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Review

A Meta-Survey on Intelligent Energy-Efficient Buildings

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Abstract: The rise of the Internet of Things (IoT) has enabled the development of smart cities, intelligent buildings, and advanced industrial ecosystems. When the IoT is matched with machine learning (ML), the advantages of the resulting enhanced environments can span, for example, from energy optimization to security improvement and comfort enhancement. Together, IoT and ML technologies are widely used in smart buildings, in particular, to reduce energy consumption and create Intelligent Energy-Efficient Buildings (IEEBs). In IEEBs, ML models are typically used to analyze and predict various factors such as temperature, humidity, light, occupancy, and human behavior with the aim of optimizing building systems. In the literature, many review papers have been presented so far in the field of IEEBs. Such papers mostly focus on specific subfields of ML or on a limited number of papers. This paper presents a systematic meta-survey, i.e., a review of review articles, that compares the state of the art in the field of IEEBs using the Prisma approach. In more detail, our meta-survey aims to give a broader view, with respect to the already published surveys, of the state-of-the-art in the IEEB field, investigating the use of supervised, unsupervised, semi-supervised, and self-supervised models in a variety of IEEB-based scenarios. Moreover, our paper aims to compare the already published surveys by answering five important research questions about IEEB definitions, architectures, methods/models used, datasets and real implementations utilized, and main challenges/research directions defined. This meta-survey provides insights that are useful both for newcomers to the field and for researchers who want to learn more about the methodologies and technologies used for IEEBs' design and implementation.

Keywords: Internet of Things (IoT); smart building; energy efficiency; intelligent energy-efficient building; machine learning; deep learning; reinforcement learning; meta-survey

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1. Introduction

The Internet of Things (IoT) [1] consists of smart interacting devices collecting vast amounts of data in several fields, such as smart cities, smart buildings, and so on. The adoption of machine learning (ML) algorithms can greatly improve how IoT-enabled environments operate and are managed [2]. ML significantly impacts data analysis and enables quick decision-making in smart buildings, where it analyzes vast volumes of data from various sensors and devices. ML algorithms can monitor environmental factors to improve the indoor environment and optimize the energy spent in buildings [3].

In the literature, ML is widely used to analyze a variety of sensor data, including temperature, humidity, occupancy, air quality, energy meters, thermostats, and so on [3]. Through the analysis of data from such sensors, ML is able to regulate lighting and Heating, Ventilation, and Air Conditioning (HVAC) systems so as to reduce consumption while still keeping a high comfort level within the buildings. Furthermore, ML is employed to detect equipment problems early, allowing for timely actions. As a result, there is a reduction in repair times, maintenance expenses, and energy consumption [4,5]. ML is also engaged in detecting and predicting occupancy in buildings [6] to automatically adjust lighting and

HVAC systems, among other things. Moreover, it is also exploited to control the actual energy usage of buildings and provide suggestions to reduce it [3].

In summary, ML is fundamental in the creation of so-called Intelligent Energy-Efficient Buildings (IEEBs) [3]. IEEBs can be defined as smart building environments in which artificial intelligence/machine learning algorithms are widely used to make specific actions to the environment itself. Such actions aim to reach, among other things, energy efficiency, inhabitants' comfort, maintenance prediction, and people security in the IEEB's systems [2]. IEEBs can play a vital role in reducing greenhouse gas emissions, which has a positive effect on climate change mitigation. Buildings are the places in which human beings spend most of their time. The Global Alliance for Buildings and Construction shows that 36% of global energy consumption is spent in buildings (UN Environment Programme, 2021 Global Status Report for Buildings and Construction. https://globalabc.org/sites/default/files/2021-10/GABC_Buildings-GSR-2021_BOOK.pdf accessed on 29 July 2024). In this context, the realization of IEEBs can lower costs, improve thermal comfort, and ensure regulatory compliance. It can ensure user satisfaction at home or in the office, also boosting work efficiency [7]. In addition, the demand for IEEB solutions is rapidly expanding due to enthusiastic building owners and government initiatives [4].

In the literature, there is an abundance of surveys and review papers on the topic of IEEB [3–23], but none of them provides a complete picture of the current state-of-the-art research. This meta-survey aims to present an in-depth and comprehensive analysis of the IEEB research domain, offering an abundance of information and insights into IEEBs. Our work aims to assist both new learners and researchers in gaining a comprehensive understanding of the domain by covering various topics related to IEEBs. In this meta-survey, we will compare and evaluate the results of various studies, review the most commonly used machine learning methods in IEEBs, examine real-world implementations, and discuss the challenges and future research directions in the field of IEEBs.

This meta-survey paper is structured as follows: Section 2 introduces the main Sensors and ML techniques used in IEEBs, Section 3 highlights the strategy followed in implementing the survey, and Section 4 compares the reviewed work by also answering some research questions. Finally, the paper presents some conclusions.

2. A Brief Background Discussion

2.1. Sensors in IEEBs

Smart buildings, in general, and IEEBs, in particular, produce a very large amount of data. Such data mainly depend on the quantity and type of the deployed sensors around an IEEB [24]. Among all the sensors, the most commonly used in buildings are the following [25]:

- Temperature sensors, which can measure the temperature levels in IEEBs;
- Humidity sensors, that track the moisture level in the air;
- Occupancy sensors, which help in detecting the presence of people in IEEBs;
- Light sensors, which measure the intensity of light in IEEBs;
- Switch contact sensors, which detect if windows/doors are opened in an IEEB;
- CO_2 and air quality sensors, which monitor the air quality in an IEEB.
- Smart meters, which measure electricity, water, and gas consumption in an IEEB.
- Smoke and fire sensors, which are used for security purposes in IEEBs.

Such sensors can be deployed as standalone devices or as part of more complex Smart Objects and can be connected through specific protocols. Such protocols are of various kinds, and several new protocols are emerging in the literature. However, currently, the most commonly used for short-range communication include the Internet Protocol Version 6 (IPv6), over Low-power Wireless Personal Area Networks (6LoWPAN), ZigBee, Bluetooth Low Energy (BLE), Z-Wave, Near Field Communication (NFC), and WiFi with MQTT and COAP [26–28]. Regarding longer-range communications, SigFox and Cellular are also frequently used [26].

All the sensors described in IEEBs can produce a dramatic amount of data that can be treated in several ways, with different instruments, and in different places. In this direction, several architectures have been defined in these works [29–31] for data collection and elaboration. Such works also clearly define where AI/ML can be applied to the collected data. We will detail this last aspect better in Section 4.3.

2.2. Overview of Supervised, Unsupervised, Semi-Supervised, and Self-Supervised Learning

In the literature, many algorithms have been used to manage this data and enhance buildings in order to reach the so-called IEEBs. These algorithms mainly belong to machine learning techniques and can be classified into supervised, unsupervised, semi-supervised, and self-supervised learning, as summarized in Figure 1.

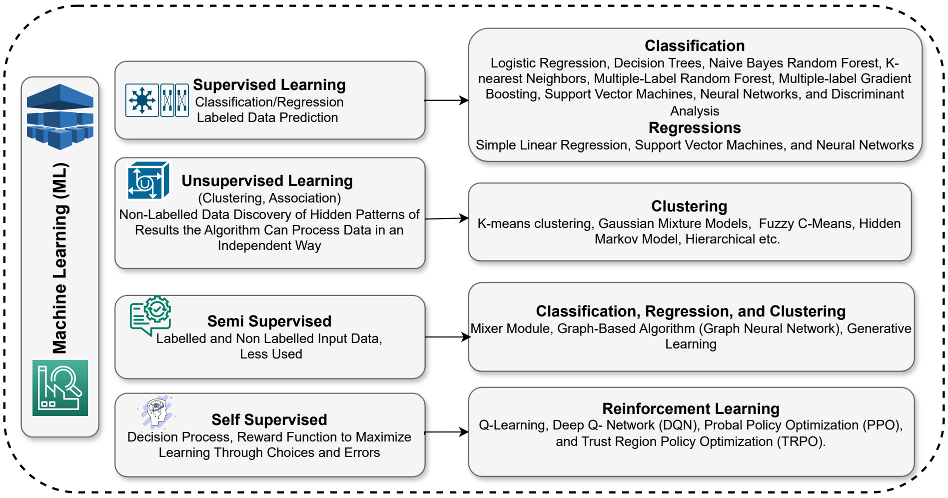

Figure 1. An overview of various applications in IEEBs.

Supervised learning involves creating a model based on labeled training data, which consist of information about the features, to enable predictions on data that are not currently available or are from the future [32]. This type of learning deals with two main problem types: classification and regression. In contrast to supervised learning, unsupervised learning deals with unlabeled or unstructured data. This approach is commonly employed to cluster data with similar characteristics or to uncover patterns and trends within a raw dataset. Unsupervised learning primarily involves two techniques: clustering and association [32]. Semi-supervised learning is a field within ML that focuses on utilizing both labeled and unlabeled data for conducting specific learning tasks. Mixer modules, graph-based algorithms (graph neural networks), generative learning, etc., are examples of semi-supervised algorithms [33]. Self-supervised learning aims to develop a system that enhances its performance through engagement with the environment. It employs an agent that strives to maximize its cumulative reward by learning through experimentation. This entails grasping its present condition's immediate advantages (reward signal) and adapting its behaviors to optimize future gains. The system's actions are assessed based on reinforcements that gauge the effectiveness of these actions, distinguishing this learning approach from conventional supervised learning [34].

2.3. Description of Specific ML Algorithms Used in IEEBs

This section will briefly explain some of the most used algorithms for implementing IEEBs to help the reader understand the rest of the paper. The aim is to provide a general knowledge of various algorithms rather than to provide a comprehensive discussion of them.

Among the supervised learning techniques, support vector machines (SVMs) are one of the most powerful and robust classification and regression algorithms. It is a method used in ML to sort items into categories. It does this by finding a dividing line (or boundary) that best separates different groups of items in a dataset. They are prominently used for solving binary classification problems, which require the classification of elements in a set of data into two different groups [35]. In the literature, SVMs are used in IEEBs mainly for occupancy prediction and energy consumption prediction [36–38]. Additionally, support vector regression (SVR) utilizes the concepts of support vector machines in the context of regression tasks. Its objective is to identify a function that stays within a specified margin of error from the observed values, aiming to minimize the error within a predefined tolerance while also seeking to maintain a flat shape as much as possible. The utilization of the SVR algorithm was examined in [39]. It also discusses how it can forecast continuous energy usage [39].

Two other supervised ML techniques frequently used in the literature for IEEBs' development are decision tree (DT) and the random forest (RF). DT is a tree-based algorithm that helps make decisions by breaking down a problem into smaller, simpler questions, leading step by step to the final answer or goal. It is utilized for both classification and regression tasks. On the other hand, an RF is a group of many DTs that work together to make better predictions or decisions than just one tree could on its own [40]. In the literature, DTs have been employed, among other things, for analyzing sensor data (e.g., CO_2 levels, temperature, sound, etc.) to perform binary classification, determining occupancy status [41]. On the contrary, a random forest aggregates predictions from multiple decision trees, with each tree trained on a subset of sensor data, with the aim of improving accuracy and robustness in predicting occupancy levels in smart buildings [42].

Naive Bayes serves as a classification algorithm in IEEBs. It determines the likelihood of each label being assigned to a specific object based on its features [43]. Subsequently, it selects the label with the highest likelihood. The Naive Bayes approach finds various uses in the field of IEEBs, including the prediction of electricity consumption [44] and the enhancement of the comfort for occupants in two non-residential buildings in Norway [45].

The ML technique called artificial neural network (ANN) is generally applied to solve regression and classification problems [46]. An ANN is like a computer brain that learns and makes decisions by finding patterns in various types of data. It is made up of digital "neurons" that are linked together and can be trained to recognize things like images and sounds or solve complex problem scenarios [47]. In the literature, ANNs are often used to assess thermal comfort in IEEBs. Forecasting the indoor temperature or air quality provides advice for maximum savings on indoor energy usage [48,49]. The ANN approach also enables real-time monitoring. One of the advantages of this method is its capacity to detect non-linearity between the input and output datasets [50]. The papers [51,52] also discuss ANN for the building's energy efficiency.

2.4. Description of Specific DL Algorithms Used in IEEBs

Deep learning (DL) techniques excel at extracting features and learning from large datasets, which is critical for IEEBs. These methods, which include deep neural networks (DNNs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), Long Short-Term Memory (LSTM), gated recurrent unit (GRU), deep reinforcement learning (DRL) and others, outperform classical ML, allowing for rapid adaptation and efficient resource utilization for improved sensory and analytic intelligence [48–50].

DNNs share many similarities with neural networks in terms of their structures. Like ANNs, deep learning networks consist of three types of layers: input, hidden, and output layers. However, in deep learning networks, there are typically more hidden layers involved than in ANNs. The depth of the architecture in these networks is determined by the number of hidden layers, as highlighted in [52]. The complexity of a layer is determined by the number of hyperparameters, also known as weights, which are utilized to characterize it [52].

Among the introduced DL techniques, CNNs, which contain three main layer types—convolutional layers (also called filters), pooling layers, and fully connected layers—are frequently employed in object/image identification and classification [34].

The convolutional layer, fundamental to CNNs, performs the majority of computations during training by using convolutional filters to process input data. It identifies spatial features by moving the filter across the input, creating a feature map. This hierarchical structure allows CNNs to efficiently recognize complex patterns and improve classification and prediction capabilities by analyzing subcomponents at multiple levels [53]. Some applications of CNNs in IEEBs are presented below. The paper [54] shows how CNNs can be applied to forecast energy loads for a single-story building using a historical dataset. The paper in [55] emphasizes the significance of smarter management and planning operations in renewable energy predictions. Additionally, the paper in [56] introduces a hybrid DL (DNN and CNN) approach to predict residential energy consumption.

Also, a neural network (NN) with multiple hidden layers is represented by the Multi-Layer Perceptron (MLP), which is useful for complex data modeling in smart buildings and was covered in the study of [57].

RNNs are a form of ANNs that find extensive use in tasks involving text processing, audio or speech recognition, and forecasting sequential data or time series. They are particularly beneficial in scenarios where retaining previous data is crucial for anticipating future trends [53,58]. RNNs are extensively used in literature to realize IEEBs. As an example, the authors of [59] presented an RNN model for examining sequential data in which they focus on time-series sensors to forecast energy usage patterns and occupancy trends, thereby enhancing the efficiency of building management. Classical RNNs have limitations in maintaining long-term temporal memory efficiently. Two specific types of RNNs are commonly employed to tackle issues related to training and memory retention: LSTM and GRUs. Typically, LSTM is utilized in various tasks such as data prediction, processing, and classification, including applications like language translation, speech recognition, time series forecasting, video analysis, and anomaly detection. The LSTM has some layers, such as the input gate, the output gate, and the forget gate. These gates regulate the flow of information, allowing the network to retain important information over long sequences and discard irrelevant data. Some examples in which LSTM is used for the realization of IEEBs are reported below. In [52], LSTMs were implemented in 201 case studies for making predictions on heating and cooling energy. Karijadi et al. in [60] explored a hybrid approach combining random forest and LSTM to enhance the accuracy of building energy consumption forecasts. Additionally, Peng et al. in [61] leveraged the LSTM technique for forecasting monthly energy consumption.

GRUs are a type of recurrent neural network architecture that simplifies the LSTM model while retaining its ability to capture dependencies in sequence data. GRUs achieve this through two main gates, the Update Gate and the Reset Gate. The Update Gate in a GRU acts as a knob to regulate the amount of previously stored data that is retained vs. the amount of newly acquired information. The Reset Gate works like a filter, determining how much of the past we should forget. These gates work together to help the GRU select what to remember and what to forget, allowing it to handle information sequences effectively. As examples, in the context of IEEBs, the work in [62] proposed the multi-directional GRU and CNN methods for load and energy forecasting, while the paper [63] discussed energy consumption prediction strategies based on random forest and CNN-GRU.

Ensemble learning is a ML/DL method where multiple models are combined to improve the overall performance of the aggregated model [64]. This approach helps to capture more details from the data and reduce errors. By leveraging the strengths of different models, ensemble learning creates a more accurate and reliable prediction system [64,65]. In the context of IEEBs, ensemble learning has been used to predict energy consumption patterns and optimize HVAC systems [66]. This leads to more efficient energy usage, reducing waste and costs. Additionally, ensemble learning can help in predicting equipment maintenance needs, preventing unexpected failures, and ensuring consistent thermal comfort for occupants [67,68]. Overall, it enables smart buildings to adapt better to changing conditions, improve sustainability, and maintain a comfortable indoor environment [64,65]. In the literature, some papers have used ensemble models. For example, the paper [69] used SVR and RF algorithms for predicting energy consumption values in smart buildings. The paper [70] proposes an ensemble learning approach using the extreme gradient boosting (XGBoost) algorithm to predict building energy loads accurately. The paper [71] proposes BiGTA-net, which combines bidirectional gated recurrent unit (Bi-GRU) with Temporal Convolutional Network (TCN) for short-term load forecasting (STLF) in urban buildings. The authors of [72] used hybrid DL (Auto Regression Integrating Moving Average and LSTM models) for occupancy prediction.

2.5. Description of Reinforcement Learning Algorithms Used in IEEBs

Reinforcement learning (RL) [73] is a type of ML in which an agent learns to make decisions by interacting with an environment to achieve a goal. The learning process involves the agent taking actions and receiving feedback in the form of rewards or penalties, which guide it in learning the best strategy or policy, to accumulate the highest possible reward over time [73]. Q-learning, deep Q-network (DQN), probal policy optimization (PPO), and trust region policy optimization (TRPO) are some of the most popular models [73]. RL models are used to design optimal control strategies for IEEBs. As an example, in the literature, the application of RL for the intelligent control of HVAC systems is shown in [74–76].

Deep reinforcement learning (DRL) combines deep learning and reinforcement learning principles to enable agents to learn optimal policies for complex decision-making tasks. It utilizes deep neural networks to approximate value functions, policies, or models of the environment, allowing the agent to interpret high-dimensional sensory input and make informed decisions. DRL extends the capabilities of traditional RL to environments with rich, complex inputs, making it suitable for applications like robotics, game playing, autonomous vehicles, and sophisticated control systems [73]. Some existing works on DRL can be found addressing energy subsystem management in Office [77–80] and home [81].

2.6. Federated and Transfer Learning

In recent years, two prominent techniques that have gained traction in the realm of IEEBs are Federated Learning (FL) [82] and transfer learning (TL) [83]. FL and TL are particularly noteworthy for their ability to work alongside existing models, enhancing their capabilities without necessitating fundamental changes. FL offers a robust data privacy and security solution by enabling machine learning models' training locally on devices, thus avoiding the transfer of sensitive data to a central server. Only models are exchanged and typically merged in the cloud. This decentralized approach ensures that the personal information of IEEB inhabitants remains secure on local devices. Similarly, TL facilitates the transfer of knowledge from one model to another, making it possible to apply learned features to new tasks, thereby improving efficiency and performance.

3. Survey Strategies: Intelligent Energy-Efficient Buildings

The objective of this study is a review of review papers, namely a "Meta-Survey", in the domain of smart buildings realized through the use of ML for reaching energy efficiency, namely in the domain of IEEBs. We have pursued an informal and individual search to accomplish our objective. It is important to note that we have specifically sought surveys, systematic surveys, reviews, or overviews in the considered domain. Consequently, we conducted a 5-year survey of articles, ranging from 2019 to April 2024, according to the guidelines of the PRISMA statement [84].

After screening records and selecting reports, we analyzed over 50 works and finally chose 21 surveys or review papers for our investigation. In particular, attention was drawn to specific survey articles related to ML, DL, and RL [3–23] with their specific contributions (such as algorithms or model comparisons) in the smart buildings field and to more general survey papers outlining definitions, objectives, and roadmaps for IEEB. More details about the paper selection will be given below.

3.1. The Goal of the Investigation

In order to compare the selected works to determine the most recent developments in IEEBs, we raised some research questions that can help readers understand some important details of the reviewed surveys. In particular, the research questions (RQ_s) are highlighted as follows.

RQ_1 How is the field related to IEEBs specified or defined?
RQ_2 What architectures are most commonly used for IEEBs?
RQ_3 Which ML methods are most commonly used in IEEBs?
RQ_4 What sort of dataset or real implementation is utilized to realize IEEBs?
RQ_5 What are the main challenges and research directions in the field of IEEB?

3.2. Inquiry Search Techniques

All authors conducted a thorough search for references in the digital libraries of Google Scholar, IEEE Xplore, Elsevier, ACM Digital Library, MDPI, Scopus, and Web of Science. The paper's references related to IEEBs were thoroughly searched, and the research was focused on locating scientific articles that proposed answers (i.e., models, strategies, approaches, use-cases, and architectures). The phrase "keyword search" was formed using the concepts regarding smart or intelligent buildings enhanced with machine learning algorithms to reach energy efficiency or reduce energy consumption.

Starting from this concept, we elaborated and used the following search phrase:

$$\begin{aligned}
&(\text{“}Smart\ Buildings'' \ OR \ \text{“}Smart\ Environments'' \ OR \\
&\text{“}Sustainable\ Buildings'') \ AND \ (\text{“}Energy\ Efficiency'' \ OR \\
&\text{“}Reducing\ Energy\ Cost'' \ OR \ \text{“}Energy\ Optimization'') \ AND \\
&(\text{“}Machine\ Learning'' \ OR \ \text{“}Deep\ Learning'' \ OR \\
&\text{“}Reinforcement\ Learning'' \ OR \ \text{“}Artificial\ Intelligence'')
\end{aligned}$$

We used the search string to find the appropriate results. The survey inquiry search techniques or search plan, including database identification, keyword search, and the selection and rejection of papers in our study, are detailed in Figure 2.

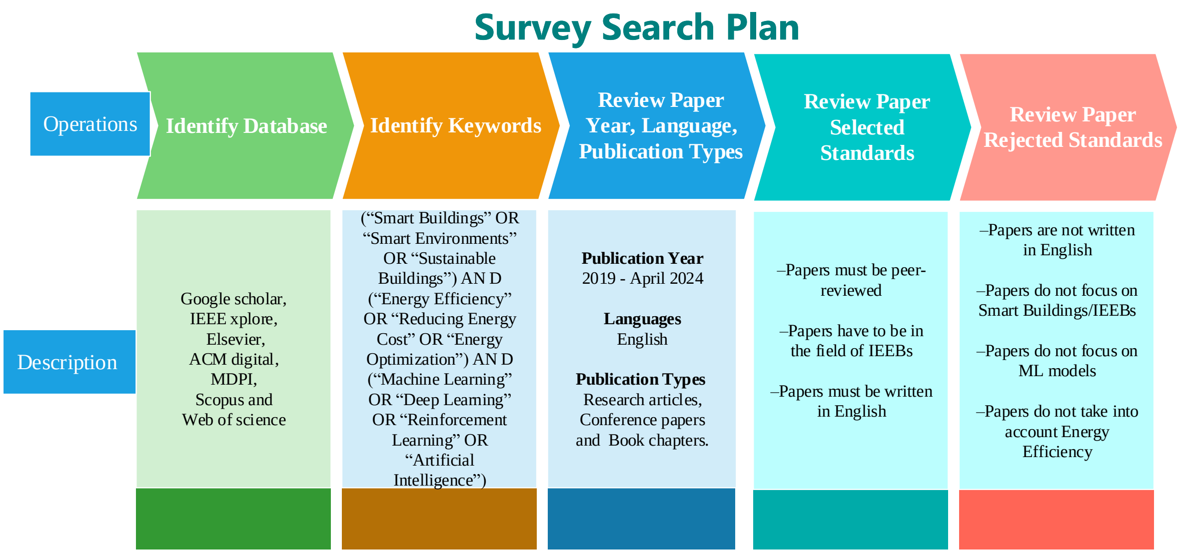

Figure 2. Detail of our meta-survey search plan.

3.3. Eligibility Criteria

The purpose of this study was to conduct a comprehensive analysis of surveys, reviews, or systematic reviews of the existing literature in the field of IEEBs. In particular, we searched for manuscripts in which Intelligent Energy-Efficient Buildings are described and machine learning is used to realize them.

If an article had one of the following in the screening, it was not included in the selection.

- Only the title, abstract, or keywords of the article contain the phrases "Machine Learning" [85,86] or "Energy Efficiency" or "Smart Buildings" [87,88] or one of their equivalents, but they are absent from the article in the main content.
- The term "ML" or one of its equivalents is either misused or poorly defined.
- The work has already been extended or is a pre-print.

3.4. Survey Preference

We can observe the flowchart of the approach taken to pick the articles in accordance with the PRISMA guidelines [84] in Figure 3. The search in the digital libraries, using the search phrase above, provided a total of 121 articles. In order to discard studies not relevant to our review, we removed the papers due to the following technical criteria, based on (i) the type of publication, by eliminating materials such as editorials, short papers, posters, theses, dissertations, brief communications, commentaries, and unpublished works; (ii) articles partially or entirely not written in English; (iii) papers with text unavailable in full. In these steps, a total of 71 papers were removed, resulting in 50 publications obtained. In order to choose the relevant studies for this review, the authors analyzed only the records of each article, including the title, abstract, and keywords, during the initial screening task. Each researcher evaluated the title and the abstract according to the eligibility criteria to decide if that paper should be included in the next screening phase.

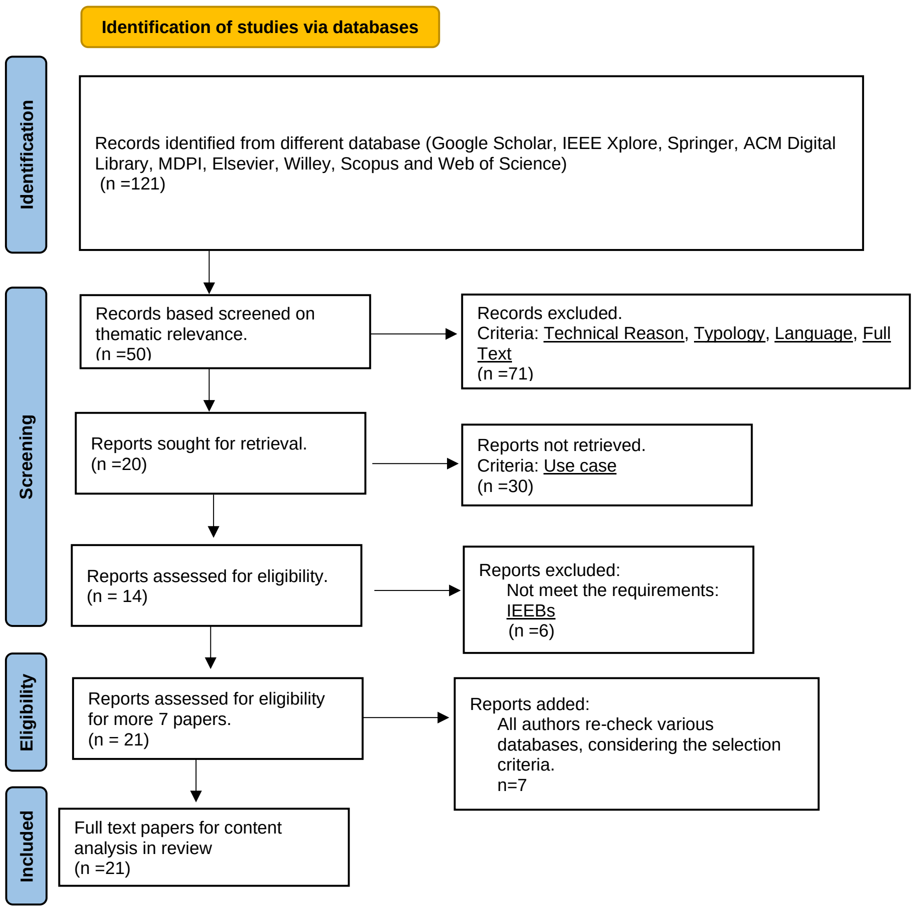

Figure 3. A Prisma-based flowchart of the selection procedure for our meta-survey.

During the second step of our screening process, we focused on the content of the papers and assessed whether the articles discussed the concept of smart buildings. This screening helped us shortlist 20 papers that met this criterion while rejecting 30 others that did not fully address this aspect.

Moving forward, we shifted our focus to the subsequent screening stage. We had a more detailed discussion about whether the IEEBs were fulfilled or not. This thorough evaluation resulted in the identification of 14 papers that not only addressed the broader concept of smart buildings but also provided significant insights into energy efficiency using ML techniques. Through this systematic screening and identification process, we've refined our selection to 14 papers that offer comprehensive perspectives on ML and its relationship with energy efficiency, specifically within the context of IEEB applications.

In the end, each author individually checked the chosen databases again, and seven more papers to be incorporated into our research went out, which met all the criteria for inclusion. The total number of papers included in our study is therefore 21.

Numerous papers were excluded during the screening phase as they merely referenced ML as a buzzword term in the title or abstract without integrating it as a core component in the research. In addition, papers written in languages other than English, short articles, and ongoing projects were excluded.

4. Literature Review: Intelligent Energy-Efficient Buildings

This section analyzes, first of all, the papers selected for this meta-survey. Then, it discusses the research questions introduced in Section 3.1. In particular, we will give answers to all of them one by one.

4.1. Overview of the Selected Surveys

All the selected survey papers taken into account for this meta-survey are summarized in Table 1, where, for each work, we also highlight (i) the year of publication, (ii) the citations on Scopus, (iii) the technologies used, (iv) if it uses the Prisma methodology, (v) the objective of the survey, (vi) the use cases used in the reviewed work, and (vii) some remarks.

In more detail, the paper in [3] compares and discusses several experiments involving ML and DL models applied to IEEBs. The study focuses on maintaining occupant comfort, health, and safety within IEEBs. Commonly used models are analyzed, including kernel-based methods such as SVM and PCA, as well as neural networks like feed-forward networks, autoregressive models, and LSTM networks. However, this work does not address data security considerations during the model training phase.

The survey paper in [8] compares various ML algorithms used for controlling lighting in buildings since 2014. It discusses classical learning methods, RL, and ensemble learning approaches. The paper provides a review of smart lighting applications within IEEBs. However, the focus on smart lighting alone can be somewhat limiting.

The paper in [5] reviews ML models, specifically supervised models, for daylighting design and control. It highlights advanced ML methods to improve daylight modeling and proposes solutions to address scalability and generalization issues in ML models. The authors emphasize the importance of optimizing daylighting performance in building design, focusing exclusively on ML, particularly ANNs, for daylighting optimization. They suggest that incorporating more features could lead to a deeper analysis and a better general understanding.

The paper in [4] reviews the role of ML and IoT technologies in enhancing smart buildings for energy efficiency. It discusses how IoT devices improve human security, monitoring, and control operations. The paper covers various algorithms, including regression models for predicting the electrical load in commercial buildings and genetic algorithms for optimizing energy consumption and predicting user comfort. However, it does not specifically identify which ML algorithms are most effective for IEEBs.

Table 1. Details about the selected paper list.

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
1. Machine Learning for Smart and Energy-Efficient Buildings [3]	2022	10	ML	No	Comparison of several works involving IEEBs for maintaining occupant comfort, health, and safety.	Smart Home	Several experiments are compared and discussed, but no discussion is presented on the data security during model training.
2. Machine learning methods in smart lighting towards achieving user comfort [8]	2022	44	ML	No	Comparison of the ML algorithms used to control the lighting in buildings.	Smart Home	This paper reviews smart lighting applications in IEEBs. However, focusing only on smart lighting can be limiting.
3. A review on the current usage of machine learning tools for daylighting design and control [5]	2022	19	ML (Supervised)	No	Comparison of works optimizing daylighting for reaching Energy Efficiency.	Smart Building	The paper exclusively focuses on ML (particularly ANNs) in daylighting optimization.
4. The role of machine learning and the internet of things in smart buildings for energy efficiency [4]	2022	29	ML	No	Exploring ML methods with IoT technologies to enhance the effectiveness of smart buildings for energy efficiency.	Smart Building	The paper discusses various perspectives on IEEB and IoT. However, the paper did not specifically mention which ML algorithms technologies are most effective for IEEBs.
5. A review of deep reinforcement learning for smart building energy management [9]	2021	141	DRL	No	Comparison of papers that used DRL for energy management.	Various Buildings	The work reviews DRL algorithms applied to energy management in Smart Buildings. However, the review misses papers introducing long learning time for DRL agents.
6. A review of reinforcement learning for autonomous building energy management [10]	2019	169	RL	No	Analysis of works that employed RL for energy management.	Various Buildings	The paper mainly reviews studies on simulated building energy management with RL, emphasizing the need for precise simulators and realistic data.

Table 1. *Cont.*

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
7. Reinforcement learning in sustainable energy and electric systems: a survey [11]	2020	148	RL	Yes	Overview of RL in sustainable energy systems, and discussion of applications, future challenges, and opportunities.	Smart Building	The paper acknowledges the potential of RL in sustainable energy. The paper also highlights its limited practical implementation.
8. Machine learning and deep learning in energy systems: A review [12]	2022	80	ML/DL	No	Review of work on energy efficiency, management and analysis.	Smart Buildings	The paper studies the methods and applications of ML and DL in energy systems. However, the authors do not cover how these systems work when things are uncertain (outcomes or conditions are not known or predictable).
9. A Review on Deep Learning Techniques for IoT Data [13]	2022	87	DL	Yes	Analysis of articles in which DL is used for IoT data processing.	Various Buildings	The article provides valuable perspectives on utilizing DL for handling IoT data, but it does not discuss the research limitations.
10. Federated learning for smart cities: A comprehensive survey [14]	2023	54	ML/DL (FL)	No	Analysis of works using ML, DL, and FL in Smart Cities applications.	Smart Cities and Buildings	The paper reviews works regarding FL integration with smart city/grid/healthcare/governance/disaster management/industries monitoring, that also consider energy efficiency. It lacks a detailed discussion on FL challenges in smart cities, including scalability, data complexity, and heterogeneity.

Table 1. *Cont.*

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
11. A Review of Federated Learning in Energy Systems [15]	2021	16	ML/DL (FL)	No	Review of works using ML, DL, and FL in various fields for energy efficiency.	Various Buildings	This article discusses energy demand response, identification, prediction, and optimizations. However, the authors do not discuss potential drawbacks or risks associated with FL in energy systems.
12. Forecasting energy use in buildings using artificial neural networks: A review [7]	2019	199	ANN	No	Analysis of works about the forecasting of energy spent in buildings by using ANNs.	Smart Building	The paper highlights the importance of ANNs in energy forecasting. However, it acknowledges the limitations of the works in literature in adapting to seasonal variations and extrapolating beyond the range of the trained data.
13. Application of machine learning in thermal comfort studies: A review of methods, performance and challenges [16]	2022	64	ML	No	Review and comparison of works focused on energy efficiency and thermal comfort.	Smart Building	In the IEEB domain, authors considered thermal comfort and energy efficiency. However, the authors do not provide a comprehensive comparison of different ML algorithms.
14. Review of occupant-centric thermal comfort sensing, predicting and controlling [6]	2020	97	ML	No	Review and comparison of works focused on energy efficiency and thermal comfort.	Smart Building	The research investigates data-driven approaches to enhance thermal comfort and energy efficiency. Yet, this study does not provide in-depth information on control strategies and the efficacy of non-invasive sensors.

Table 1. *Cont.*

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
15. A review of the applications of artificial intelligence and big data to buildings for energy-efficiency and a comfortable indoor living environment [17]	2019	117	AI, ML and DL	No	Review on AI and Big data applications for IEEBs.	Smart Building	This work analyzes AI techniques to design energy-efficient buildings. However, this paper suggests exploring data mining and optimal weather data for better energy efficiency.
16. An overview of machine learning applications for smart buildings [18]	2021	141	ML	No	Focuses on energy management in IEEBs.	Smart Building	The paper provides an overview of IEEBs focusing on the learning ability from a system-level perspective. There is a lack of discussion on implementing autonomous AI agents and training environments in real-world building scenarios.
17. Artificial intelligence evolution in smart buildings for energy efficiency [19]	2021	79	AI and ML	No	AI technologies applied to IEEBs with a focus on Building Management Systems and demand response programs.	Smart Building	The study explores the latest advancements in AI-based modeling techniques for predicting building energy consumption, encompassing various areas like energy efficiency, occupant comfort, architectural design, and facility upkeep. However, it does not delve into aspects such as security, analysis of occupant behavior, or predictive maintenance.

Table 1. *Cont.*

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
18. Intelligent deep learning techniques for energy consumption forecasting in smart buildings: a review [21]	2024	0	ML and DL	No	Review of forecasting methodologies for energy consumption in smart buildings.	Smart Building	This study examines the dataset, types of load, prediction, precision, and assessment criteria in IEEBs. For additional exploration, hybrid models that merge various DL structures could enhance accuracy with extensive datasets.
19. Digital twin technology for thermal comfort and energy efficiency in buildings: A state-of-the-art and future directions [20]	2023	07	ML and Digital Twins	No	Review of digital twin technology for thermal comfort and energy management in smart buildings by using DL.	Smart Building	Digital twins can help occupants, increase human-centered solutions, and boost energy prediction levels. However, the paper does not cover the challenges and benefits of digital twins in IEEBs that take care of thermal comfort.
20. A review of building digital twins to improve energy efficiency in the building operational stage [22]	2024	0	ML and Digital Twins	No	It focuses on digital twins for energy efficiency operations in buildings.	Various Building	The paper examines the use of digital twin technology in IEEBs for building operations. It outlines five primary applications, which include monitoring components, detecting anomalies, and optimizing operations. However, a significant obstacle lies in effectively integrating data acquisition systems with Building Management Systems.

Table 1. *Cont.*

Title	Year	Citations *	Technology Used in the Reviewed Papers	Prisma	Objective of the Review	Use Cases Highlighted	Comments/Remark
21. Machine Learning Applications for Smart Building Energy Utilization: A Survey [23]	2024	0	ML	No	Systematic review of applications and ML methods for optimizing energy utilization.	Smart Building	The paper offers a unique classification system (taxonomy) for energy applications in IEEBs. It proposes further research in decentralized, diverse real building structures, but it does not discuss the potential challenges involved in this endeavor.

* The Citation Number Has Been Taken from Scopus and Updated on 28 March 2024.

The papers [9–11] discuss various agent-based RL methods in IEEBs. The paper in [9] focuses on DRL for smart building energy subsystems such as HVAC and reviews DRL methods for residential and commercial building energy systems. While it provides an excellent overview of DRL algorithms applied to energy management in smart buildings, it fails to address the long learning times required for DRL agents. Mason et al. [10] explore the application of RL models, such as actor–critic learning, DQN, and A3C, for HVAC, water heater, and lighting control. The paper emphasizes how RL can learn the best control policies to minimize energy consumption effectively. It also discusses factors that increase complexity in applying RL to building energy management, mainly reviewing studies on simulated building energy management with RL and highlighting the need for precise simulators and realistic data. In [9], the authors focus on RL applications in sustainable energy and electric systems, along with smart buildings. The paper acknowledges the potential of RL in sustainable energy while also pointing out its limited practical implementation.

The paper [12] provides a detailed study of ML and DL applications in energy systems, covering common uses such as optimization, forecasting, and fault detection. It examines the methods and applications of ML and DL in energy systems. However, the authors do not address how these systems perform under uncertainty, where outcomes or conditions are unpredictable.

The paper [13] reviews DNN architectures and DL algorithms in IoT applications, along with their challenges in IEEBs. It also explains LSTM data storage, error reduction, and BPTT training for various IoT data. While the paper provides valuable insights into using DL for handling IoT data, it does not discuss the research limitations.

The papers [14,15] discuss FL approaches in various applications with a focus on privacy concerns. More specifically, the paper [14] highlights the importance of FL for smart cities and smart buildings in various applications, showcasing smart city projects that integrate FL for transportation, healthcare, and more. It reviews FL integration with smart city grids, healthcare, governance, disaster management, and industry monitoring, also considering energy efficiency. However, it lacks a detailed discussion of FL challenges in smart cities, including scalability, data complexity, and heterogeneity. The paper in [15] provides an overview of the FL paradigm, and global model generation methods in energy systems and discusses challenges, opportunities, and limitations. It covers energy demand response, identification, prediction, and optimization. However, the authors do not address the potential drawbacks or risks associated with FL in energy systems.

The paper [7] reviews the use of ANNs for building energy forecasting since 2000. It identifies research gaps and future directions in ANNs for energy forecasting and provides heuristics for selecting ANN architecture parameters. The paper highlights the importance of ANNs in energy forecasting but acknowledges the limitations in the literature regarding adaptation to seasonal variations and extrapolation beyond the range of the trained data.

The paper [16] provides an overview of ML algorithms, including supervised learning, unsupervised learning (such as SVM, ANN, KNN, and RNN, RL), and RL in thermal comfort studies for IEEBs. It explores the high prediction accuracy of personal comfort models using ML and recommends further investigation into personal comfort models and sample sizes. In the IEEB domain, the authors consider both thermal comfort and energy efficiency. However, they do not provide a comprehensive comparison of different ML algorithms.

The paper [17] discusses applications of AI and big data for energy-efficient buildings, highlighting how these technologies enhance energy efficiency and cost-effectiveness in smart buildings. It also examines how AI and big data improve indoor environment quality in both commercial and residential buildings. The paper analyzes various AI techniques for designing energy-efficient buildings and suggests further exploration of data mining and optimal weather data for achieving better energy efficiency.

The works [18,19] review papers about IEEBs in which the thermal comfort is also taken into consideration. In particular, the paper [18] explores an overview of autonomous ML applications for building energy management. It discusses autonomous AI agents and offers an overview of IEEBs from a system-level perspective. However, it lacks a discussion on implementing autonomous AI agents and training environments in real-world building scenarios. The paper in [19] reviews recent work on smart buildings using AI for energy efficiency through sensors and big data. It highlights how AI technologies reduce energy consumption and improve control, reliability, and automation. It also discusses open challenges and future research directions for AI in buildings. The study explores the latest advancements in AI-based modeling techniques for predicting building energy consumption, covering areas such as energy efficiency, occupant comfort, architectural design, and facility upkeep. However, it does not delve into security, analysis of occupant behavior, or predictive maintenance.

The paper [21] reviews ML and DL models for forecasting in IEEBs. It identifies research gaps and suitable prediction methodologies to address current issues. The paper explores contributions and inferences from previous research in energy forecasting, examining datasets, types of loads, prediction accuracy, and assessment criteria in IEEBs. For further exploration, the study suggests that hybrid models combining various DL structures could enhance accuracy with extensive datasets.

The papers [20,22] review recent work on IEEBs, including the digital twins paradigm. The paper [20] reviews digital twin technology for thermal comfort in IEEBs. It focuses on methods, technologies, algorithms, and approaches in digital twins. This work also emphasizes limitations such as sensor adoption, occupant perception, and algorithm comparison. Digital twins can help occupants, increase human-centered solutions, and boost energy-prediction levels. However, the paper does not cover the challenges and benefits of digital twins in IEEBs concerning thermal comfort. The paper [22] identifies the main applications of digital twins in IEEBs. It highlights challenges like reliance on Building Information Modeling and emphasizes future research directions for digital twin development. The paper examines the use of digital twin technology in IEEBs for building operations, outlining five primary applications, including monitoring components, detecting anomalies, and optimizing operations. However, a significant obstacle lies in effectively integrating data acquisition systems with Building Management Systems.

Finally, the paper [23] presents a systematic review of applications and ML methods for optimized energy utilization. It provides a detailed analysis of solutions and techniques for electric grids, maintenance, and security. The paper offers a unique classification system (taxonomy) for energy applications in IEEBs. It proposes further research in decentralized, diverse real building structures but does not discuss the potential challenges involved in this endeavor.

4.2. Research Question 1

Referring to RQ_1, in the field of IEEB, there is no common definition due to the research focus on individual aspects. The field of IEEB is complex and constantly evolving, which makes it difficult to establish a consensus on a universal definition. This is because stakeholders and research scientists have different perspectives on what constitutes an IEEB based on their specific objectives and technologies. The following are some ways we could define IEEBs.

According to the review works in [9–11,18,23], we could identify IEEBs as the smart buildings in which some energy management techniques are applied. These IEEBs encompass the application of ML models to optimize building energy consumption and enhance energy efficiency. It involves leveraging data from various IEEB systems, such as HVAC, lighting, and occupancy sensors, to develop predictive models and make informed decisions about energy usage.

According to the surveys in [8,11,12], we may define an IEEB as a machine-learning-driven smart building capable of making specific actions on the environment. In particular, an IEEB can control and automate HVAC and lighting (day and night) based on occupancy, weather conditions, and energy consumption patterns. It can also collect and analyze data from various sensors, such as accelerometers, temperature, and current consumption, to identify anomalies that may indicate potential equipment issues.

Moreover, as reported in [6,16,20], thermal comfort is essential for IEEB indoor environmental quality, significantly affecting human well-being, productivity, and health. It involves creating a satisfying indoor climate, considering factors such as air temperature, humidity, air movement, and radiant temperature. Much of the literature tries to consider thermal comfort by focusing on the energy efficiency of buildings. Researchers try to achieve these two aims by integrating ML into their works. This involves the use of algorithms to analyze sensor data, user preferences, and environmental factors. This analysis enables predictive modeling of occupant thermal comfort, allowing, for example, proactive adjustments to HVAC systems to maintain comfort and prevent overuse. Additionally, ML optimizes HVAC operations by learning energy consumption patterns and occupancy schedules, leading to more efficient energy use and reduced costs.

In addition, the studies [20,22] describe a collaborative method in which ML algorithms utilize information from different sensors in a building to instantly forecast and enhance energy usage and thermal comfort levels. Concurrently, a digital twin functions as a digital copy of the building, mimicking its physical and operational attributes. This allows for analyzing, visualizing, and testing energy efficiency measures and comfort strategies in a virtual environment before implementing them in the real world, leading to more informed decision-making and improved building performance.

Last but not least, several works in the literature consider predictive maintenance in IEEBs [12,13,15]. This is achieved by using ML to analyze sensor data and predict equipment failures. This technique enables proactive maintenance scheduling, reducing unexpected downtime and maintenance costs, and enhancing IEEB systems' overall reliability and efficiency. By leveraging data-driven insights, traditional maintenance practices can be transformed into more efficient, cost-effective, and reliable processes.

4.3. Research Question 2

Referring to RQ_2, in this section, we will discuss the various architectures used in the literature for the implementation of IEEBs. In this context, architectures typically involve edge [89], fog [90], cloud [91], and distributed computing [92], with each playing a distinct role in the overall system. In the review in [8], for example, cloud computing offers several advantages for smart lighting. Also, the papers [19–21] discuss cloud computing in their study. However, cloud computing can introduce some limitations, such as delay and privacy. The concept of fog computing is applicable to overcoming these limitations [8,9] by keeping data closer to the producers. In several scenarios, edge computing architecture enables data processing at the data collection site, like within the building, rather than being sent to the cloud for processing [93]. This approach is particularly useful for real-time data processing and immediate actions, such as adjusting HVAC systems or lighting based on current conditions [9,13]. Edge computing reduces the latency in decision-making, thereby minimizing the need for continuous data transmission to the cloud, saving bandwidth, and reducing response times. It is ideal for applications that require quick, localized decisions and for situations where continuous cloud connectivity might not be guaranteed [9,13].

As another architecture, distributed computing [14] is a model that uses computing resources across different locations, including edge devices, local servers, and the cloud. This approach creates a more robust system that can continue processing even if a segment of the network fails unexpectedly.

According to the reviewed work, in the context of IEEBs, architecture discussions mainly revolve around edge and cloud computing [8,19–21,93] . These two architectures play a critical role in managing the enormous amount of data and complex processing requirements of interconnected devices, systems, and services that are inherent in IEEB environments. In Table 2, we report the architectures that have been predominantly used in the works reviewed by the surveys we have analyzed in this meta-survey. Moreover, the table shows the pros and cons of each architecture type.

Table 2. The Architectures most commonly used for IEEB implementation.

Architecture	Pros	Cons
Edge	Minimal latency, real-time control	Limited computational resources
Fog	Localized handling, reduced latency	Limited scalability compared to cloud computing
Cloud	Scalable, robust computing resources	High latency, data transfer expenses
Hybrid	Low latency for latency-sensitive tasks, access to cloud resources	Needs more complex management and orchestration
Distributed	Scalable, high performance	Can be complex to maintain and deploy

4.4. Research Question 3

Regarding RQ_3, various ML techniques have been employed in IEEBs. The analyzed review papers highlight that the most common ML methods used for IEEB are the ones reported in the following. In particular, SVM has proven to be effective in energy efficiency applications [37]. In fact, it performs very well in predicting future energy consumption patterns and identifying abnormal energy usage by using historical energy data and associated parameters, enabling proactive energy management strategies [3,21]. DT and RF [19] are also popular ML methods that are frequently used in IEEBs. DT delivers a rule-based framework to classify and predict occupant behavior, allowing for personalized energy management techniques. RF, which consists of multiple DTs, offers improved accuracy and robustness in energy-related predictions [3,19,21]. ANNs have also gained significant traction in the optimization of energy efficiency in buildings. According to the literature, they are particularly useful in projects like load forecasting [21], energy optimization [23], and adaptive control [18], as they excel in modeling complex nonlinear relationships. By training ANNs with collected energy data and taking into account outside factors, such as weather conditions, these models can forecast future energy demand and optimize energy use according to [5,17,19,23]. Clustering algorithms are frequently used to recognize patterns in energy use and classify households according to their energy consumption profiles. By identifying particular groups of users with comparable energy usage patterns and customizing interventions accordingly, these algorithms enable targeted energy management strategies [4].

In general, ML techniques such as SVM, DT, RF, ANNs, and clustering algorithms have demonstrated significant promise for improving energy efficiency in buildings. These techniques allow IEEBs to achieve data-driven decision-making, adaptive energy management, and personalized control strategies, leading to significant energy savings and increased sustainability.

Various papers have explored the use of DL models in IEEBs. Specifically, the review articles [12–15,17,21] highlight the use of DL methods (ANN, DNN, Deep Belief Network (DBN), RNN, CNN, LSTM, GRU, and hybrid models) in IEEBs. The paper [21] discussed all popular DL algorithms (ANN, DNN, DBN, RNN, CNN, LSTM, and GRU) for forecasting energy consumption in smart buildings. Furthermore, this paper analyzes the dataset, load types, prediction accuracy, and evaluation of various metrics. The review paper [17] emphasizes the potential of combining AI with big data to significantly boost IEEBs and ensure a comfortable indoor living environment using DL models such as NN, ANN, RNN, DBN, and so on. The paper [13] has given importance to DL (RNN, CNN, LSTM, GRU, DBN, auto-encoder, transformer, and many more) models to improve IoT applications from various perspectives in IEEBs. The paper [12] provides a comprehensive study on the methods and applications of ML and DL in energy systems, highlighting their importance in addressing the increasing energy demand in various energy systems. The papers [14,15] explore the DL models combined with the Federated Learning approach to limit privacy issues in many areas, such as smart cities, smart buildings, and diverse energy systems.

Other promising strategies for energy management in IEEBs regard RL and DRL techniques. DRL enables IEEBs to autonomously learn the best control policies by focusing on DNN with RL methods. DRL models can dynamically adapt energy usage patterns to minimize consumption while ensuring occupant comfort through ongoing feedback and rewards based on energy efficiency objectives [9,18,23]. Several DRL models have been used for a variety of energy management tasks in IEEBs, including Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), Double DQN, Dueling DQN, Trust Region Policy Optimization (TRPO), and Deep Deterministic Policy Gradient (DDPG). demand response optimization, HVAC control, energy load forecasting, and building energy scheduling [9–11,18,21,23].

Mason and Grijalva in [10] focus solely on RL techniques, particularly for autonomous building energy management, emphasizing the use of RL algorithms like Q-learning and SARSA to optimize energy consumption through intelligent control and decision-making. Yang et al. [11] showcases a survey on RL applications in sustainable energy and electric systems, including IEEBs, emphasizing RL's use for load control, efficient HVAC systems, and renewable energy integration. Forootan et al. [12] provide a review of ML and DL in energy systems, including RL, discussing its application in energy management and optimization goals such as load scheduling and demand response. These papers demonstrate how RL or RL-based models can be used to maximize energy savings, enhance energy efficiency, and enable intelligent decision-making in various aspects of IEEB energy management. RL allows IEEBs to learn optimal control policies, adapt to changing conditions, and optimize energy usage in real time, resulting in improved energy efficiency and reduced energy costs.

In today's world, the pursuit of IEEBs has driven the creative merging of ML and digital twin technologies [20,22]. Smart buildings, which are equipped with these sophisticated tools, signify a notable advancement in the management and enhancement of living and working spaces. In the context of smart buildings, digital twin technology offers a dynamic virtual representation of the physical building, enabling real-time monitoring, simulation, and predictive analysis. This collaboration between ML and digital twins sets the stage for unparalleled levels of control and effectiveness, leading to a substantial decrease in energy consumption and an enhancement in occupant comfort. The papers [20,22] seek to investigate the methodologies utilized in leveraging these technologies to develop smarter, more efficient, and more comfortable buildings.

In the last few years, other common techniques used for IEEBs regard decentralized approaches such as FL [82] and TL [83]. FL and TL offer a data privacy and security solution, as they enable training ML models without transferring sensed data to a central server. By only sharing the models computed at the edge, such techniques are becoming increasingly popular in the context of the IEEBs [14]. Regarding this, the authors of [14] and [15] discussed how FL plays a vital role in energy efficiency and data privacy. In particular, in these papers, the authors discussed communication efficiency, data security, data partitioning, non-identical distribution problems, learning efficiency, multitasking learning, and personalized learning. In terms of robustness, FL is decentralized, so it is more resistant to attacks and system failures.

4.5. Research Question 4

Referring to RQ_4, in the context of IEEBs, various types of datasets have been used to develop and train predictive models. These datasets commonly include information about building operations, energy usage, environmental conditions, and other relevant parameters. Below, we will first discuss the datasets used in the literature and, later, introduce some real-world experimentations from the reviewed work.

The survey in [9] is focused on papers considering datasets that include records of the building's historical energy consumption, providing information about its electricity, heating, cooling, and lighting usage. These data are crucial for training models to recognize patterns and correlations in energy usage. The work in [21] highlights the importance of a dataset based on smart meter data. Smart meters collect data at intervals of seconds, minutes, or hours and can help to analyze usage patterns and trends. In some works [94,95], researchers and analysts also use publicly available smart meter datasets to develop and test energy consumption forecasting models, identify anomalies [96], and create smart building and energy management applications. Other reviews [7,10,23] devote their attention to datasets comprehending a plethora of sensor data gathered in IEEBs equipped with various sensors that measure parameters such as temperature, humidity, occupancy, light levels, and more. The papers [3,6,13,16] acknowledge the challenge of class imbalance in thermal comfort datasets, where there is an unequal distribution of data among different thermal preference classes. Some works also focus on weather data [97] since these data can heavily impact the IEEBs. To create models that adjust building operations in response to environmental conditions, weather data, including temperature, humidity, solar radiation, and wind speed, are frequently integrated [98]. Also, occupancy data [99], knowing when and where occupants are present in the building, helps optimize heating, cooling, and lighting systems. Occupancy data can come from sensors, badge swipes, Wi-Fi networks, UWB radars, and so on. Moreover, information about a building structure, insulation, windows, HVAC systems, and other components is sometimes used to create a holistic understanding of the IEEB's energy dynamics [36].

In the reviewed works, several real-world experiments [9–11,18,21,23] involving IEEBs were conducted and were shown to validate the effectiveness of the proposed approaches. Several of them deploy various sensors throughout an IEEB to monitor parameters such as occupancy, temperature, lighting levels, and HVAC operation [75] with the aim, among others, of predicting occupancy patterns, adjusting HVAC settings based on real-time occupancy, optimizing lighting schedules, and so on. All the experiments demonstrated substantial reductions in energy consumption while maintaining occupant thermal comfort.

Regarding adaptive thermal comfort, ML algorithms have been used to learn the comfort preferences of building occupants and adjust HVAC settings accordingly [6,16,100]. This approach helps prevent excessive heating or cooling, leading to energy savings. Several aspects regarding comfort within IEEBs are discussed in [101,102]. Also, the works in [6,16] take into consideration occupant behavior and analyze solutions for having personalized energy conservation tips, which can help foster energy-conscious habits among occupants. Again, regarding the pursuit of comfort, adaptive ventilation control is a key element in IEEBs. In the literature, ML is used to analyze real-time indoor air quality and adjust ventilation rates dynamically based on occupancy [103], pollutant levels, and outdoor air conditions. This ensures optimal indoor air quality while minimizing unnecessary energy use [11]. Regarding visual comfort, smart lighting control is also frequently considered in IEEBs. By adjusting brightness and turning lights on and off based on occupancy and ambient lighting levels, comfort has been reached, together with energy optimization [5,8].

Other experiments often documented in the reviewed works focused on anomaly detection using historical sensor data to identify irregular energy consumption patterns indicative of equipment malfunction or inefficiency [104,105]. By training ML models to recognize these anomalies, maintenance teams could proactively address specific issues by also reaching energy efficiency and reducing downtime. All these experiments collectively underline the potential of ML in IEEBs to achieve significant energy savings, operational enhancements, and sustainability goals [76,106,107]. Regarding predictive maintenance, the works in [10,11] show how electric appliances, such as boilers, refrigerators, and pumps, can have their performance continuously monitored by ML models relying on sensor data and previous maintenance logs. These models can predict when equipment may break down or require maintenance. With prompt maintenance, equipment efficiency is improved, energy waste is reduced, and unexpected breakdowns can be avoided [10,11].

The reviewed works also describe applications regarding appliance scheduling. In particular, the papers in [10,11] describe how smart appliances are integrated to use energy during off-peak hours, taking advantage of lower energy costs [108]. This task is closely related to renewable energy generation prediction using weather forecasts and historical data [7]. Such prediction helps optimize the use of renewable energy sources and supply electricity when conditions are favorable. Also, ML can be used for the demand response market [109] by analyzing energy demand patterns and identifying peak demand times. By participating in demand response programs, IEEBs can reduce costs during peak hours [10,75]. Finally, in the reviewed work, several efforts have been made in the IEEB context to use FL to reduce costs in the training phases of ML models by collaboratively calculating the ML model itself in energy-constrained devices [14,15].

4.6. Research Question 5

Regarding RQ_5, below, we discuss the challenges and research directions in the context of IEEBs.

Data Collection and Big Data Handling [3,8,12,17,19,23] is one of the biggest challenges for IEEBs. Sensing technologies generate large amounts of personal data in these environments, requiring efficient pre-processing and long-term storage methods. Current research efforts also address the challenges and opportunities relating to handling the streaming of personal big data in IEEBs, including storage and processing using high-performance platforms and stream processing tools [110–112]. Moreover, new research is presenting frameworks providing flexibility to accommodate different data sources and the integration of ontologies with the data sets, enabling data fusion techniques and a higher degree of flexibility for data manipulation [113].

Another relevant challenge regards the *ML Model Selection* [6,7,13,18,21] for realizing IEEBs. The right model to be used should be chosen based on the goals of the specific study, with white-box models (e.g., NB, DT, and KNN), which provide explicit expressions that, anyway, may not capture all the subjective elements, or black-box models (e.g., SVM, ANN, and ensemble learning), which are suitable for complex situations but are difficult to comprehend and time-consuming. Additionally, the right ML model should be evaluated based on its predictive ability, complexity, and computational cost for practical applications in specific places [3–23].

Sometimes, the right ML model has to be chosen based on contrasting goals. An example is the balancing of energy efficiency and occupant thermal comfort [6,16,20]. In this case, the pursuit of energy savings often involves adjusting heating, cooling, and lighting systems to minimize energy consumption. However, these adjustments must not compromise the well-being of the building occupants. Creating sophisticated models that consider both environmental parameters and human factors is necessary to achieve a balance between energy efficiency and thermal comfort. The algorithms actually used in the literature for this aim include RL, DRL [74,114], and other ML/DL models [115–117]. Lastly, in the literature, some researchers are trying to propose solutions in which ML models are selected among a set of ML models based on some parameters [118].

In IEEB, *Real-time Responsiveness* [9,10,12] can be another important challenge due to the fact that some controls and actuation, especially regarding safety and security [9,14], need to be processed in real time or nearly real time. Achieving real-time responsiveness requires algorithms that can process data quickly and make prompt decisions while also integrating advanced ML methodologies and efficient computational architectures. In the current literature, this type of responsiveness is obtained by processing data at the edge, close to the point at which data are produced [14,119]. It involves deploying fast algorithms directly within the building's infrastructure. Also, using lightweight/tiny ML models ensures quick processing without sacrificing accuracy. Techniques like FL, where models learn on-site and share only necessary information centrally, maintain privacy and speed up response times. Finally, using specialized processors for AI tasks boosts speed further. By combining these methods—edge computing, lightweight models, and optimized hardware—IEEB systems can achieve fast, effective responses for managing energy efficiently while keeping buildings safe and secure [120,121].

In the field of IEEBs, researchers are trying to pursue the *realization of digital twins* of such buildings or, at least, of some systems within them [20,22,122]. This is a very challenging task due to the complexity of the actual buildings and the limited information available for some of them (typically part of Building Information Modeling [20]). A digital twin of an IEEB can allow designers and operators to emulate politics and algorithms within a building without using the real one for experimentation. This can speed up the deployment of already tested intelligent systems without spending time testing them in real environments. In fact, researchers are developing digital twins for IEEBs by integrating data from sources like Building Information Modeling and real-time sensors. They use advanced modeling techniques and ML to predict building behavior, optimize energy usage, and enable the real-time monitoring and adjustment of building operations [123]. Robust cybersecurity measures ensure data integrity for confident decision-making in building management and optimization, aiming to accelerate smart building technology deployment while minimizing costs and risks [123,124].

In the realm of IEEBs, ML models have shown great promise in enhancing energy efficiency. However, a significant challenge remains: the effective management of the *uncertainties associated with external factors* such as weather fluctuations or the variation in the occupants' behaviors. Addressing these uncertainties is crucial for the development of robust and adaptive energy management strategies. Therefore, several works in the literature focus on exploring and devising methods that can anticipate and mitigate these variables, thereby ensuring the reliability and effectiveness of energy management in IEEBs under a range of unpredictable conditions. This approach will not only improve the resilience of energy systems but also maximize their efficiency and adaptability in real-world environments [6,16,18,20,21,23].

Many ML algorithms require a significant amount of data to be trained effectively. However, this can be a challenge for new smart buildings with limited historical data. Researchers are exploring ways to make ML models available for new smart buildings by using *transfer learning* [18] to address this issue. This involves transferring knowledge from one task to another. While some previous works have attempted to apply transfer learning [18], they have mainly focused on simple scenarios where the similarity gap between source and target smart buildings is small. When the similarity gap is large, such as when the state and action spaces differ significantly between two smart buildings, designing an efficient intertask mapping function and selecting the appropriate form of transferred knowledge becomes much more challenging [18].

In the context of IEEBs, the aspects of *privacy and security in data sharing* are also of paramount importance. IEEBs generate a large amount of personal data that must be protected from unauthorized sharing. For this reason, much work in the literature is addressing this topic in several ways. One method used is the introduction of decentralized approaches that ensure limited data sharing while preserving the privacy of IEEB users. Among these, Federated Learning [82] is gaining much attention due to its capacity to elaborate models where data are gathered and share only these models with external entities. Another emerging technology increasingly utilized in the literature for achieving integrity, transparency, traceability, and enabling secure data exchange and storage is the blockchain [125]. These advancements aim to enhance the reliability of energy management systems while safeguarding personal information in IEEBs.

Finally, recent trends in the literature are increasingly emphasizing the optimization of building energy utilization within IEEBs while also addressing the effective management of the Smart Grid [126]. This integration represents a promising avenue for adapting control systems to fluctuating environmental conditions and enhancing real-time operational efficiency. These advancements are critical for ensuring the reliability and effectiveness of energy management systems in smart buildings [23]. In recent years, there has been an increasing interest in the merging of the IEEBs with Smart Grids to create so-called Zero-Energy Buildings, since these two systems together can work for the optimization of energy usage inside energy communities [127].

5. Conclusions

In this meta-survey, we comprehensively analyzed 21 survey papers in the field of Intelligent Energy-Efficient Buildings, aiming to provide a holistic overview of the current state-of-the-art research in this domain. Through our investigation, we identified key trends, challenges, and research directions within the field of IEEBs. Our findings revealed a broad spectrum of methods used in IEEBs. These include various machine learning algorithms for energy optimization, as well as the use of IoT-based systems combined with edge-cloud computing solutions. In this direction, we have reviewed the most frequently used algorithms in literature for the realization of IEEBs, and we have categorized them.

In this paper, we have also proposed and answered five important research questions regarding IEEBs. In more detail, we have highlighted how the field related to IEEBs is specified or defined in literature; the most commonly used architectures for IEEBs; which ML methods are most used for IEEB implementation; what type of datasets or real implementations are utilized to realize IEEBs; and what challenges and research directions are presented in the literature in the field of IEEB.

By analyzing the reviewed work, we observed a growing emphasis on real-world implementations and the validation of proposed solutions using both simulated and real-world datasets. We also found very important challenges in the field of IEEBs, such as big data management, model selection, and the real-time responsiveness of the used models alongside promising research directions, including digital twins realization, data privacy, and Smart Grid integration.

This meta-survey synthesizes existing research findings and provides insights into the surveyed literature, aiming to facilitate advancements in the development of more intelligent, energy-efficient, and sustainable IEEBs. Indeed, readers of our meta-survey who wish to develop IEEBs will gain a competitive advantage by acquiring knowledge about the most commonly used methodologies in the literature for IEEBs. Additionally, they will be familiar with the most common architectures, case studies, and technologies. Finally, by being aware in advance of the most common challenges from the literature, they can take proactive measures to address them.

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