output variable. Using data from 768 residential buildings, they trained and validated their model, reporting a prediction accuracy of 99.60%. Similarly, Namli et al. [95] used AI-based models for the prediction of the energy loads in buildings. Truong et al. [96] proposed the use of an additive artificial neural network (AANN) for the prediction of energy use in a residential building. They evaluated the AANN model using data from a residential building using solar renewable sources and an hourly dataset for one year. They compared the results obtained between the AANN, ANN and SVR. They concluded that the AANN outperformed the other models with a 4.6% increment in accuracy in the mean absolute percentage error (MAPE) compared to the ANN. Qurat-Ul-Ain et al. [97], to ensure thermal comfort is not sacrificed in energy consumption reduction, introduced humidity as an additional parameter in a fuzzy logic (FL) system for the main setpoints on the thermostat. They identified the possibility of making manual errors in defining rules as they increase, and they proposed automatic rule-based generation. Their method allows for a flexible and energy-efficient decision-making system that does not compromise the user's thermal comfort. Upon validation using simulations, they confirmed a 28% reduction in energy consumption. Rocha et al. [98] used a combination of three AI algorithms to solve the energy demand planning in SH, using an elitist non-dominated sorting genetic algorithm II (NSGA II) and SVR. They were able to achieve a 51.4% reduction for SH with distributed generation and battery bank. Dhage et al. [99], using gradient boosting and SVM, were able to predict the amount of solar radiation produced using weather data to help SH efficiently utilize solar energy available.

3.2.3. For Anomaly Detection

Studies have been carried out on the use of AI-based tools for anomaly detection in buildings. Hollingsworth et al. [100] applied DL algorithms (recurrent neural network—RNN) with forecasting in the detection of anomaly energy consumption in buildings. Comparing the results obtained between the autoregressive integrated moving average (ARIMA) model, the LSTM model, and the combination of ARIMA and LSTM models, the authors concluded that the combination is the most effective in predicting the energy demand as it delivered the highest accuracy while showing the time of the anomaly incident. On the other hand, ref. [101] also employed the use of LSTM in anomaly detection of energy consumption in buildings, but with a novel approach using both clustering and prediction methods to predict the next-hour data consumption, using auto-encoders to predict the day of the anomaly and the novel approach to predict the exact time of the anomaly. Himeur et al. [102], on the other hand, employed the combination of a visual technique to a deep neural network (DNN) on a micro-moment architecture for the detection of anomalous energy consumption in buildings. The results were said to be promising as the micro-moment architecture outperformed the other ML algorithms. Table 5 presents the studies found for the anomaly detection area, the algorithms used and the building types.

Table 5. Application area: Anomaly detection.

Reference	Year	Algorithm	Application Area		
			Anomaly Detection	Forecasting/Prediction	Building Type
[100]	2018	DL (RNN), ARIMA, LSTM, Hybrid of ARIMA and LSTM	✓	✓	Business and residential buildings, anomaly detection in energy consumption
[101]	2020	LSTM	✓	✓	Residential buildings, anomaly detection of power consumption using data from Pecan Street, United States
[102]	2020	DNN	✓	✓	Educational building, energy laboratory, anomaly detection appliance level

Note: ✓ denotes inclusion.

3.2.4. For Predicting Indoor Temperature

Refs. [103,104] have both applied ANN models for the prediction of indoor temperature and RH. This was applied in a school building to forecast the daily mean indoor temperature; they used indoor temperature and indoor RH data obtained during the summer of 2009 to train their model [103]. In [104], an ANN was applied in a tropical humid region in Cameroon, where experimental data for indoor air temperature and RH were collected for about 24 months. In both cases, the ANN results were accurate, with the potential of reducing energy consumption in the buildings. Eini et al. [105] proposed a learning-based model predictive control (MPC) approach for thermal control in smart buildings. While estimating occupancy profiles with an ANN in a long-term horizon, the data collected were fed into the predictive model to predict the indoor temperature. The results showed the proposed approach is better than conventional MPC, with 40.56% less consumption for cooling and 16.73% less for heating. Table 6 presents all the studies analyzed for predicting the indoor temperature, the algorithms used and the building type.

Table 6. Application area: Predicting indoor temperature.

Reference	Year	Algorithm	Application Area		
			Energy Efficiency/ Management	Forecasting/ Prediction	Building Type
[103]	2012	ANN	✓	✓	Educational building, prediction of daily indoor temperature and relative humidity
[104]	2016	ANN	✓	✓	Modern building, prediction of hourly indoor temperature and relative humidity for the humid region
[105]	2019	MPC, ANN	✓	✓	Smart building, thermal management

Note: ✓ denotes inclusion.

3.2.5. For HVAC Controls

Some studies have applied AI and ML-based techniques for HVAC controls, as the standard ON/OFF and proportional-integral-derivative (PCID) controls do not operate optimally in terms of energy consumption management. Ruano et al. [106], during a pilot program, used a model-based predictive control (MBPC) strategy to control the HVAC equipment at the University of Algarve, Portugal, with the aim of minimizing energy consumption while maintaining acceptable thermal conditions. The results showed a possibility of 50% energy savings for a typically occupied building. Zhu et al. [107] developed a dynamic ventilation control using wireless communication technology for transmission combined with a fast prediction model (low-dimensional linear ventilation model, LLVM-based ANN). With this approach, there is no need for an increased number of sensors to monitor the air quality and thermal comfort in a dynamic environment. This approach used a dynamic ventilation system that allows for fast prediction and real-time control with limited sensors to optimize the air-change rates per hour in the building to achieve about 60% energy savings in ventilation while balancing IEQ with consumption. Brandi et al. [108], in a study, identified the limitations of previous HVAC control methods for HVAC systems using model predictive control (MPC) as it requires pre-definition of accurate models for a controlled environment. They proposed the use of DRL, a model-free approach that learns from the environment using a delayed reward mechanism. Table 7 presents the studies on the application of AI for HVAC controls, the models and the building types.

Table 7. Application area: HVAC controls.

Reference	Year	Algorithm	Application Area					
			Thermal Comfort	Energy Efficiency/ Management	Controls	Forecasting/ Prediction	Light	Building Type
[106]	2012	MBPC	✓	✓	✓	×	×	Educational building, HVAC control and energy consumption reduction with acceptable thermal conditions
[107]	2022	IoT, LLVM-based ANN	✓	✓	✓	✓	×	Office building, dynamic ventilation control system with IoT for indoor comfort in a dynamic environment
[108]	2020	MPC, DRL	✓	✓	✓	×	×	Office building, to control the supply water temperature setpoint to terminal units of a heating system
[109]	2020	DL, AI_IDP combination	×	✓	✓	✓	×	Subway station, energy-efficient optimal ventilation operational policy for indoor comfort using 24 h predicted outdoor conditions
[110]	2022	MOGA	×	✓	✓	✓	×	Educational building, prediction of IEQ of a school building, integrated HVAC control for indoor condition optimization
[111]	2021	Fuzzy model	×	✓	✓	×	×	Educational building, sports complex of a university, indoor air quality control
[112]	2022	SVR, ML combined with engineering analysis	×	✓	✓	×	×	Office building, predictive intelligent indoor environmental control
[113]	2021	ANN- BR, LSTM, SL, IoT	✓	×	✓	×	×	Educational building, control of indoor conditions by collecting data, predicting comfort and forecasting CO_2 concentration
[114]	2019	ML plus automation	×	×	✓	×	✓	Office and residential building, framework for activity-driven and user-centered building automation to

Note: ✓ denotes inclusion and × exclusion.

Again, in 2020, Nam et al. [109] developed AI-based models to improve the efficiency of the ventilation system in a subway station. Using a DL and artificial intelligence iterative dynamic programming (AI-IDP) combination, the DL was used to predict the weather conditions of the influencing outdoors for 24 h ahead, while the AI-IDP was used to optimize the operations of the ventilation system for the same predicted period. They achieved an 8.68% improvement in efficiency, reducing CO_2 by 96 tons, and USD 4217 savings per year on operation costs. Cho et al. [110] also designed an optimal multi-objective genetic algorithm (MOGA) and an integrated ANN model for the enhancement of IEQ and HVAC controls by predicting the PMV, CO_2, PM_{10} and $PM_{2.5}$ in school buildings. The results showed high accuracy for the root mean square error (RMSE) between the predicted and observed data: PMV 0.2243, CO_2 0.8816, 0.4645 and 0.6646, respectively, for PM_{10} and $PM_{2.5}$, indicating good applicability for buildings' integrated controls. Omarov et al. [111] applied a fuzzy algorithm to intelligently optimize the control system for electric drive ventilation and an air-conditioning system for indoor CO_2 reduction. They applied the developed model to a sports complex at a university, and they obtained promising results, showing the developed fuzzy model was more effective than the traditional automatic control system. Qin et al. [112] suggested a novel approach by combining ML and engineering analysis to implement a predictive intelligent indoor environmental control. In this study, intelligent control was applied to the air-conditioning system to enhance thermal comfort and energy consumption. Their approach included modeling and simulating a built environment, and the result of the simulation would be used to guide the setup and placement of sensors for indoor environment parameter data collection. An SVR was then used as a predictive model using the collected data, while reinforcement learning was used to train an intelligent agent for the air-conditioning system's intelligent controls. This approach was evaluated in an office space with a 150 m^2 area. They reported low energy consumption as the method produced high accuracy and efficiency. Tagliabue et al. [113] presented research on the integration of data from sensors to optimize HVAC control systems in educational buildings. Their goal was to reduce the CO_2 concentration and improve comfort by defining opening and closing patterns to regulate the HVAC system, thereby improving IAQ. They trained ANN models with actual data monitored from the classroom; this will trigger ventilation rate control using an IoT protocol. The outcome showed reliable forecasting of the CO_2 concentration and the comfort level was improved by increasing the ventilation rate in the classroom. Ahmadi-Karvigh et al. [114] applied ML to enhance the adoption of automation, such that automation procedures in buildings can learn users' preferences in different conditions to control the building service system fully or partially.

4. Discussion

Five application areas for the use of AI, ML and IoT for energy management, energy efficiency and IEQ have been identified and critically analyzed. The use of AI techniques to address energy-related issues has been categorized into thermal comfort and IAQ control; energy management and energy consumption prediction; anomaly detection; predicting indoor temperature; and HVAC controls. All the application areas in buildings are closely interconnected and summarily mean reducing energy without compromising IEQ. The areas with more studies and the models and techniques used in each study have been highlighted in Tables 3–7. It is also important to note that most of these studies employed more than one model, and in many cases, compared several methods for the same application. The results show more articles on energy management and energy consumption prediction than in the other four areas, with the least applications in the areas of anomaly detection and predicting indoor temperatures. Studies focused on the use of AI for energy management and consumption prediction accounted for about 48% of the articles analyzed. The most used models were the ANN, SVM and SVR, together with IoT frameworks. It is hard to establish the most effective of these models as each study used different approaches, techniques and building types. Most of these studies focused on residential buildings and a few specifically on smart homes and green buildings. About 27% of the articles were on thermal comfort and IAQ control in buildings, and the most used methods or models were the ANN, RF and SVM in descending order. With more studies on educational buildings, residential buildings and office buildings follow, respectively. For HVAC controls, most articles focused on the different models and techniques, combining deep learning and other models with automation and the IoT. The bulk of these studies were for educational and office buildings. In the area of predicting indoor temperature, the ANN model was used in all the studies, while ref. [105] introduced MPC. In anomaly detection for building energy, deep learning and LSTM were the most used methods, covering residential, educational, and business building types. In all the application areas, the ANN was the most recurrent model used. Still, it is a challenge to identify the most suitable and effective model due to the varying techniques and standards used by the different authors. The areas of lighting/visual comfort and sound/acoustic comfort have hardly been explored in these studies.

4.1. Unexplored Area

Aside from the discussed application areas, there are other application areas in buildings where AI-based applications or techniques can be applied to enhance energy management and energy efficiency in buildings.

4.1.1. Lighting

Lighting can be natural or man-made. A crucial means of energy management in buildings is the reduction of energy consumption for lighting. This lighting load in buildings can be reduced by the optimization of natural lighting [115–118]. A few studies have explored the application of AI in building design for the optimization of natural light [119] or in the optimization of building controls to foster energy saving [120,121]. Only two authors highlighted applying AI/ML to the lighting system in buildings. Refs. [113,114] briefly discussed the application of AI-based techniques to lighting. There is a need for more research and studies in this area beyond the optimization of natural light as it is relatively unexplored.

4.1.2. Acoustic Comfort

Acoustic comfort is one of the IEQ parameters that is usually evaluated when undertaking IEQ assessment. To the best of the authors' knowledge, there are very few studies applying AI solutions to acoustic comfort that were not included in this study as they may not have met the search criteria. One study is a Ph.D. thesis that proposed "Intelligent Passive Room Acoustic Technology for Acoustic Comfort in New Zealand Classrooms" [122,123], which explored both intelligent passive room acoustic technology (IPRAT) and the integration of passive variable acoustic technology (PVAT) into acoustics in buildings. These studies are still progressive and require a lot of work in the coming years. Within this review, no literature was found to apply AI or ML techniques for improving acoustic comfort in buildings. It is also a challenge to make a direct link between sound, acoustic comfort, and energy management with the use of AI solutions beyond building design. This study [124] explored the impact of acoustics and the acoustics requirements of buildings on the energy efficiency protocols. More studies on the effects of building acoustics on energy efficiency are required, which will encourage further explorative work on the use of AI solutions in this area.

4.1.3. Real-Life Application

Many of the AI methods or algorithms used in these studies were developed using different criteria and their application was limited to specific use cases. This has created some challenges with adaptability to real-life scenarios. The "identified gaps" subsection highlights some of these challenges.

4.2. Identified Gaps

Although there have been a considerable number of studies on the use of AI in buildings to improve energy efficiency, energy management and IEQ, there are several gaps that have been identified in this study and previous studies as follows:

- Studies have highlighted that AI-based controls are not yet completely satisfactory, and a major contributor is a need for a large amount of high-quality real-world data, which are not readily available. More research is needed on the development of solutions that will require less data and are still able to produce accurate results.
- Very few studies have highlighted the importance of sensor positioning and the negative outcome of wrongly positioned sensors. IEQ studies should follow established methods and standards, which include accurately positioning sensors for optimal results. The use of AI tools without following established methods diminishes the reliability of the results obtained.
- There is a gap in the availability of sensor installation standards. Ref. [125] highlights the effects of the scarcity of sensor standards and positioning.

- Most studies only consider a few variables, especially in the case of thermal sensation, limiting the variables to just temperature and sometimes relative humidity. It is important for studies to adequately consider other variables influencing occupants' thermal sensations.
- The use of poorly produced and calibrated sensors will affect the results produced by AI and machine learning.
- The need for more real-world trials and pilot programs for AI methods to be implemented for both thermal comfort and energy consumption control with the dynamic interactions of occupants. Most models are trained and tested in simulated or control areas, which may not completely embody all the complex interactions in residential or office environments.
- As highlighted by [36], very few studies apply AI/ML methods for visual/lighting and acoustic comfort. These are important IEQ comfort parameters that need to be paid adequate attention.
- Privacy regulations on data collection. There is a need for clear data collection policies that protect occupants' privacy during continuous monitoring or continued use in buildings. Sensors that collect data with little or no disturbance of occupants' comfort need to be designed and developed.
- Most studies use different models, algorithms, and techniques with varying input data types. There is therefore no uniformity, making it impossible to apply the models in a differently featured built environment.
- There are a lot of models and algorithms available, which creates difficulty in selecting the best approach or model for specific problems.

To promote further research and deployment of AI/ML in buildings for energy and IEQ, standards and procedures have to be established. The authors suggest ethical considerations in the deployment of AI in buildings, which include data privacy of occupants, transparency of results and fairness [126,127]. Studies should be carried out on a broad spectrum without limitation to a specific location, race or gender to avoid both algorithm bias and result bias [128]. Finally, there should be governance, continuous monitoring and auditing [127]. AI/ML and IoT technologies have immense benefits in the built environment, but a lot of research and development is required to transform these tools into usable products. The limitations of this study include the exclusion of articles published outside of 2013 to 2023; the IEQ measuring procedures and standards applied in each article were not investigated; and the sensor selection process and placement were not thoroughly discussed. One of objectives of this study is to shed light on the existing challenges in the application of AI to real-life scenarios and the need for policy improvement to encourage more research.

5. Conclusions

Energy management, energy efficiency and IEQ are important factors to be considered when addressing energy consumption challenges in buildings and AI technologies are currently being explored to address these challenges. This article presents an extensive and comprehensive review of the various AI, ML and IoT methods in use and the techniques and approaches applied to address energy management, energy efficiency and IEQ challenges in buildings.

AI/ML techniques are data-driven and many times require large amounts of historical data to train and validate algorithms and models. The aim is for these models to be able to find patterns or generalize and make accurate predictions. The challenge of having reliable historic data to train and validate models has been highlighted by recent reviews and articles. Despite these challenges, AI and ML solutions are still being explored within five identified use areas: thermal comfort and IAQ control; energy management and energy consumption prediction; anomaly detection; indoor temperature prediction; and HVAC controls. Often, the AI/ML solutions do not address only one area, so a fuzzy logic or ANN model for thermal comfort or IAQ control also delivers an energy-saving potential. A multi-criteria optimization technique is used. For thermal comfort control, ANN, fuzzy logic and other ML techniques are commonly used to either predict PMV, the thermal behavior of occupants or balancing heating and cooling. For energy management and consumption prediction, hybrid models are often preferred, where a bidirectional gated recurrent unit (BDGRU) is optimized using a PSO algorithm to achieve better energy efficiency. Also, ANN and MLR algorithms are used to predict and monitor energy consumption. They are found to be very effective. Deep learning, ARIMA, LSTM and hybrid methods are also commonly used for anomaly detection and unusual energy consumption in buildings. This area of use requires more research, as only a few articles were found for this area. For indoor temperature and RH prediction, MPC, ANN or a combination of both models are used to forecast the daily mean temperature, and with good accuracy the heating and cooling consumption can be reduced. Many studies on HVAC controls show that MPC, DRL, MOGA, ANN, SVR, LSTM and fuzzy logic are the widely used models to optimize the operations of ventilation systems. With fast and accurate predictions, they optimize the air-change rate in the building for energy-saving opportunities.

One profound realization is that the most suitable AI/ML model for each application is yet to be identified, as each study applied different approaches and methods to address similar challenges. This further amplifies the challenge of adapting these solutions for real-life scenarios. Again, most studies considered a few variables in the area of improving thermal comfort. They limit the factors influencing thermal sensation to the generic temperature and relative humidity. This may lead to the wrong use of AI/ML tools, as incomplete or inaccurate parameters will only produce inaccurate and unreliable results.

Some limitations of this review article include the lack of adequate consideration of the selection process of sensors used: the type, quality, calibration, and sensitivity. The exclusion of articles published outside 2013 to 2023. Also, the non-in-depth discussion on the need for IEQ procedures, standards and guidelines in the monitoring and data collection process as outcomes may be questionable when the guidelines laid down are not followed.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16093627/s1. PRISMA 2020 Checklist.

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Appendix A

Table A1. List of studies for application areas.

Reference	Year	Application Area							
		Algorithm	Thermal Comfort	Energy Efficiency/ Management	Controls	Anomaly Detection	Forecasting/ Prediction	Lighting	Acoustic
[54]	2010	ANN	✓	✓	×	×	×	×	×
[55]	2011	Adaptive ANFIS, non-adaptive ANFIS, ANN	✓	✓	×	×	×	×	×
[56]	2013	ANN	✓	✓	×	×	×	×	×
[57]	2010	ANN, NNARX, NNARMAX, NNOE	✓	✓	×	×	×	×	×
[58]	2021	Deep Q-learning in RL	✓	✓	×	×	×	×	×
[59]	2020	MLP, RBF	✓	✓	×	×	×	×	×
[60]	2017	ANN, PMV	✓	✓	×	×	×	×	×
[61]	2019	RF	✓	✓	×	×	×	×	×
[62]	2019	RF, SVM	✓	✓	×	×	×	×	×
[63]	218	RF	✓	✓	×	×	×	×	×
[64]	2010	SVM	✓	✓	×	×	×	×	×
[65]	2016	SVM	✓	✓	×	×	×	×	×
[66]	2019	DRL	✓	✓	×	×	×	×	×
[67]	2016	ANN, TRNSYS	✓	✓	×	×	×	×	×
[68]	2022	NN of the radial base function	✓	✓	×	×	×	×	×
[69]	2019	Hybrid FA and GA	✓	✓	×	×	×	×	×
[70]	2009	Bilinear model-based predictive control	✓	✓	×	×	×	×	×
[71]	2021	convLSTM, BDGRU	×	✓	×	×	✓	×	×
[72]	2022	LSTM	×	✓	×	×	×	×	×
[73]	2019	IoT, cloud-based ML	×	✓	×	×	×	×	×
[74]	2021	AI and IoT	×	✓	×	×	×	×	×
[75]	2022	PSO and BPNN (optimized and non-optimized)	×	✓	×	×	×	×	×
[76]	2022	IoT and AI-based framework	×	✓	×	×	×	×	×
[77]	2019	AI-based MPC	×	✓	×	×	✓	×	×
[78]	2021	ML	×	✓	×	×	✓	×	×
[79]	2023	T2-FWNN	×	✓	×	×	✓	×	×
[80]	2022	LR, SVM, FR and ANN	×	✓	×	×	✓	×	×
[81]	2022	MLR, ANN	×	✓	×	×	✓	×	×
[82]	2016	MLP, RBF and SVM	×	✓	×	×	×	×	×
[83]	2019	ANN, SVM, HyFIS and WM, GFS.FR.MOGUL	×	✓	×	×	✓	×	×
[84]	2021	ANN, MOPSO, BPO	×	✓	×	×	×	×	×
[85]	2017	GBRT, ML (RF, extra-tree)	×	✓	×	×	×	×	×
[86]	2021	ANN	×	✓	×	×	✓	×	×
[87]	2019	SVR	×		×	×	✓	×	×
[88]	2015	LSSVM, DSORCGA, RCGA	×	✓	×	×	✓	×	×
[89]	2018	ANN, GA, MPC	×	✓	×	×	×	×	×
[90]	2023	AI	×	✓	×	×	×	×	×
[91]	2020	RF, M5P, RT	×	✓	×	×	✓	×	×
[92]	2019	Optimized ANN, TRNSYS	×	✓	×	×	✓	×	×
[93]	2017	ANN	×	✓	×	×	×	×	×
[94]	2019	ANN	×	✓	×	×	✓	×	×
[95]	2019	ML(tree-based, lazy learning), MLP, SVR	×	✓	×	×	✓	×	×
[96]	2021	AANN, SVR	×	✓	×	×	✓	×	×

Table A1. *Cont.*

Reference	Year	Application Area							
		Algorithm	Thermal Comfort	Energy Efficiency/ Management	Controls	Anomaly Detection	Forecasting/ Prediction	Lighting	Acoustic
[97]	2018	FL, IoT	✕	✓	✕	✕	✕	✕	✕
[98]	2021	Elitist NSGA II, SVR	✕	✓	✕	✕	✕	✕	✕
[99]	2021	Gradient boosting and SVM	✕	✓	✕	✕	✓	✕	✕
[100]	2018	DL (RNN), ARIMA, LSTM, Hybrid of ARIMA and LSTM	✕	✕	✕	✓	✓	✕	✕
[101]	2020	LSTM	✕	✕	✕	✓	✓	✕	✕
[102]	2020	DNN	✕	✕	✕	✓	✕	✕	✕
[103]	2012	ANN	✕	✓	✕	✕	✓	✕	✕
[104]	2016	ANN	✕	✓	✕	✕	✓	✕	✕
[105]	2019	MPC, ANN	✕	✓	✕	✕	✓	✕	✕
[106]	2012	MBPC	✓	✓	✓	✕	✕	✕	✕
[107]	2022	IoT, LLVM-based ANN	✓	✓	✓	✕	✓	✕	✕
[108]	2020	MPC, DRL	✕	✓	✓	✕	✕	✕	✕
[109]	2020	DL, AI_IDP combination	✕	✓	✓	✕	✓	✕	✕
[110]	2022	MOGA	✕	✓	✓	✕	✓	✕	✕
[111]	2021	Fuzzy model	✕	✓	✓	✕	✕	✕	✕
[112]	2022	SVR, ML combined with engineering analysis	✕	✓	✓	✕	✕	✕	✕
[113]	2021	ANN- BR, LSTM, SL and IoT	✓	✕	✓	✕	✕	✕	✕
[114]	2019	ML plus automation	✕	✕	✓	✕	✕	✓	✕

Note: ✓ denotes inclusion and ✕ exclusion.

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