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Review

AI-Driven Innovations in Building Energy Management Systems: A Review of Potential Applications and Energy Savings

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Abstract: Despite the tightening of energy performance standards for buildings in various countries and the increased use of efficient and renewable energy technologies, it is clear that the sector needs to change more rapidly to meet the Net Zero Emissions (NZE) scenario by 2050. One of the problems that have been analyzed intensively in recent years is that buildings in operation use much more energy than they were designed to. This problem, known as the energy performance gap, is found in many countries and buildings and is often attributed to the poor management of building energy systems. The application of Artificial Intelligence (AI) to Building Energy Management Systems (BEMS) has untapped potential to address this problem and lead to more sustainable buildings. This paper reviews different AI-based models that have been proposed for different applications and different buildings with the intention to reduce energy consumption. It compares the performance of the different AI-based models evaluated in the reviewed papers by presenting the accuracy and error rates of model performance and identifies where the greatest potential for energy savings could be achieved, and to what extent. The review showed that offices have the greatest potential for energy savings (up to 37%) when they employ AI models for HVAC control and optimization. In residential and educational buildings, the lower intelligence of the existing BEMS results in smaller energy savings (up to 23% and 21%, respectively).

Keywords: artificial intelligence; buildings; energy efficiency; saving potential; HVAC; BEMS

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1. Introduction

The operation of buildings accounts for 30% of global final energy consumption and 26% of global energy-related emissions [1], and this sector has remained a priority for sustainable development for decades. Although minimum performance standards and building energy codes are becoming more comprehensive and stringent across countries, and the use of efficient and renewable building technologies is increasing, the IEA reports that energy consumption in the buildings sector is still an issue, as global growth in floor space is more than offsetting the increased efficiency and decarbonization efforts [1]. In addition, there is plenty of evidence that even new buildings do not perform as well as they were designed to (a problem called the Energy Performance Gap), which is presented in detail in the recent review of Bai et al. [2]. It is obvious that the sector needs faster change to get on track towards the Net Zero Emissions (NZE) scenario by 2050.

The European Union's (EU) increased climate and energy ambition requires all new buildings to be zero-emission by 2030 and existing buildings to be zero-emission by 2050. The recent recast of the EPBD [3] pays more attention to the energy efficiency of existing buildings, as 75% of EU buildings are still energy-inefficient. New policy measures emphasize the importance of digitalization, monitoring, building automation and smartness (IoT), data collection, and sharing, which can be listed as follows:

- Deployment of High-Capacity Communication Networks: to facilitate smart homes and well-connected communities.
- Targeted Incentives: to promote smart-ready systems and digital solutions in the built environment.
- Use of Digital Technologies: for the analysis, simulation, and management of buildings.
- Smart-Readiness Indicator: to measure the capacity of buildings, to use information and communication technologies and electronic systems, and to adapt their operation to the needs of occupants and the grid.
- Building Automation and Electronic Monitoring: to improve the energy efficiency and overall performance of buildings and to provide confidence to occupants about actual savings.
- National Databases for Energy Performance: to collect data on the energy performance of buildings and transfer this information to the EU Building Stock Observatory.

All these tools and technologies are familiar to scientists and pioneers in the building sector. However, regulating them will significantly speed up their practical application. This includes artificial intelligence, which, while not explicitly mentioned, is inherently connected to the aforementioned areas.

The practical use of IoT and AI in building systems management is still in its early stages, but the future is exceedingly promising. Some believe that facilities management could be the industry to gain the most from AI in the coming years, particularly due to the high volume of repetitive and time-consuming tasks. With the AI-powered management of buildings, better energy efficiency is expected first and foremost, accompanied by additional benefits, such as lower overall maintenance costs, better contractor relationships, and enhanced asset reliability.

The IEA estimates that digitalization could cut total energy use in residential and commercial buildings by around 10% by 2040 [4]. But what contribution and potential does the application of AI offer, bearing in mind that not all buildings can benefit from sophisticated control due to the low level of intelligence of their systems? Which buildings have the highest energy-saving potential, and what AI models demonstrate the highest performance? The answers to these questions will be further provided in this review.

1.1. AI Applications

AI has rapidly permeated many aspects of our lives and has revolutionized industries and enhanced efficiency in various domains, such as healthcare, education, manufacturing, finance, and transportation. Additionally, AI has emerged as a powerful tool for achieving sustainability in the building sector. Its technologies and methodologies have demonstrated great potential in increasing energy efficiency and reducing costs [5]. In the context of BEMS (Building Energy Management Systems), AI has been applied in predicting and forecasting a building's energy consumption, providing occupant behavior insights, achieving thermal comfort, improving indoor air quality, as well as enhancing maintenance and operational efficiency [6]; on top of that, other applications can be found, as presented in several review papers [7–9]. The difference is not just in the application but also in the models that are employed.

AI is a broad field that aims to create systems capable of performing tasks that require human intelligence. The field of AI encompasses a wide range of domains and includes learning as well as non-learning methods, such as robotics, natural language processing, autonomous systems, and expert systems. Different AI models are designed to perceive, analyze, learn, reason, find patterns, and make decisions and predictions based on the information and data provided [5]. They could be generally categorized into different types, each serving different uses and objectives and employing various techniques. One such technique is Machine Learning (ML). ML is a field of study within AI that focuses on developing algorithms that enable computers to learn from data and improve their performance over time. While all ML is part of AI, not all AI equals ML. AI is the broader concept of intelligent machines, whereas ML is a specific approach within AI that focuses on learning from data [10]. ML has been recently gaining popularity due to its ease of use, wide applicability, continuous learning, abundant and cheap computation, and the fact that ML-based models do not require human intervention [11]. The most popular ML algorithms are broadly divided into three categories: supervised, unsupervised, and reinforcement learning. Supervised learning is further categorized into classification and regression. Classification techniques include Naive Bayes classifiers, decision trees, support vector machines, random forests, and K-nearest neighbors, whereas regression methods include linear regression, neural network regression, decision tree regression, lasso regression, and ridge regression. Unsupervised learning focuses on clustering techniques like K-means clustering, mean shift clustering, and Gaussian mixtures. On the other hand, reinforcement learning involves models such as Q-learning, R-learning, and temporal difference learning. Each of these approaches has specific applications and strengths, contributing to the diverse capabilities of machine learning in solving real-world problems [12,13]. ML is prominent and extensively applied in BEMS. A wide range of studies applying ML models have been discussed in this paper. Therefore, in addition to "Artificial Intelligence", "Machine Learning" has been included in the list of keywords to capture as many relevant studies as possible.

Different review papers were analyzed and compared in this paper to find what is still not identified regarding the application of AI for the improvement of buildings' energy efficiency. They are presented below.

1.2. Related Reviews

Using the keyword string mentioned in the "Methodology" section in the search engine "SCOPUS", as of 30 April 2022, with only review papers included, the number of review papers after the title and abstract screening was 54. The number of review papers in the field has been growing, reflecting a growing interest among researchers in this study area (Figure 1).

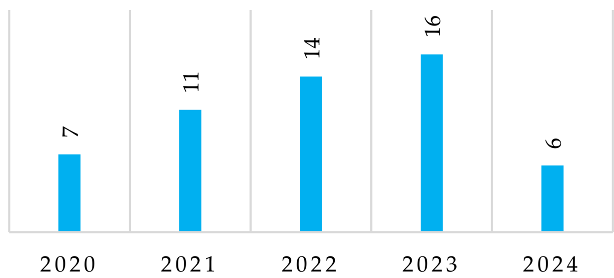

Figure 1. Number of Review Papers relevant in recent years [SCOPUS].

The following paragraphs discuss just the review papers selected. The papers were selected based on their topics being relatively similar to this review paper and having conclusions that are relevant to the scope covered.

Reviews on energy consumption behavior and prediction. Wu et al.'s [14] review aimed to analyze energy consumption behavior and assess the prediction performance and interpretability of ML-based baseline modeling techniques across various major building types. The authors identified the key factors influencing the performance of energy baseline modeling for different buildings and investigated and compared building profiles to further explain the differences in baseline modeling results [14]. Moghimi et al. [15] reviewed ML methods applied to improve building energy consumption in modern building data processing, focusing on their accuracy and efficiency, and found that hybrid ML models predict energy consumption with an accuracy up to 15% higher compared to that of single ML models. Farzaneh et al. [9] provided an in-depth review of recent studies on the application of AI technologies in smart buildings through the concept of the building management system and demand response programs. In their research paper, they mentioned some future directions and recommendations, like the need to improve prediction methods that consider building characteristics and environmental conditions, develop standardized protocols and policies as guidance for AI technology implementation, and address the security and privacy concerns associated with the data collected [9].

Thermal comfort and energy efficiency. Merabet et al. [16] discussed the application of AI and focused mainly on improving thermal comfort and energy efficiency in building control systems. They concluded that AI technology's application in building control shows great promise but remains an ongoing challenge, as the performance of AI-based control systems is not yet entirely satisfactory, mainly because these algorithms require substantial amounts of high-quality real-world data, which are often lacking in the building energy sector. From 1993 to 2020, AI techniques and personalized comfort models have demonstrated average energy savings between 21.81% and 44.36%, with comfort improvements ranging from 21.67% to 85.77% [16]. A review by Ghahramani et al. [8] emphasizes the necessity of a cohesive system comprising sensors, infrastructure, learning algorithms, and actuators governed by a central intelligent system to improve comfort and energy efficiency. The paper concludes that improvements in all aspects of a smart system are needed to achieve a better determination of the correct combination of systems to increase the system's overall efficiency and improve comfort [8].

The IoT and AI for building energy control. A review paper by Broday et al. [7] examines how the IoT is being used in building control to save energy and monitor indoor environmental quality. Their findings show that the main application of the IoT in buildings is to reduce energy consumption and that ML methods are mainly used to save energy and understand occupant behaviour to achieve thermal comfort [7]. A review by Sayed et al. [17] explores various DL models like CNNs, RNNs, LSTMs, GANs, and autoencoders and their advantages and limitations in occupancy detection, where the authors concluded that several directions are provided to reduce privacy problems by employing forthcoming technologies such as edge devices, Federated Learning, and blockchain-based IoT [17].

Reviews on models and their reliability. Bashir et al. [18] discuss the various models used for predicting the cooling and heating loads in smart buildings and the role of accurate load prediction in enhancing energy efficiency by including a detailed analysis of AI algorithms, such as ANN, SVM, and DL, presenting their advantages and limitations in load forecasting. The review shows that AI-based models achieve higher accuracy but often require extensive data and computational resources [18]. A review by Rodrigues et al. [19] systematically analyzes various modeling techniques for STLF in the residential sector over the past decade, identifying various modeling techniques and associated algorithms. Additionally, the paper discusses AI models' advantages in handling nonlinear problems and the necessity of adequate historical data for optimal performance [19]. Runge et al. [20] discuss the application of DL models in predicting energy consumption in buildings, where their key findings reveal that DL models, such as RNNs, CNNs, and DBNs, offer better performance in handling large datasets and extracting features compared to the traditional methods.

Model performance, challenges, and future directions. According to a review by Mohgimi et al. [15], DL models such as DNN and LSTM have shown high accuracy in predicting energy consumption and managing building systems. However, despite their accuracy, these models demand significant computational resources and extended training times. These models are evaluated based on their effectiveness in reducing energy consumption and operational costs, particularly in smart building applications [15]. A review by Runge et al. [20] discussed that white-box models use detailed physical equations to represent energy systems, offering deep insights into system dynamics but requiring extensive parameter measurements. Data-driven models, including black-box and grey-box types, rely on data to establish mathematical relationships without detailed system knowledge, making them easier to implement but often less interpretable. Performance-wise, deep learning models like RNNs and DNNs excel in accuracy with large datasets but demand significant computational resources [20].

A review by Mousavi et al. [21] identified some challenges, such as the difficulty in understanding the reasoning behind the model's decisions because most AI-based predictive models are black-box by nature. The review also pointed out the limitations of supervised learning, stating that the building industry relies heavily on supervised learning methods, which require labeled data, and that alternative learning methods, such as semi-supervised learning or reinforcement learning, could eliminate this issue [21]. In the context of short-term household forecasting, Ma et al. [22] stated the importance of enhancing the generalization ability of DL models, as they are prone to overfitting. Household forecasting involves many uncertain factors, and integrating these uncertainties into DL models is a challenging problem [22]. Shaqour et al. [23] provided a review of the recent advancements in DRL-based BEMS for different building types. The authors observed that residential and office buildings were the most explored types of buildings. There is still a clear gap in real implementations and system validations, where only 11% of the recent works have been reported so far. The authors suggested that future research should focus on the data efficiency of DRL models due to the lack of real-world validations. This could be accomplished by using virtual building systems for offline pretraining and exploring methods for reducing the requirement for large amounts of data [23].

Based on other reviews, it can be concluded that when AI models are used in predictions, the building type matters. Also, in their reviews, different authors demonstrated that models used in predictions provide different reliabilities in different situations, and many authors discuss issues related to the quality, reliability, and amount of data. Also, different authors agree that in real-life applications, the ability to integrate AI-based models into controllers is still in its infancy and is limited.

This review paper aims to present AI's contributions to BEMS, identify which types of buildings, varying in their level of intelligence, have the highest energy-saving potential, and determine which AI models perform the best in this area by estimating the overall efficiency.

To identify the added value of the paper, it was compared to the outcomes of the three most similar review papers: Ardabili et al. [24], Yan et al. [25], and Tien et al. [26]. The reviews by Ardabili et al. [24] and Yan et al. [25] both share a similar scope with our work. They explore various AI models applied to building applications such as energy consumption prediction, load forecasting, occupant detection, and optimization. Ardabili et al.'s paper also discussed the evaluation criteria [24,25]. Meanwhile, the review by Tien et al. [26] also closely aligns with our work. However, compared to these reviews, the added value of our paper is (1) our review stands out by providing detailed numerical values and discussing the different building types where these AI models have been applied, which were not covered in either Ardabili et al. [24] or Yan et al.'s [25] reviews; (2) our review stands out in its distinct structure of application areas, its inclusion of study locations, and its more in-depth discussion of evaluation metrics compared to Tien et al.'s review paper [26].

2. Methodology

The methodology implemented in this review paper is the Systematic Literature Review (SLR). This methodology comprises the following steps: formation of the research question(s), validation of keywords, setting eligibility and inclusion criteria, systematic search, screening and exclusion criteria, and analysis and synthesis [27]. To ensure transparency, the review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines and checklists.

The search process aims to find relevant studies based on the research question, defined based on the article's objective. The research question was formulated following the widely known PICO method, which covers four elements of a search question: Population (Who?), Intervention (What?), Comparison (Compared to what?), and Outcome (What are you trying to accomplish/improve?) [27]. The questions for outlining PICO components are presented in Table 1.

Table 1. Questions for outlining PICO components.

P	I	C	O
Population	Intervention/ factors	Comparison/ Circumstances	Outcome
Buildings	Various AI models and their reliability	Compare the reliability/accuracy and error rate of AI models used to achieve energy efficiency in buildings	Efficiency and potential savings achieved by AI-based models and their contribution to enhancing BEMS for energy efficiency

The research question of this review is formulated as follows: What AI models are employed in BEMS, and how do they contribute to energy savings?

Search Strategy

The initial keywords have been defined as follows: Artificial Intelligence, Buildings, Energy, HVAC, Control, Optimization, Forecasting, and Occupancy Detection. The keyword string used in the search engines is shown in Figure 2.

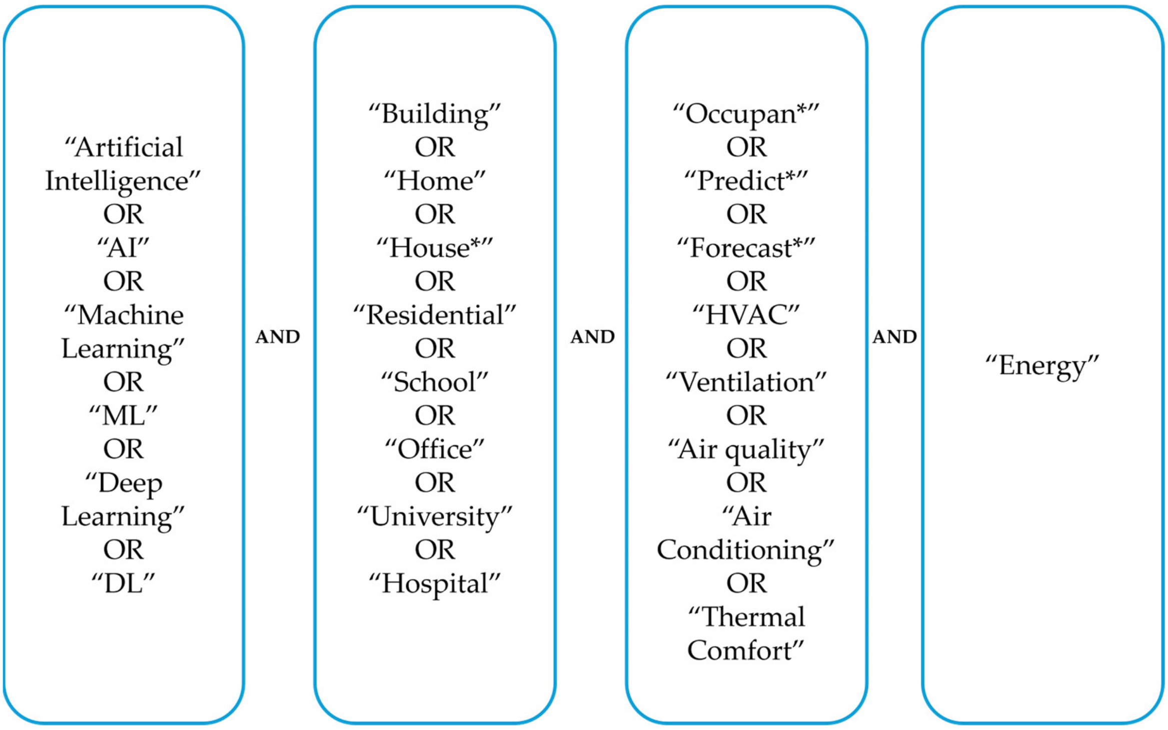

Figure 2. Keywords string.

The search engines "SCOPUS" and "Web of Science" were explored on 30 April 2024.

The inclusion criteria for the selected publications and the keyword search string are as follows:

- Recent publication: publications not older than five years (2019–2024).
- Language: any.
- Publication type: journal articles, conference papers, and books.
- Geographic coverage: worldwide.

The selection criteria have been implemented in the selection process to determine which papers to include in the analysis, as presented in Figure 3. It illustrates the exclusion criteria for studies in the research selection process. The initial step checks if the study includes all the necessary information (title, author, abstract). If it does, the next criterion ensures the study is recent (published within the last 5 years). The third step verifies that the study is not a review paper, as review papers are discussed separately in the *Introduction*. Following this, the study must not cover renewable energy systems, as including them would broaden the scope and slightly divest from the core subject of this paper, which is AI for energy management and optimization in buildings, without necessarily altering the primary energy sources of these buildings. Additionally, both areas present distinct challenges. Energy management for energy efficiency mainly deals with challenges related to occupant behavior, load control, and reducing consumption using intelligent systems. By contrast, renewables involve storage and grid compatibility challenges, which are out of this review's scope. Therefore, limiting this review to non-renewables ensures a more explicit comparative analysis of the AI models specifically designed for energy management systems and a clearer comparison of error metrics and performance measures. Then, the study should include a developed AI model. Finally, the study must provide performance reliability, savings, error metrics, or similar measures for the AI model. If all these criteria are met, the study is included; otherwise, it is excluded at the corresponding step.

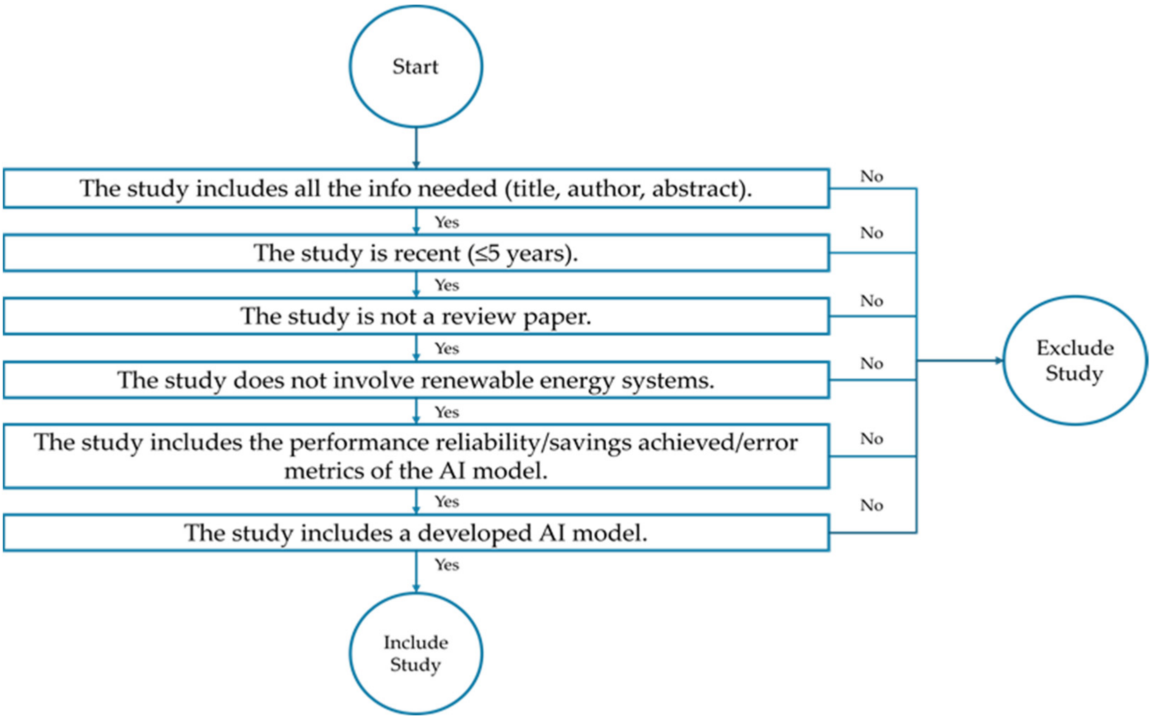

Figure 3. Paper selection criteria.

A PRISMA chart is a flow diagram used to present the different stages of the selection process in systematic reviews. It helps visualize the number of studies identified, screened, and included in the review [28]. The PRISMA chart ensures transparency in reporting and explains how the final set of studies was determined [28]. As can be seen from the PRISMA chart (Figure 4), 1396 records were initially identified through a SCOPUS database search, and 414 were identified through Web of Science. After eliminating duplicates, 1615 records remained. A total of 419 records were screened based on their title and abstract, resulting in the exclusion of 1196 records. Finally, 148 full-text articles were assessed for eligibility, and 271 were excluded for not meeting the selection criteria.

The papers selected are systemized and analyzed from different perspectives in a bid to find the answers to the raised research question.

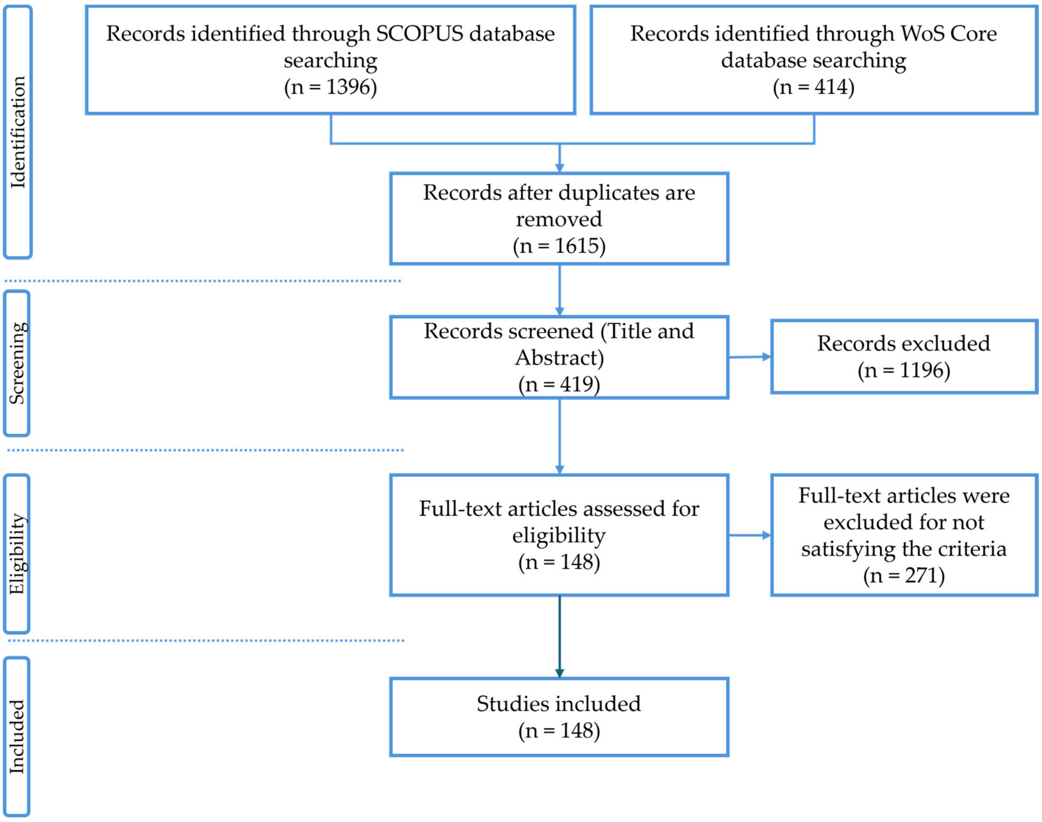

Figure 4. PRISMA Chart.

3. Results

The following subchapters compare a wide range of AI models used for various applications, such as energy consumption forecasting, load forecasting, HVAC control and optimization, and occupant detection, in different types of residential and non-residential buildings. Key performance metrics like RMSE, MSE, MAE, MAPE, and R^2 (coefficient of determination) are provided. These metrics are crucial for evaluating the accuracy and effectiveness of these AI models, as well as potential energy and cost savings, demonstrating their practical benefits in real-world applications.

- RMSE is a widely used metric for measuring the differences between values predicted by a model and values that are observed. It is sensitive to large errors, providing a clear picture of the model's performance [29]. RMSE is expressed in the same units as the dependent variable (e.g., kWh or kWh/m^2 for energy consumption). It can also be expressed in many other units across different fields, including temperature in °C (Celsius), °F (Fahrenheit), or K (Kelvin), pressure in Pa (Pascals) or bars, and concentration in ppm (parts per million) or µg/m^3 (micrograms per cubic meter) [29].
- MSE is similar to RMSE but does not involve taking square roots. It averages the squares of the errors, emphasizing larger errors more than smaller ones. MSE measures the average magnitude of errors in a set of predictions without considering their direction. It provides a straightforward interpretation of error magnitude [29]. It is expressed in squared units of the dependent variable (e.g., (kWh)^2 or (kWh/m^2) as well as many other units in different fields [29].
- MAPE expresses accuracy as a percentage, making it unit-free [30]. It is useful for comparing model performance across different buildings or energy systems with varying energy consumption scales and communicating results to non-technical stakeholders, as percentages are easily understood [30].
- R^2 indicates how well the model's predictions match the actual data, with values closer to 1.0 indicating a better pair [31]. R^2 allows for an easy comparison between

different AI models. By comparing R^2 values of models with different input features, researchers can assess which building characteristics or environmental factors have the most significant impact on energy consumption predictions [31].

When choosing error metrics, it is crucial to consider the designed model's specific objectives, the data's characteristics, and the target audience for the results. RMSE and MSE metrics are scale-dependent, where their values are influenced by the scale of the target variable. This can make comparing models across different buildings or energy systems with varying energy consumption scales challenging. In practice, RMSE and MSE are often used with metrics like MAPE and R^2 to evaluate AI model performance in building energy efficiency applications better [32]. Employing multiple metrics offers a more thorough evaluation of model performance and aids in identifying potential limitations or areas for improvement in AI-based building energy efficiency models [32].

3.1. Energy Consumption Forecasting

AI is widely applied to forecast energy consumption, and different methods are used in the literature for that purpose. Table A1 in Appendix A presents a variety of AI models that can be applied and assigned to different categories based on their underlying algorithms and techniques. These models fall broadly into traditional machine learning, deep learning, and hybrid models.

ML models and reliability. Traditional ML models include algorithms like SVR, Decision Trees, and ensemble methods like Random Forests and Gradient Boosting. For example, in reference [33], linear regression, ANN, and regression trees are used in commercial buildings. Reference [34] also includes models like ANN, SVM, and DNN applied in a residential building. These models are often more straightforward and require less computational power than other DL models, making them suitable for smaller datasets and less complex prediction tasks [35].

Deep learning models, a subset of ML, involve neural networks with multiple layers that can capture complex patterns in data [11]. Notable examples in the table include CNN and LSTM. Reference [36] mentions an LSTM neural network used in an educational facility, while reference [37] applies asymmetric encoder–decoder DL algorithms. DL models, such as those listed in references [38,39], are effective for handling large datasets, making them ideal for accurate energy consumption predictions, with the RMSE ranging between 0.07 and 0.09 and the R^2 amounting to 0.90, respectively.

Hybrid models combine traditional ML and DL elements to exploit both approaches' strengths. These models often integrate various techniques to improve prediction accuracy and robustness. The model in reference [40] combines ANFIS and GDFA applied to an educational facility. Similarly, the study in reference [41] implemented a hybrid CNN with LSTM AE used in a commercial building. By combining different methods, these models can capture both linear and non-linear relationships in the data, providing a comprehensive solution for energy prediction tasks and better accuracy, where nMAE = 0.168 and R = 95.09% in reference [40], and MSE = 0.19, MAE = 0.31, and RMSE = 0.47 in reference [41].

Building types. Table A1 in Appendix A shows a variety of buildings. However, residential buildings are the most common building type studied, with numerous studies applying AI models like LSTM, DRNN, and various ensemble models, where some studies achieve RMSE values as low as 0.1183 [42] and MAPE improvements of up to 0.54% [43]. Educational facilities are also prominently featured, employing models like LSTM, DNN, and hybrid methods [36,44,45]. Office buildings are popular as well, with models showing notable accuracy improvements, with MAPE values as low as 4.97% [46]. Although less common than residential and educational types, commercial buildings receive attention with models like DNN and DF [39,47]. Manufacturing facilities are studied less frequently. Lastly, mosques represent a unique category with fewer studies. To summarize, residential buildings dominate the research landscape, followed by educational and office buildings, while manufacturing facilities and mosques are studied less frequently.

3.2. Load Forecasting

Energy load forecasting plays a pivotal role in efficient energy management. It contributes to the optimization of energy production, distribution, and consumption. Accurate energy load forecasts help in the reduction in operational costs and the improvement of reliability [48].

AI models. AI is also used to forecast energy loads across different building types. Table A2 in Appendix A showcases an overview of various AI models used in studies, such as ensemble models combining ML algorithms, ANN, and DT in reference [48], as well as LSTM, GRUs, and Bi-directional LSTM applied in references [49,50]. Additionally, hybrid models, such as the ones presented in references [51–53], which combine XGBoost with LSTM or CEEMDAN with Bi-LSTM, are also applied to enhance the performance of the models in forecasting energy loads. Bio-inspired algorithms, used in references [54,55], have also been applied in the research area. Traditional ML algorithms like RF and Gaussian Radial Basis Function Kernel Support Vector Regression, used in references [32,56], demonstrate their relevance in energy load forecasting.

Reliability and performance. The performance metrics across the studies vary, reflecting the diverse approaches to evaluating model efficacy. MAPE has been frequently applied, with values ranging from 0.07% in reference [57] to around 35.9% in reference [58]. This indicates a significant variation in model performance. RMSE is another common metric reported in several studies ranging from 0.01 [59] to over 100 kW [60].

R^2 was used in references [32,52,61] with values above 0.9, suggesting high model reliability. As presented in reference [62], some studies also employ specialized metrics, such as accuracy improvement percentages, to highlight specific advantages of their approaches.

Building types. The types of buildings examined in these studies are diverse. Many references, including [48,50,51,54], focus on residential buildings, highlighting the high demand for efficient energy management in this sector. Educational facilities are also examined often, as shown in references [49,62–64], exploring models applied in schools and universities. Studies in references [32,58] address commercial and office buildings. Hotels, public buildings, and hospitals are also included, as seen in references [52,65–67], demonstrating the adaptability of AI models to diverse building types.

3.3. HVAC Control and Optimization

The control of HVAC systems is critical for maintaining indoor comfort and regulating temperature, humidity, and air quality in buildings while minimizing energy consumption [68]. Optimizing these systems can significantly reduce energy usage and operational costs, contributing to environmental sustainability [69]. Integrating AI models in HVAC control presents a promising advancement, allowing for more precise and adaptive energy management [68].

AI models. Table A3 in Appendix A presents various studies that have utilized different AI models for HVAC and their reliability across different building types.

The studies feature many AI models in references [68,70–75], such as LSTM, DRL, FIS, AMADRL, YOLOv5, SVM, RF, and DNN Bilinear Koopman Predictor. This variety illustrates the potential of AI in enhancing HVAC system efficiency, with each model bringing distinct advantages.

Reliability and performance. The performance of these models is evaluated using multiple metrics, including RMSE, MSE, and energy savings percentages. In reference [70], LSTM and DRL achieved an MSE of 0.0015 and energy savings from 27% to 30%. Shallow ANN models in reference [76] demonstrated improvements in energy consumption and thermal comfort, with heating energy consumption reductions ranging from 0.6% to 29% and thermal comfort improvements of up to 58.8%. YOLOv5 in reference [73] achieved an accuracy of 88.1%, while the ensemble approach in reference [74] demonstrated reductions in natural gas consumption (22.2%) and building heating demand (4.3%), with an RMSE value of 32.1 kW.

Building types. The studies cover a range of building types. Educational facilities are prominently featured, with models like Shallow ANN [76], ANN [77], YOLOv5 [73], and the ensemble approach [74] showing energy and thermal comfort improvements. Models like DRL [78] and DQN [79] have been applied to residential buildings, enhancing PM2.5 levels and overall energy consumption.

AI models applied in offices also showed promising results, as presented in references [80,81]. Additionally, specialized buildings such as sports halls [82] and churches [71] were considered, demonstrating the versatility of AI applications in different building environments.

3.4. Occupant Detection

Occupant detection contributes to reducing energy consumption in buildings. Various technologies are used to identify and detect people's presence, number, and activities in a building. This information is important in optimizing building energy management systems by ensuring that resources are used efficiently [83].

AI models. Table A4 in Appendix A presents various AI models applied for occupant detection across different types of buildings, such as CNNs, DMFF, YOLO, LTSM networks [83–86], and other advanced machine learning techniques like 1D CNN and RL [87], as well as traditional methods like MLR [88]. Each model demonstrates certain strengths in terms of accuracy and performance.

Reliability and performance. The performance of these models is evaluated using different metrics, such as accuracy, RMSE, MAE, MAPE, NRMSE, and correlation coefficients. Metrics specific to occupant detection have also been used, like thermal comfort improvement and CO_2 levels. Accuracy is the most common across the studies, where the DMFF model [84] achieves a high accuracy of 97%, while Faster R-CNN variants achieve accuracies between 78.39% and 98.9% [89,90]. Energy savings is also an important metric highlighting AI models' potential benefits. YOLOv5, for example, shows annual HVAC and lighting energy savings of 10.2% [85], while DMFF reports up to 30% energy savings [84]. RMSE, MAE, and MAPE are used to measure prediction errors. The YOLOv4 model in office settings has an RMSE of 0.883 and an NRMSE of 0.141, indicating high precision in maintaining indoor CO_2 levels [91]. The GA-LSTM and PSO-LSTM models exhibit high correlation coefficients (99.16–99.97%), indicating strong predictive capabilities [86].

Building types. The models presented in the studies have been applied across different building types, including residential, office, and educational facilities. A range of models, including CNN, YOLOv5, Faster R-CNN, and LM-BP, have been employed in offices [83,90,92,93]. In educational buildings, Faster R-CNN demonstrates high people-counting accuracy of 98.9% and activity detection of 88.5% [94].

3.5. Other Areas of Application

Table A5 in Appendix A presents various studies implementing AI models in different applications in buildings, such as thermal comfort prediction, air quality prediction, and indoor temperature prediction. The discussion below addresses the AI models utilized, the performance metrics reported, and the types of buildings considered in these studies.

AI models. The studies employ a wide array of AI models, such as ANN and SVM, which are used for their robustness in handling non-linear relationships in the study [95] for thermal comfort prediction. LTSM and RNN, suitable for time-series predictions, are applied in the study [96]. Hybrid models combining multiple techniques are also utilized, such as CNN-GRU-MLP [97] and FL-BM-ANFIS-BM [98]. Models such as Radial Basis Function Networks [99] and GNN [100] were applied for different prediction tasks.

Reliability and performance. The studies in Table A5 in Appendix A report a variety of metrics that are crucial for evaluating AI models. High R^2 values, such as 0.976 and 0.981 in reference [97], demonstrate excellent model performance. Reference [101] reports an MSE of 0.04, indicating high precision in temperature prediction. RMSE measures prediction error magnitude, with values like 0.705 in reference [97] indicating reliable performance.

PPD reflects the practical impact of the model, such as a 43.7% cooling load reduction in reference [98].

Building types. AI models' effectiveness varies across building types due to varying environmental conditions and usage patterns. According to Table A5 in Appendix A, residential buildings focus on thermal comfort and air quality. Reference [95] employs ANN and SVM for thermal comfort prediction, achieving an MSE of 0.8179, and reference [96] uses 1D-CNN, RNN, and LSTM for air quality prediction, reporting an RMSE of 10 ppm. Indoor temperature and air quality are important for occupant productivity in offices; reference [102] uses CNN-LSTM, achieving an R^2 of 0.936 and 50% energy savings, and GNN models, used in reference [100], improve thermal comfort by up to 81.3%. Models like FL-BM and ANFIS-BM [98] in educational facilities report significant improvements in thermal comfort and cooling load reduction. The MLP model [103] also achieves errors as low as 0.069 for temperature predictions.

4. Discussion

The main aim of this study was to determine what AI models are used in BEMS and how they contribute to energy savings. Tables A1–A5 show a wide range of different AI models and combinations of multiple AI models applied to enhance and optimize building energy efficiency. The reliability metrics of the AI models prove that AI-driven tools play a significant role in improving building energy management.

Reliability is the model's ability to predict parameters that control the system. In Tables A1–A5, different indicators are used to measure the reliability, such as the Root Mean Square Error (RMSE), R^2, and Mean Square Error (MSE), the performance of the AI models, and their impact on energy savings, cost reductions, and thermal comfort improvements.

An analysis of papers on AI models used in BEMS shows that the most commonly applied topics include the following focus areas: error rate, energy savings, accuracy, performance, and cost reduction. Figure 5 shows the different criteria papers used to evaluate the reliability of AI models. The predominant metric is the error rate, accounting for 63.3% of the evaluations. This indicates a strong emphasis on minimizing errors to enhance the reliability of AI models. Although, at 16.5%, energy savings is the next most significant factor, it is still relatively low, especially when the study's main purpose is to reflect how the model applied contributes to energy savings. Accuracy, at 7.6%, and performance, at 6.3%, show that different papers use different metrics to evaluate the AI models, making it slightly difficult to compare the models in the studies. This indicates the need for a unified dataset for comparison.

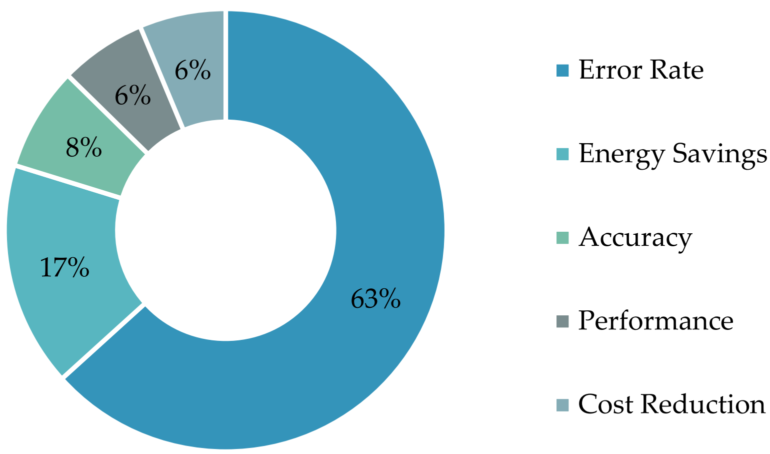

Figure 5. Presentation of the focus areas of the study results.

Figure 6 shows the number of studies conducted in different countries, emphasizing the top countries contributing to the field. China leads significantly with nearly 35 studies. South Korea and the USA follow, with about 15 studies each. The UK comes next with around 10 studies, and France has approximately 8. These data highlight China's dominant role in this research area and the other countries mentioned as key players in advancing this field of study. This also indicated that the amount of research in Europe needs to increase to achieve the Paris Agreement goals.

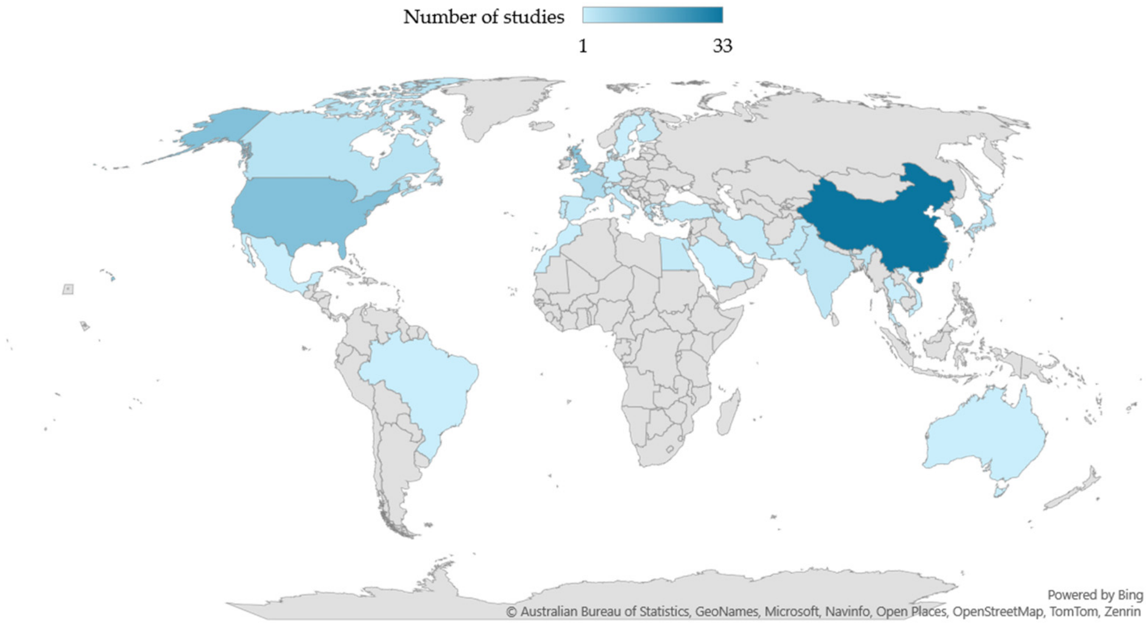

Figure 6. The number of studies conducted per country.

Figure 7 shows the distribution of different building types for various application areas. Educational facilities and residential buildings are the most common, especially for forecasting energy consumption and HVAC control/optimization. Offices and commercial buildings are also popular in several application areas. Public buildings, hospitals, and sports halls mainly focus on energy consumption forecasting and air quality. Churches and mosques are less frequently studied.

Figure 8 shows the number of papers dedicated to each application area. Energy consumption forecasting is the area researched the most, with 57 papers covering it. HVAC control/optimization follows with 37 papers, highlighting a significant focus on improving building efficiency. At 30 papers, load forecasting is also relatively high, followed by occupancy detection, with 25 papers. Indoor temperature prediction, air quality, and thermal comfort are less frequently studied. Therefore, these papers were systematically analyzed to determine how AI models used in BEMS contribute to energy savings, cost reductions, and thermal improvements. The results of this analysis are presented in Table 2.

As shown in Table 2, the highest energy-savings potential (of up to 37%) can be found in offices when AI models are used for HVAC control and optimization, as demonstrated by Wang et al. [104] in their study. The authors developed a DRL-based HVAC control algorithm that optimized the thermal comfort and energy efficiency of an open-plan office with a multi-VAV HVAC system. Using AI models for HVAC control in offices can also reduce costs by up to 14.5%.

Compared to offices, residential buildings can achieve higher cost reductions of up to 24.29%. However, the energy savings are smaller (up to 23% in residential and 21% in educational buildings), likely due to the lower level of intelligence of existing building management systems or installed baseline controllers of the HVAC equipment, as indicated by An and Chen [79] and Chemingui et al. [68].

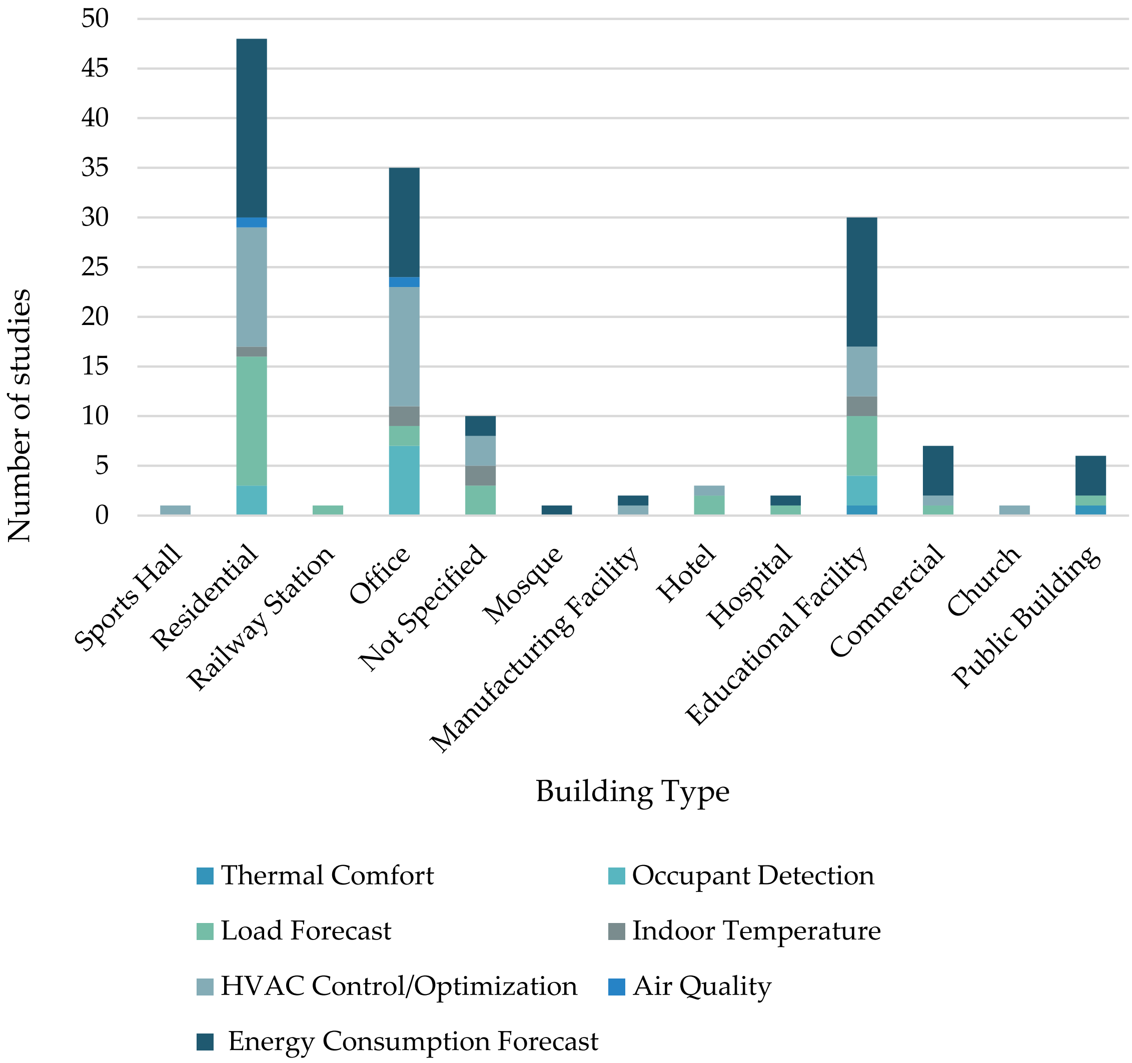

Figure 7. The distribution of building types for each area of application.

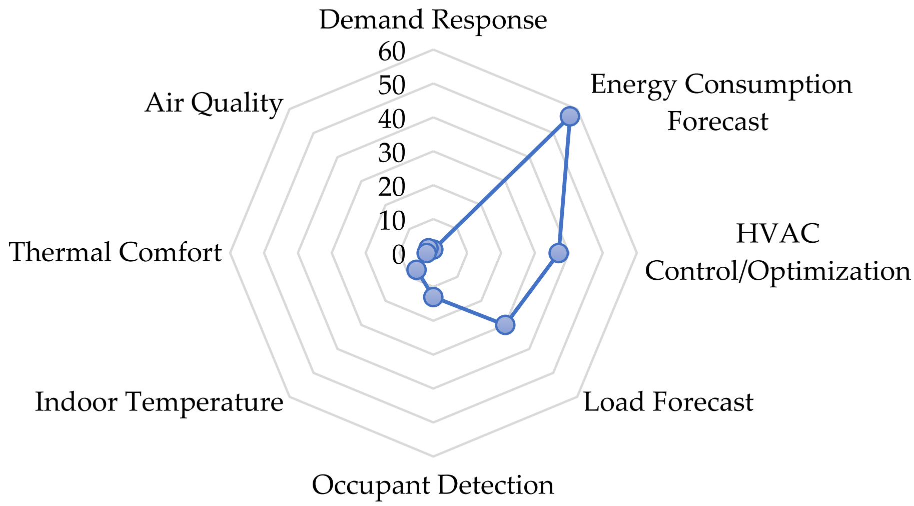

Figure 8. The number of papers per application area.

Table 2. The benefits of using AI models to save energy, reduce costs, and improve thermal comfort.

AI Models Applications	Building Type	Energy Savings, %	Cost Reductions, %	Thermal Comfort Increase, %
Energy consumption forecasting	Office	17.4	-	16.9
	Commercial	median of 57.38% in air conditioning system	-	-
HVAC control and optimization	Residential	5–23	6.1–24.29	16
	Office	5–37	14.5	-
	Educational	21 0.6–29 in heating energy	-	-
	Commercial	10	-	-
Occupancy detection	Residential	30	-	-
	Office	2.3–8.1 10.2 in HVAC and lighting energy	-	43–73

An and Chen [79] used a DRL algorithm to develop a deep-Q network controller that controls windows, air cleaners, and air conditioners to reduce indoor air pollution and maintain thermal comfort with relatively low energy consumption in residential buildings. Similarly, Chemingui et al. [68] applied a DRL framework to control a school building's indoor environmental conditions and optimize energy consumption. Their technique, enhanced with behavioral cloning, was designed to find optimal HVAC control decisions for different weather conditions throughout the year, minimizing energy consumption, maintaining thermal comfort, and reducing indoor contaminant levels in a multi-zone environment.

Each of these studies demonstrated significant improvements in energy efficiency and environmental conditions by using DRL to control and optimize different HVAC systems across various building types—offices, residential buildings, and schools. Therefore, DRL-based methods are well suited for achieving optimal HVAC control strategies and balancing the trade-offs between building indoor comfort and energy consumption.

The use of AI models to predict energy consumption also shows potential energy savings of up to 17.4% and improved thermal comfort of up to 16.9% in offices. However, the results of the papers analyzed show that the integration of AI models for HVAC control and optimization is more efficient and gives better energy savings potential.

Another promising and efficient application of AI models is occupancy detection, which can deliver relatively high energy savings of up to 8.1% in offices and improve thermal comfort by 43% to 73%.

In conclusion, the integration of AI models into BEMS is an effective solution for ensuring higher energy efficiency in buildings while maintaining a high level of comfort, if the existing BEMS is open-source and the existing controllers are programmable.

4.1. Estimation of AI Model Reliability

In this review, we aimed to compare the various AI models employed to enhance energy efficiency in buildings, focusing on their accuracy. To achieve this, we classified the error metrics as low, medium, and high. However, the comparison posed a challenge due to the nature of different error metrics. Unlike R^2, which ranges from 0 to 1 and provides a standardized measure of model accuracy, other metrics like RMSE, MAPE, MAE, and MSE depend on the data's scale and distribution, making direct comparison difficult. These metrics can vary significantly in magnitude and units, thus complicating the process of establishing a uniform classification.

For instance, RMSE is sensitive to large errors, while MAE provides a linear perspective on errors. This makes RMSE and MAE values difficult to interpret uniformly across different datasets and models. In building energy management, the variability in building types, sizes, and energy usage patterns intensifies these issues, as noted by Ahmad et al. [105]. Moreover, these error metrics do not consider factors unique to building energy efficiency implementation, such as retrofit schedules, occupancy patterns, and renewable energy integration. As a result, the effectiveness of one model in one building or scenario may not be directly comparable to another, even when using the same error metric, which Zhao et al. [106] further elaborate on. Therefore, because of its straightforward and standardized scale, we used R^2 as the primary metric for comparing the AI model's accuracy in the diverse and complex field of building energy management. In this review paper, R^2 values were classified as follows: high accuracy (1.00–0.66), medium accuracy (0.65–0.36), and low accuracy (0.00–0.35).

The highest reported accuracy was selected for papers that presented a range of accuracies. From the studies reporting R^2 in Table A6 in Appendix B, the R^2 values range from 0.99911, the highest achieved by a GA model for energy consumption forecasting in residential buildings, to the lowest value with medium accuracy, according to our assessment criteria, of 0.4872, achieved by an ANN model for thermal comfort prediction in residential buildings. The most common area of application reported in Table A6 in Appendix B is the energy consumption forecast, with various AI models being applied across different building types. Other high R^2 values in this application area include RNN with R^2 values of up to 0.999 and the hybrid DNN-LSTM model with an R^2 of 0.9991. Residential buildings are predominant; several AI models were applied to residential buildings for energy consumption forecasting and load forecasting, indicating a significant focus on this building type in these application areas. Followed by offices and educational buildings, Table A6 in Appendix B highlights that DL, like DNNs, CNNs, and hybrid models, is highly effective in predicting energy consumption, with R^2 values frequently exceeding 0.9, indicating high accuracy.

4.2. Limitations

Despite the comprehensive approach in conducting this systematic literature review, it is important to acknowledge certain limitations. The methodology employed may not have captured all relevant papers in the field of AI models for building energy efficiency. Though we aimed to be thorough, the effectiveness of our search depended heavily on the chosen keywords and search strings, meaning some relevant studies may have been omitted. Differences in terminology and indexing across various databases also added to this challenge. As a result, our review provides valuable insights but represents only a portion of the available research in this domain. Future studies should consider expanding the search criteria and incorporating additional sources to build on this review.

5. Conclusions

This study is designed to contribute and complement existing research in the area of AI models used in BEMS and their impact on energy savings. The review highlights several aspects regarding the evaluation and application of AI models in various areas of buildings. First, the lack of standardized metrics for assessing AI model reliability complicates the comparison of different studies. This highlights the need for a unified dataset for more meaningful comparisons. Additionally, many studies do not report savings as error metrics, which is crucial for understanding the practical impact of these models. While other error metrics are used, translating these into actual savings is essential for evaluating the models' effectiveness. Furthermore, the extent of research in Europe is relatively limited compared to that in the USA and China. To meet the Paris Agreement sustainability goals, Europe must increase its research efforts in this field. Integrating different AI algorithms in model design is a popular way to go, which indicates that a combination approach performs better. Moreover, the review shows that energy consumption and load forecasting are the most common application areas, whereas air quality receives the least attention. This distribution highlights the need for a broader focus on diverse application areas to achieve comprehensive advancements in AI-driven sustainability. The main findings of this study in relation to the research questions are as follows:

1. The use of AI models in BEMS for energy consumption forecasting, HVAC control and optimization, occupancy detection, and the prediction of indoor climate parameters is a valuable contribution to building energy efficiency, additional energy savings, cost reductions, and thermal improvements.
2. The highest energy savings potential of up to 37% can be found in offices, smaller savings of up to 23% can be found in residential buildings, and savings of 21% can be found in educational buildings when DRL-based models are used to optimize HVAC control strategies and balance the trade-offs between indoor comfort and energy consumption, compared to baseline rule-based methods.
3. AI models, particularly deep learning architectures like DNNs, CNNs, and hybrid models, are highly effective in predicting energy consumption, with R^2 values frequently exceeding 0.9, indicating high accuracy. The most common application area is energy consumption forecasting, with residential buildings being a predominant focus.

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Abbreviations

AE	Autoencoder
AI	Artificial Intelligence
AMADRL	Asymmetric Multi-Agent Deep Reinforcement Learning
AN	Artificial Neural
ANFIS	Adaptive Neuro-Fuzzy Inference System
ARIMA	AutoRegressive Integrated Moving Average
BBO	Biogeography-Based Optimization
BDQ	Big Data Query
BEMS	Building Energy Management Systems
Bi-GRU	Bidirectional Gated Recurrent Unit
Bi-LSTM	Bidirectional Long Short-Term Memory
CEEMDAN	Complete Ensemble Empirical Mode Decomposition with Adaptive Noise
CIFG	Coupled Input Forget Gate
CNN	Convolutional Neural Network
ConvLSTM2D	Convolutional Long Short-Term Memory 2D
CV	Cross-Validation
CVRMSE	Coefficient of Variation of the Root Mean Squared Error
DBN	Deep Belief Network
DF	Decision Forest
DFNN	Deep Feedforward Neural Network
DRL	Deep Reinforcement Learning

DNN	Deep Neural Network
DQN	Deep Q-Network
DRLC	Deep Reinforcement Learning Control
DRNN	Deep Recurrent Neural Network
DRNN-GRU	Deep Recurrent Neural Network-Gated Recurrent Unit
DRL	Deep Reinforcement Learning
DUMSL	Deep Unsupervised Multilayer Stacking
DUMSL-DNN	Deep Unsupervised Multilayer Stacking Learning-Deep Neural Network
DT	Decision Tree
EPBD	Energy Performance of Buildings Directive
EMD	Empirical Mode Decomposition
FF	Feed-Forward
FFNN	Feed-Forward Neural Network
FIS	Fuzzy Inference System
FL-BM	Fuzzy Logic-Based Model
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GB	Gradient Boosting
GDFA	Generalized Dynamic Fuzzy Automata
GFS.FR.MOGUL	Generalized Fuzzy Systems with Fuzzy Regression-Modified Global Universe of Discourse
GMTCN	Gated Memory Time Convolutional Network
GNN	Graph Neural Network
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
GRU-RL	Gated Recurrent Unit-Reinforcement Learning
HHT	Hilbert–Huang Transform
HHO-ANFIS	Harris Hawks Optimization-Adaptive Neuro-Fuzzy Inference System
HVAC	Heating, Ventilation, and Air Conditioning
HyFIS	Hybrid Fuzzy Inference System
IEA	International Energy Agency
IoT	Internet of Things
IPWOA	Improved Particle Whale Optimization Algorithm
KNN	K-Nearest Neighbors
LR	Linear Regression
LSSVR	Least Squares Support Vector Regression
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MAQMC	Multi-Agent Quantum Monte Carlo
Metaheuristic-based LSTM	Metaheuristic-based Long Short-Term Memory
ML	Machine Learning
MLR	Multiple Linear Regression
MSE	Mean Square Error
MR	Multiple Regression
NARX-MLP	Nonlinear Autoregressive with Exogenous Inputs-Multilayer Perceptron
NRMSE	Normalized Root Mean Square Error
nMAE	Normalized Mean Absolute Error
NZE	Net Zero Emissions
OBC	Optimal Bayesian Control
PMV	Predicted Mean Vote
PPO	Proximal Policy Optimization
PPD	Predicted Percentage Dissatisfied
PSO	Particle Swarm Optimization

R	Correlation Coefficient
R^2	Coefficient of Determination
RBFNN	Radial Basis Function Neural Network
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SADLA	Self-Attentive Deep Learning Algorithm
Seq2Seq	Sequence to Sequence
SNNs	Spiking Neural Networks
SOS	Symbiotic Organisms Search
SPSA	Simultaneous Perturbation Stochastic Approximation
ST-GCN	Spatio-Temporal Graph Convolutional Network
STLF	Short-Term Load Forecasting
SVR	Support Vector Regression
SVM	Support Vector Machine
TST	Temporal Self-Tracking
VSCA	Very Short-term Climate Anomaly
WM	Wavelet Model
YOLO	You Only Look Once

Appendix A. AI Models Used for Different Applications

Table A1. Comparison of AI models used for energy consumption forecasting.

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[33]	Linear regression, ANN, Regression trees	Commercial	- Best results with MAPE = 1%
[34]	ANN, GB, DNN, RF, Stacking, KNN, SVM, DT, LR	Residential	- DNN: R^2 = 0.95, RMSE = 1.16 - ANN: R^2 = 0.94, RMSE = 1.20 - GB: R^2 = 0.92, RMSE = 1.40
[36]	LSTM neural network	Educational Facility	- Daily energy consumption forecast MAPE reduction compared to ARIMA = 11.2%, Hourly = 16.31%. - Daily energy consumption prediction MAPE reduction compared to BP = 49%, Hourly = 36.6%
[37]	Asymmetric encoder-decoder DL algorithm	Educational Facility	- Single-step forecasting average R^2 = 0.964 - Three-step ahead multi-step forecasting average R^2 = 0.915
[38]	LSTM, Bidirectional LSTM, CNN, Attention Mechanism, Soft Actor-Critic, RL	Office	Energy savings = 17.4% Thermal comfort improvement = 16.9% - RMSE = 0.07–0.09
[39]	DF	Commercial	R^2 = 0.90
[40]	ANFIS, GDFA	Educational Facility	- ANFIS-SC: nMSE = 49.16, nMAE = 0.452, R = 58.71%. - ANFIS-FCM: nMSE = 53.48, nMAE = 0.517,R = 56.44% - AR-ANFIS-GDFA-SC+: nMSE = 7.25, nMAE = 0.168, R = 95.09%
[41]	Hybrid CNN with LSTM-AE	Commercial	- MSE = 0.19 - MAE = 0.31 - RMSE = 0.47
[42]	VSCA, ConvLSTM2D model with Conv2D attention mechanism and roll padding	Residential	- MSE = 0.0140 - RMSE = 0.1183 - MAE = 0.0875

Table A1. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[43]	LSTM	Office	- MAPE improvement = 0.54%
[44]	Deep learning autoencoder coupled with LSTM	Educational Facility	CV(RMSE) < 9%
[45]	MR, RF, ANN-FF, SVR, GB, DNN	Educational Facility	- DNN R^2 = 0.87 - DNN CV-RMSE = 24.4% - GB CV-RMSE = 26.5% - SVR CV-RMSE = 26.5% - ANN-FF CV-RMSE = 27.9% - RF CV-RMSE = 35.3% - MR CV-RMSE = 39.4%
[46]	Adaptive decomposition, multi-feature fusion RNNs	Residential	- MAE = 4.4–21.4 W, - MAPE = 4.97–21.97% - RMSE = 8.8–37.8 W - R^2 = 0.974–0.999
[47]	21-layer Fully Connected DNN	Commercial	- Energy savings: Median = 57.38%, Maximum = 90% - Energy consumption prediction(test): RMSE = 213 W, R^2 = 0.72, MAPE = 15.1%
[107]	SOM, CNN, GA	Public building	-Training dataset accuracy = 89.03%, Standard error = 0.3 - Validation dataset accuracy = 88.91%, Standard error = 0.33
[108]	A3C, DDPG, RDPG	Office	- Compared to traditional models, DDPG and RDPG performed better in Single-step prediction = 16–14%, Multi-step prediction = 19–32%.
[109]	DFNN, DRNN	Manufacturing Facility	- Energy consumption prediction accuracy: DFNN = 92.4%, DRNN = 96.8% - Air temperature accuracy: DFNN = 99.5%, DRNN = 99.4% - Humidity accuracy: DFNN = 64.8%, DRNN = 57.6%
[110]	CNN	Mosque	- MAPE = 4.5% - R^2 = 0.98
[111]	PSO, Particle Swarm, Stacking ensemble model. PFS	Educational Facility	RMSE = 1.71 lower than that of common ML algorithms.
[112]	SVR	Educational Facility	-R^2 = 0.92
[113]	Metaheuristic-based LSTM network	Residential	- MAPE = 0.05–0.09 - MAE = 0.04–0.07 - RMSE = 0.13–0.16 - MSE = 0.04–0.05
[114]	LSTM	Residential	- Daily model: RMSE = 0.362, MAE = 19.7% - Monthly model: RMSE = 0.376, MAE = 17.8%
[115]	ANN, SVM. HyFIS, WM, GFS.FR.MOGUL	Office	-SVM MAPE = 7.19% - WM MAPE = 8.58% - HyFIS MAPE = 8.71% - ANN MAPE = 10.23% - GFS.FR.MOGUL MAPE = 9.87%

Table A1. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[116]	HHT, RegPSO, ANFIS	Educational Facility	- MAPE = 1.91%
[117]	Bidirectional LSTM, stacked unidirectional LSTM, and fully connected layers optimized DTO	Residential	- RMSE = 0.0047 - R^2 = 0.998
[118]	LSTM, NARX-MLP, GRU, DT, XGBoost	Educational Facility	- Best model RMSE = 0.23
[119]	Adaboost-BP	Residential	- Average prediction accuracy = 86%
[120]	MgHa-LSTM	Not Specified	- MSE = 0.2821
[121]	RNN, LSTM, GRU, TST, Ensemble	Residential	- RNN MSE = 0.00279 - LSTM MSE = 0.00571 - GRU MSE = 0.00483 - TST MSE = 0.00771 - Ensemble MSE = 0.00289
[122]	DRNN	Residential	- RMSE = 0.44 kWh - MAE = 0.23 kWh
[123]	LSTM, GRU, EMD	Hospital	- Best MAPE = 3.51% - Best RMSE = 55.06kWh
[124]	GPR	Public Building	- R^2 = 0.9917 - CV-RMSE = 0.1035
[125]	LSTM	Office	- Air conditioning prediction: MSE = 519.77, CV-RMSE = 0.1349, MAE = 14.52
[126]	LSTM, CNN	Residential	- LSTM RMSE = 0.0693 - CNN RMSE = 0.0836
[127]	SADLA	Office	SADLA highest R^2 = 0.976
[128]	LR, SVM, RF, MLP, DNN, RNN, LSTM, GRU	Educational Facility	- One month ahead prediction: R^2 = 88% - Three months ahead prediction: R^2 = 81%
[129]	Proposed eight-layer deep neural network	Residential	- R^2 = 97.5% - RMSE = 111 W
[130]	DUMSL-DNN	Residential	- Lowest RMSE = 0.5207 - Lowest MAE = 0.3325
[131]	DRL, DDPG, DF	Office	- Compared to DDPG, the proposed DF-DDPG method decreased MAE by 7.15% MAPE by 12.71% RMSE by 18.33% Increased R^2 by 1.3%
[132]	DNN with Stacked Boosters	Office	NRMSE = 2.35%
[133]	A-LSTM, LSTM, RNN, DNN, SVR	Educational Facility	- RMSE decreased by 3.06% - MAE decreased by 6.54% - R^2 increased by 0.43%
[134]	IILSTM	Public Building	- MAE = 0.015 - RMSE = 0.109
[135]	Vanilla LSTM	Residential	Best RMSE = 4.4776

Table A1. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[136]	LSSVR, RBFNN, SOS	Residential	- RMSE = 36.31 kWh - MAE = 29.45 kWh - MAPE = 8.90% - R^2 = 0.93
[137]	EDA-LSTM	Office	- R^2 = 98.45% - RMSE = 4.02 - MAE = 2.87
[138]	CNN, GRU	Residential	- IHEPC Dataset: RMSE = 0.42, MSE = 0.18, MAE = 0.29 - AEP Dataset: RMSE = 0.31, MSE = 0.10, MAE = 0.33
[139]	BiGTA	Educational Facility	- MAPE = 5.37% - RMSE 171.3 kWh
[140]	kCNN-LSTM	Educational Facility	- MSE = 0.0095 - RMSE = 0.0974 - MAE = 0.0711 - MAPE = 0.2697
[141]	DNN, GA	Office	MAPE: Training = 1.43%, Testing = 4.83% R^2: Training = 0.993, Testing = 0.960 RMSE: Training = 4.33 kW, Testing = 10.29 kW
[142]	CNN	Residential	-RMSE = 0.6170 - MSE = 0.3807 - MAE = 0.4490
[143]	DBN, ELM	Not Specified	Improved accuracy by ~20%
[144]	EWKM, RF, SSA, BiLSTM	Public Building	- MAE = 1.30 - RMSE = 1.63 - MAPE = 0.02
[145]	SVR, LSTM, GRU, CNN-LSTM, CNN-GRU	Residential	- CNN-GRU daily MAE = 0.151 - CNN-GRU hourly MAE = 0.229 - LSTM daily MAE = 0.183 - LSTM hourly MAE = 0.228
[146]	VMD, LSTM	Office	- Improved R^2 by 10% - Decreased MAE by 48.9% - Decreased RMSE by 54.7%
[147]	Hybrid DNN-LSTM	Residential	- R^2 = 0.99911 - RMSE = 0.02410 - MAE = 0.01565 - MAPE = 0.01826

Table A2. Comparison of AI models used for load forecasting.

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[32]	RF, ELM, IPWOA	Commercial	- RMSE = 2.8735 and 4.7721. - MAPE = 0.2% and 0.45%.
[48]	Ensemble, ML, ANN, DT	Residential	- MAPE = 5.39%

Table A2. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[49]	LSTM, Bi-LSTM, GRU	Educational Facility	- LSTM RMSE = 0.0600–0.7527 kW - Bi-LSTM RMSE = 0.0430–0.3960 kW - GRU RMSE = 0.0413–1.3805 kW - LSTM MAE = 0.0003–0.0078 kW - Bi-LSTM MAE = 0.0005–0.0041 kW - GRU MAE = 0.0005–0.0144 kW
[50]	DRNN-GRU	Residential	-RMSE = 0.510 - MAE: 0.345 - MAPE: 3.504%
[51]	BP, XGBoost, LSTM	Residential	- Minimum MAAPE = 18.70% - Maximum MAAPE = 45.95% - Average MAAPE = 31.20%
[52]	GMTCN, Bidirectional LSTM. SPSA	Hotel	- MAPE reduced by 27.48%, 14.05%, and 13.38% for 1-step, 6-step, and 12-step predictions, respectively. - R^2 = 0.971, 0.923, and 0.885 for 1-step, 6-step, and 12-step predictions, respectively.
[53]	CNN, LSTM, Bi-LSTM, GRU, CEEMDAN, ARIMA	Educational Facility	Best model (CEEMDAN-Bi-LSTM-ARIMA): - R^2 = 0.983 - RMSE = 70.25 kWh - CV-RMSE = 1.47%
[54]	BBO	Residential	- Heating load training, MAE = 2.15. - Cooling load training, MAE = 2.97
[55]	BBO	Residential	- Heating load R^2 = 0.94 - Cooling load R^2 = 0.99 - Heating and cooling RMSE = 0.148–0.149
[56]	Gaussian radial basis function kernel support vector regression	Residential	- Heating and cooling load prediction MAE = 4% less.
[57]	LSTM	Residential	- MAPE = 0.07
[58]	CNN	Office	Average MAPE reduction of 29.7%, 32.8%, 35.9%, and 25.3% compared to that of GRU, ResNet, LSTM, and GCNN, respectively.
[59]	TRN	Office	- RMSE = 0.01 - MAE = 0.03 - R^2 = 0.98
[60]	CNN-BiGRU and PSO optimization	Residential	- RMSE = 44.28 MW - MAPE = 3.11% - MAE = 29.32 MW - R^2 = 0.9229
[61]	HHO-ANFIS	Residential	- R^2 = 98% - RMSE =0.08281
[62]	BiLSTM, LSTM, CNN	Educational Facility	- Accuracy improvement = 20–45% - RMSLE = 0.03 to 0.3
[63]	iCEEMDAN-BI-LSTM hybrid model	Educational Facility	-MAE = 40.8411 - RMSE = 59.6807 - MAPE = 2.56% - R^2 = 0.9869
[64]	XGBoost, LSTM	Educational Facility	- XGBoost CVRMSE = 21.1% on test set, - LSTM CVRMSE = 20.2%
[65]	LSTM, CIFG, GRU, ANN	Public Building	- Most accurate RMSE = 0.770

Table A2. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[66]	FFNN	Hospital	- MAPE = 6.6–7.0%
[67]	1D-CNN, Seq2Seq	Hotel	- MAPE = 10% less
[148]	ANFIS, BGA-PCA	Residential	- MAPE = 1.70%, 1.77%, 1.80%, and 1.67% for the summer, fall, winter, and spring seasons, respectively.
[149]	3RF	Not Specified	- Heating load, R^2 = 0.999 - Cooling load, R^2 = 0.997
[150]	CNN, LSTM	Residential	- Error rate reduction over the IHEPC dataset: MAE = 15.6 MSE = 8.77% RMSE = 4.85% - Error rate reduction over the PJM dataset: RMSE = 3.4%
[151]	DRL, DDPG. TD3	Not Specified	- Error = 4.56%
[152]	LSTM, Bi-LSTM, GRU, Bi-GRU	Railway Station	- Best MAPE = 0.2%
[153]	CNN-LSTM, EMD, Bayesian	Residential	RMSE = 98.82 for six timestep
[154]	Seq2Seq LSTM	Residential	- MAE = 35.1 (60 timesteps), 46.5 (120 timesteps), 38.5 (180 timesteps) - MAPE = 10.93% (60 timesteps), 12.22% (120 timesteps), 13.32% (180 timesteps) - RMSE: 82.75 (60 timesteps), 86.50 (120 timesteps), 88.65 (180 timesteps)
[155]	ANFIS	Educational Facility	- Training R = 0.98017 - Testing R = 0.9778 - Validation R = 0.97593
[156]	Bayesian RNN, Bayesian LSTM, Bayesian GRU	Not Specified	- MAPE reduction = 15.4%

Table A3. Comparison of AI models used for HVAC control and optimization.

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[68]	DRL	Educational Facility	- Energy consumption reduction = 21%
[69]	ANN	Office	- Thermal energy consumption reduction 58.5%
[70]	LSTM, DRL	Not Specified	- MSE = 0.0015 - Energy savings = 27–30%
[71]	FIS	Church	- Operation time reduction = 5.7%
[72]	AMADRL	Office	- Energy consumption reduction = 0.7–4.18%, - Thermal comfort deviation = 64.13–72.08%
[73]	YOLOv5	Educational Facility	- YOLOv5 model accuracy = 88.1%
[74]	GPR, ANN, SVM, DT, RF	Educational Facility	- Reduction in natural gas consumption = 22.2% - Reduction in building heating demand = 4.3% - GPR for heating demand RMSE = 32.1 kW
[75]	DNN Bilinear Koopman Predictor	Office	- CVRMSE: 9.62–19.15% - Energy Savings Ratio = 33.71%
[76]	Shallow ANN	Educational Facility	- Heating energy consumption reduced by 0.6% to 29.0% - Thermal comfort improved by 0% to 58.8% - Maintained indoor CO_2 below 1000 ppm for 89.2%

Table A3. *Cont.*

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[77]	ANN	Educational Facility	- PMV RMSE = 0.2243 - CO_2 RMSE = 0.8816 - PM10 RMSE = 0.4645 - PM2.5 RMSE = 0.6646
[78]	DRL	Residential	- Energy consumption reduction = 5–14%
[79]	DRL, DQN	Residential	- PM2.5 healthy period increased by 21% - Thermal comfort period increased by 16% - Energy consumption reduced by 23%
[80]	BDQ	Office	- Cooling energy reduction = 11%
[81]	GRU-RL	Office	- Cost reduction = 14.5%
[82]	ANN	Sports Hall	- Energy reduction = 46% - Average RMSE = 0.06 - Average R = 0.99
[157]	RL	Hotel	- Estimated energy savings = 21%
[158]	DRL	Residential	- Cost reduction up to 21%
[159]	DRL	Office	- Energy savings compared to baseline controller = 5–12%
[160]	Double DQN	Residential	- Energy cost reduction 7.88–8.56%
[161]	DRL, PPG	Not Specified	- Energy consumption reduction 2–14%
[104]	DRL	Office	- HVAC energy consumption reduction = 37%
[162]	MLP, DL	Residential	- Energy savings = 12.24% - Cost savings = 12.91%
[163]	ANN	Commercial	- Energy savings = 10%
[164]	DDPG	Residential	- Energy consumption reduction = 65%
[165]	AFUCB-DQN	Not Specified	- Energy savings = 21.4–22.3%
[166]	MAQMC	Residential	- Energy consumption reduction = 6.27%
[167]	DDPG	Office	- Energy savings = 13.71%
[168]	RNN, NARX	Office	- Energy savings = 26%
[169]	DDPG	Residential	- Cost savings compared to DQN = 15%
[170]	SNNs	Office	- Heating energy savings = 36.8% - Cooling energy savings = 3.5% to 33.9%
[171]	DDPG	Residential	- Cost savings = 12.79%
[172]	OBC, DRLC	Office	- OBC energy savings = 7% - DRLC energy savings = 2.4%
[173]	DRL, PPO, DDPG	Office	- Energy savings = 13.1–14.3%
[174]	MARL, DQ	Residential	- Cost savings = 19%
[175]	DDPG	Residential	- Cost savings = 6.1–10.3%
[176]	PPO, LSTM	Residential	- Cost savings = 23.63–24.29% - PMV = 83.3–87.5%

Table A4. Comparison of AI models used for occupant detection.

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[83]	CNN	Office	- Accuracy = 80.62%
[84]	DMFF	Residential	- Accuracy = 97% - Energy Savings: Up to 30%
[85]	YOLOv5	Office	- NRMSE = 0.0435 - Annual HVAC and lighting energy savings = 10.2%
[86]	GA-LSTM, PSO-LSTM, LSTM	Residential	Correlation coefficients for all predictions = 99.16–99.97%
[87]	1D CNN, RL	Not Specified	- Reduction in thermal discomfort = 10.9%
[88]	MLR	Educational Facility	- RMSD = 4.8 - MAE = 2.5
[89]	Faster R-CNN with InceptionV2	Office	- Equipment detection accuracy = 78.39% - Occupancy activity detection accuracy = 93.60%
[90]	Faster R-CNN	Office	- Average detection accuracy for all activities = 92.2%
[91]	YOLO v4	Office	- RMSE = 0.883 - NRMSE = 0.141 - Maintained indoor CO_2 < 1000 ppm - Heating energy savings = 27%
[92]	LM-BP	Office	- RMSE = 15.59 - MAE = 10.16 - MAPE = 6.35
[93]	YOLOv5	Office	Thermal comfort improved by 43–73% - Energy savings = 2.3–8.1% - Occupant detection accuracy = 80–97%
[94]	Faster R-CNN	Educational Facility	- People counting accuracy = 98.9% - Activity detection accuracy: 88.5%
[177]	ST-GCN	Educational Facility	- Action recognition accuracy = 87.66% - Average thermal comfort prediction accuracy = 82.5%

Table A5. Comparison of AI models used for other areas of application.

Reference	AI/ML Model	Building Type	Reliability (Accuracy/Savings) Error (RMSE, MSE, MAPE), Savings (%)
[95]	ANN, SVM	Thermal Comfort Prediction	Residential
[96]	1D-CNN, RNN, LSTM	Air Quality Prediction	Residential
[97]	CNN-GRU, MLP	Indoor Temperature Prediction	Not Specified
[98]	FL-BM, ANFIS-BM	Thermal Comfort Prediction	Educational Facility
[99]	Radial basis function NN	Air Quality Prediction	Office
[100]	GNN	Indoor Temperature Prediction	Office
[101]	ANN	Indoor Temperature Prediction	Educational Facility
[102]	CNN-LSTM	Indoor Temperature Prediction	Office
[103]	MLP	Indoor Temperature Prediction	Educational Facility
[178]	SVR-DNN	Thermal Comfort Prediction	Residential
[179]	MLPNN, GA	Thermal Comfort Prediction	Public Building

Appendix B. Accuracy of AI Models Used for Different Applications

Table A6. Comparison of AI models according to R^2 values.

Reference	Application Area	AI Model	Building Type	R^2	Assessment
[34]	Energy Consumption Forecast	ANN, DNN, GB	Residential	DNN: R^2 = 0.95 ANN: R^2 = 0.94 GB: R^2 = 0.92 RF: R^2 = 0.88	High
[37]	Energy Consumption Forecast	Asymmetric encoder–decoder deep learning algorithm	Educational Facility	R^2 = 0.964	High
[39]	Energy Consumption Forecast	DF	Commercial	R^2 = 0.90	High
[45]	Energy Consumption Forecast	DNN	Educational Facility	R^2 = 0.87	High
[46]	Energy Consumption Forecast	RNNs	Residential	R^2 = 0.999	High
[47]	Energy Consumption Forecast	21-layer Fully Connected DNN	Commercial	R^2 = 0.72	High
[108]	Energy Consumption Forecast	A3C, DDPG, RDPG	Office	A3C: R^2 = 0.925 DDPG, RDPG: R^2 = 0.993	High
[110]	Energy Consumption Forecast	CNN	Mosque	R^2 = 0.98	High
[112]	Energy Consumption Forecast	SVR	Educational Facility	R^2 = 0.92	High
[117]	Energy Consumption Forecast	Optimized deep network model with bidirectional LSTM, stacked unidirectional LSTM, and fully connected layers optimized using DTO	Residential	R^2 = 0.998	High
[121]	Energy Consumption Forecast	Ensemble	Residential	R^2 = 0.92601	High
[124]	Energy Consumption Forecast	GPR	Public Building	R^2 = 0.9917	High
[127]	Energy Consumption Forecast	SADLA	Office	R^2 = 0.967	High
[128]	Energy Consumption Forecast	LR, SVM, RF, MLP, DNN, RNN, LSTM, GRU	Educational Facility	R^2 = 88%	High
[129]	Energy Consumption Forecast	Proposed eight-layer deep neural network	Residential	R^2 = 97.5%	High
[136]	Energy Consumption Forecast	Ensemble model combining LSSVR and RBFNN, optimized by SOS	Residential	R^2 = 0.93	High
[137]	Energy Consumption Forecast	EDA-LSTM	Office	R^2 = 98.45%	High
[141]	Energy Consumption Forecast	GA	Office	R^2 = 0.993	High
[147]	Energy Consumption Forecast	Hybrid DNN-LSTM	Residential	R^2 = 0.99911	High
[97]	Indoor Temperature Prediction	Multitask learning	Not Specified	R^2 = 0.981	High

Table A6. *Cont.*

Reference	Application Area	AI Model	Building Type	R^2	Assessment
[102]	Indoor Temperature Prediction	Transformer NN	Office	$R^2 = 0.936$	High
[52]	Load Forecast	GMTCN combined with Bidirectional LSTM with SPSA	Hotel	$R^2 = 0.971$	High
[53]	Load Forecast	CEEMDAN and ARIMA	Educational Facility	$R^2 = 0.983$	High
[54]	Load Forecast	Multi-layer Perceptron NN optimized with BBO	Residential	$R^2 = 0.920$	High
[55]	Load Forecast	BBO-MLP	Residential	$R^2 = 0.94$ for heating load, $R^2 = 0.997$ for cooling load	High
[59]	Load Forecast	TRN	Office	$R^2 = 0.98$	High
[60]	Load Forecast	DL with CNN-BiGRU and PSO optimization	Residential	$R^2 = 0.9229$	High
[61]	Load Forecast	HHO-ANFIS	Residential	$R^2 = 98\%$	High
[63]	Load Forecast	iCEEMDAN-BO-LSTM	Educational Facility	$R^2 = 0.9869$	High
[65]	Load Forecast	LSTM, CIFG, GRU	Public Building	Respectively, LSTM: $R^2 = 0.920$, CIFG: $R^2 = 0.914$, GRU: $R^2 = 0.925$	High
[149]	Load Forecast	3RF	Not Specified	$R^2 = 0.999$ for heating load, $R^2 = 0.997$ for cooling load	High
[95]	Thermal Comfort Prediction	ANN	Residential	$R^2 = 0.4872$	Medium

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