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Review

Data-Driven Technologies for Energy Optimization in Smart Buildings: A Scoping Review

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Abstract: Data-driven technologies in smart buildings offer significant opportunities to enhance energy efficiency, sustainability, and occupant comfort. However, the existing literature often lacks a holistic examination of the technological advancements, adoption barriers, and business models necessary to realize these benefits. To address this gap, this scoping review synthesizes current research on these technologies, identifies factors influencing their adoption, and examines supporting business models. Inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, a structured search of the literature across four major databases yielded 112 relevant studies. The key technologies identified included big data analytics, Artificial Intelligence, Machine Learning, the Internet of Things, Wireless Sensor Networks, Edge and Cloud Computing, Blockchain, Digital Twins, and Geographic Information Systems. Energy optimization is further achieved through integrating renewable energy resources and advanced energy management systems, such as Home Energy Management Systems and Building Energy Management Systems. Factors influencing adoption are categorized into social influences, individual perceptions, cost considerations, security and privacy concerns, and data quality issues. The analysis of business models emphasizes the need to align technological innovations with market needs, focusing on value propositions like cost savings and efficiency improvements. Despite the benefits, challenges such as high initial costs, technical complexities, security risks, and user acceptance hinder their widespread adoption. This review highlights the importance of addressing these challenges through the development of cost-effective, interoperable, secure, and user-centric solutions, offering a roadmap for future research and industry applications.

Keywords: smart buildings; data-driven technologies; energy optimization; artificial intelligence; internet of things; energy management systems; technology adoption; business models; systematic review

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1. Introduction

Buildings account for approximately 40% of global energy consumption, largely due to essential activities such as lighting, cooling, and heating [1–3]. This substantial energy demand poses economic, resource, and environmental challenges, underscoring the need for more efficient energy management in building environments [4]. Data-driven technologies have emerged as a critical solution for addressing these challenges, enabling smart buildings to optimize energy use, improve occupant comfort, and support sustainable operations [5–7]. For example, smart buildings equipped with IoT devices can collect granular energy data to inform load management and optimize energy efficiency [6]. Studies illustrate diverse applications: multi-sensor data collection for space utilization [4], motion sensors in libraries for lighting control [8], and Digital Twins for real-time energy efficiency management [9]. These examples highlight the potential for data-driven technologies to transform energy consumption dynamics within buildings through tasks like monitoring, forecasting, and anomaly detection [10].

Recent advancements in Machine Learning (ML) and reinforcement learning frameworks have enabled the development of highly adaptive Home and Building Energy Management Systems (HEMS and BEMS) [11]. These systems optimize energy usage through real-time data-driven decision-making approaches, leveraging techniques like frequent itemset mining, deep reinforcement learning, and advanced optimization algorithms to minimize costs and enhance efficiency [12]. By dynamically integrating real-time inputs from IoT sensors, such as temperature, occupancy, and energy usage patterns, these systems enable smart buildings to autonomously adjust HVAC settings, lighting, and energy loads. Such capabilities not only enhance operational efficiency but also contribute to occupant comfort and sustainability [13].

Although the existing literature acknowledges the benefits of data-driven technologies, many studies lack a holistic examination of factors influencing technology adoption. For instance, there is limited research integrating technical performance with socio-economic factors that impact adoption, such as user behavior, regulatory frameworks, and cost implications. Additionally, while studies explore individual technologies like IoT or AI, they rarely provide insights into how these technologies can be integrated within a unified framework to address energy optimization comprehensively. Furthermore, the dynamic nature of energy markets and evolving sustainability goals highlight the need for research that bridges technological innovation with practical implementation strategies, including business models that can scale these solutions effectively. This gap in the literature raises the following crucial question:

What is the current state of data-driven technologies for energy optimization in smart buildings considering technological advancements, adoption barriers, and supporting business models?

To address this question, this scoping review aims to perform the following:

- Synthesize current research on data-driven technologies for energy optimization in smart buildings.
- Identify the factors influencing the adoption of these technologies.
- Examine supporting business models that facilitate their implementation.

In total, 33 review articles were found in the literature (as shown in Table A1, Appendix A), covering the following key themes:

- Energy Management Systems: emphasize energy-saving, optimization, and control mechanisms.
- Building Energy Efficiency: implement strategies for enhancing energy performance.
- User Behavior and Social Factors: emphasize the influence of occupant behavior on energy use.
- Data-Driven Approaches: employ the use of advanced analytics and AI for predictive insights.
- Renewable Energy and Smart Grids: integrate renewables and smart grid interactions.

Compared to the existing review articles, this review advances the literature by categorizing and evaluating emerging data-driven technologies, including Artificial Intelligence (AI), Machine Learning (ML), Big Data, Blockchain, and Digital Twins. While previous reviews discuss AI and ML generally, they rarely address the unique roles and interdependencies of each technology within an integrated framework. Machine Learning (ML), a subset of Artificial Intelligence (AI), serves as a critical enabler of intelligent decision-making within smart buildings. While AI encompasses the broader capability of machines to simulate human intelligence, ML focuses on developing algorithms that allow systems to learn from data and improve their performance over time without explicit programming. For instance, ML algorithms such as Artificial Neural Networks (ANNs) and Deep Learning models can analyze complex data patterns, identify energy consumption anomalies, and optimize predictive models for Building Energy Management. In doing so, ML supports autonomous decision-making processes, where AI systems can dynamically adjust HVAC settings, lighting, and energy loads in response to real-time inputs from IoT sensors, thereby enhancing operational efficiency and occupant comfort. Additionally, this paper uniquely examines barriers to adoption, such as security, privacy, and costs, as well as the need for new business models to support sustainable technology implementation. These aspects are essential for realizing the full potential of data-driven systems in energy optimization and are underexplored in existing reviews. Overall, this scoping review aims to provide a comprehensive view of the current state of data-driven technologies in smart buildings, highlight critical adoption barriers, and identify gaps in business model frameworks that could facilitate broader implementation.

The organization of this paper is as follows: Section 2 provides a background on smart building technologies, highlighting the primary building types, unique challenges, and opportunities influencing technology adoption. Section 3 describes the scoping review method and process used in this paper. Section 4 discusses the foundational technologies and system integration approaches that enable energy optimization in smart buildings. Section 5 explores the influential factors affecting the adoption of data-driven technologies and examines the business models that support their implementation. Section 6 presents a discussion synthesizing key findings, implications, challenges, and limitations. Finally, Section 7 concludes with insights and directions for future research, emphasizing the need for enhanced security measures, user-centric designs, and innovative business models to advance the smart building domain.

2. Background

Smart building technologies are transforming the way energy, comfort, and security are managed in various types of buildings. The types of buildings that implement smart technologies often determine the specific technologies and functionalities that are prioritized. This section provides an overview of the primary building types within the smart building ecosystem and highlights the unique challenges and opportunities that influence technology adoption.

The building can be a residential, commercial, or industrial building, as shown in Table 1. Residential buildings [14,15] comprise houses [16,17] or homes [18–22] and flats [17]. Residential buildings are developed for various purposes, including multi-dwelling units [23], passive house design [24], and home-based small businesses [25].

In residential settings, smart technologies primarily focus on occupant comfort, energy efficiency, and security. Their key functionalities often include automated lighting, climate control, and security systems, alongside renewable energy integration and energy management systems that allow homeowners to monitor and optimize consumption. Technologies such as IoT-enabled sensors and smart thermostats are popular in this sector, balancing convenience with energy savings to meet consumer preferences.

Commercial buildings are structures utilized for business activities, including offices [17,26–30], school buildings [3,7,17,30,31], public buildings [32,33], libraries [8], retail shops [15], and research and development buildings [34]. Other types of commercial buildings are airports [28], hotels [17,28], banks [17], restaurants [17], and hospitals [17].

Commercial buildings, including office complexes, retail spaces, and hotels, prioritize occupant comfort, efficient space utilization, and optimized energy consumption. Given the high energy demands in these environments, smart building solutions often involve advanced HVAC control systems, occupancy-based lighting, and Building Management Systems (BMS) that integrate multiple functions for centralized management. Data analytics and AI-driven predictive maintenance are also commonly used to reduce operational costs and improve building performance.

Government buildings, hospitals, and schools, which fall under institutional categories, often prioritize sustainability, occupant well-being, and public safety. Smart building technologies in these spaces frequently include energy-efficient HVAC systems, emergency response automation, and environmental monitoring to ensure healthy indoor air quality. Digital twin technologies are increasingly being explored in these settings for scenario planning and efficient resource management.

Additionally, industrial buildings [15] are structures used for production or manufacturing, such as data centers [35] and warehouses [14]. In industrial facilities such as factories and warehouses, the focus shifts to operational efficiency, safety, and resource management. Smart technologies for these buildings may include IoT-enabled machinery monitoring, energy-intensive process optimization, and robust security and safety systems. Technologies in industrial buildings are often integrated with energy management and automation systems to optimize production processes while reducing downtime and energy use.

Cognitive buildings incorporate the Internet of Things (IoT) and other related technologies to develop an information-driven environment [36]. Similarly, smart buildings are equipped with intelligent systems to automatically control building technologies (e.g., heating, lighting, ventilation), aiming to minimize energy usage while ensuring occupant comfort and operational efficiency [37]. For example, smart homes [1,38–54], considered smart buildings, are equipped with a unified and centrally integrated system that manages electrical devices and appliances [40].

Table 1. Overview of the building types in data driven smart buildings and energy in the literature.

Buildings	**Sub-Type**	**References**
Advanced Buildings	Cognitive buildings	[36]
	Smart buildings Smart homes	[1,37–55]
Residential Buildings	Home or house	[16–22]
	Multi-dwelling buildings	[23]
	Home-based small businesses	[25]
	Passive house	[24]
	Flats or apartments	[17]
Commercial Buildings	Offices	[15,17,26–29]
	University, campus or school	[3,7,17,30,31]
	Public or government buildings	[32,33]
	Library buildings	[8]
	Research and development building	[34]

Table 1. *Cont.*

Buildings	Sub-Type	References
Commercial Buildings	Airport	[28]
	Hotels	[17,28]
	Banks	[17]
	Restaurants	[17]
	Hospitals	[17]
	Retail shops	[15]
Industrial Buildings	Data center	[35]
	Warehouse	[14]

3. Materials and Methods

This scoping review was conducted to systematically explore the role of data-driven technologies in optimizing energy consumption in smart buildings. The methodology was inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [56], adapted to the broader objectives of a scoping review. The review aimed to map existing research, identify key themes and gaps, and provide an overview of advancements in data-driven technologies, adoption barriers, and business models relevant to smart buildings.

To ensure a structured and transparent approach, the review incorporated elements of the PRISMA framework, including clearly defined eligibility criteria, comprehensive database searches, and a systematic study selection process illustrated by a PRISMA flow diagram. The selection process involved several stages: (1) identification through automated database searches, (2) screening based on titles and abstracts, and (3) full-text assessments against predefined criteria (Table A2). Studies were included if they specifically addressed data-driven technologies in smart buildings with a focus on energy optimization, adoption barriers, or business models. Exclusion criteria included studies lacking primary data or robust methodologies, publications not in English, or those with a focus outside smart building contexts.

During the screening stage, duplicates were first removed, and titles and abstracts were reviewed independently by two authors. Conflicts were resolved through discussion or consultation with a third author. Examples of excluded studies included those focusing on generic smart technologies without reference to energy systems (e.g., IoT for healthcare) or articles presenting conceptual frameworks without empirical support. The eligibility phase involved a detailed examination of full texts for relevance and methodological soundness. Reasons for exclusion at this stage included an insufficient focus on data-driven energy optimization (e.g., discussions limited to structural engineering) and the lack of a peer-reviewed status. The final synthesis included 112 studies.

While formal quality appraisal and meta-analysis were not performed—consistent with the aims of scoping reviews—a narrative synthesis and thematic categorization were used to analyze the findings. This approach allowed for the inclusion of diverse evidence types and a broad exploration of the research landscape.

3.1. Protocol and Registration

A review protocol was developed prior to the commencement of this scoping review to ensure methodological rigor, transparency, and consistency. The protocol outlined the review's objectives, eligibility criteria, data sources, search strategies, study selection process, and data extraction methods. This scoping review was not formally registered in any public database, such as PROSPERO, as scoping reviews are currently not eligible for registration there. However, to maintain transparency, the protocol was internally reviewed and approved by the research team before implementation. Any deviations from the initial protocol during the review process were documented and justified within the review. The protocol is not publicly available; however, detailed descriptions of the methodology, including the eligibility criteria, information sources, search strategy, and data extraction process, are provided in the section below to ensure transparency and reproducibility.

3.2. Eligibility Criteria

The inclusion and exclusion criteria were carefully defined to align with the research question, which aims to explore the role of data-driven technologies in optimizing energy consumption within smart buildings, as shown in Figure 1. The criteria prioritized research that provided empirical evidence, insights into user experiences, and practical applications of these technologies. The focus on peer-reviewed publications ensured the inclusion of high-quality research, acknowledging that it might introduce potential bias by excluding valuable information from gray literature. The language restriction was due to resource constraints, and the publication year timeframe captured the period of significant advancements in the field. By clearly defining these criteria, this review provides a comprehensive and rigorous analysis of the selected literature.

Criteria	Inclusion	Exclusion
Study Focus	- Studies on data-driven technologies for optimizing energy consumption in smart buildings, including development, implementation, and evaluation. - Studies on integrating renewable energy technologies into smart buildings for efficiency and sustainability. - Research on energy management and automation systems in smart buildings (residential and commercial). - Studies focusing on energy modeling and simulation for designing energy-efficient buildings. - Research on fault detection and diagnosis (FDD) systems using AI and ML for anomaly detection and proactive maintenance in smart buildings.	- Studies not addressing data-driven technologies for energy optimization in smart buildings. - Research focusing only on general building automation systems without data-driven approaches for energy management. - Studies solely on renewable energy technologies without smart building integration. - Publications primarily discussing theoretical concepts or frameworks without empirical evidence or practical applications.
Study Designs	- Quantitative studies (e.g., experimental, quasi-experimental, simulations) with empirical data on data-driven energy optimization. - Qualitative studies (e.g., case studies, interviews, focus groups) exploring user experiences, challenges, and best practices in adopting data-driven technologies. - Mixed-methods studies combining quantitative and qualitative approaches for comprehensive insights.	
Publication Types	- Peer-reviewed journal articles in reputable academic journals on smart buildings, energy efficiency, data science, and related fields. - Conference papers presented at peer-reviewed international conferences.	- Non-peer-reviewed literature (e.g., editorials, opinion pieces, book chapters, reports). - Abstracts without full texts. - Duplicate records.
Publication Years	**- Studies published between 2000 and 2023.**	
Language	- Publications written in English.	

Figure 1. Eligibility criteria.

3.3. Information Sources

To comprehensively capture relevant studies on data-driven technologies for energy optimization in smart buildings, a systematic search was conducted across multiple information sources, ensuring a broad and representative coverage of the field. To ensure comprehensive coverage, multiple electronic databases were searched, including Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The search included articles published up to February 2024, ensuring that the most recent developments were considered. Meanwhile, domain experts were consulted to validate the comprehensiveness of the search strategy and identify any potentially overlooked key studies.

3.4. Search Strategy

A systematic and transparent search strategy was employed to identify the relevant literature. The primary objective of the search strategy was to identify a comprehensive dataset of peer-reviewed studies that address the intersection of smart building technologies, data-driven approaches, and adoption barriers or facilitators. The search also sought to include diverse research contexts across building types (residential, commercial, and industrial buildings). The search strings were tailored for each database, applying filters for language and document type. Domain experts were consulted to confirm the strategy's coverage and relevance. The full search strings and details on how the strategy was refined are provided in Appendix B.1. Search strategy.

3.5. Study Selection

The selection of studies followed a structured, multi-stage approach designed to ensure rigor and transparency. After removing duplicates, two independent reviewers initially screened all titles and abstracts against the predefined inclusion and exclusion criteria (Table A2). Studies meeting these criteria or considered potentially relevant were then assessed through a full-text examination. Throughout both the screening and full-text review stages, any disagreements were resolved through discussion, and when necessary, a third reviewer served as an adjudicator to maintain impartial decision-making. The PRISMA flow diagram (Figure 2) below summarizes the selection process, and Appendix B.2, Study Selection, provides a comprehensive record of the inclusion decisions and justifications.

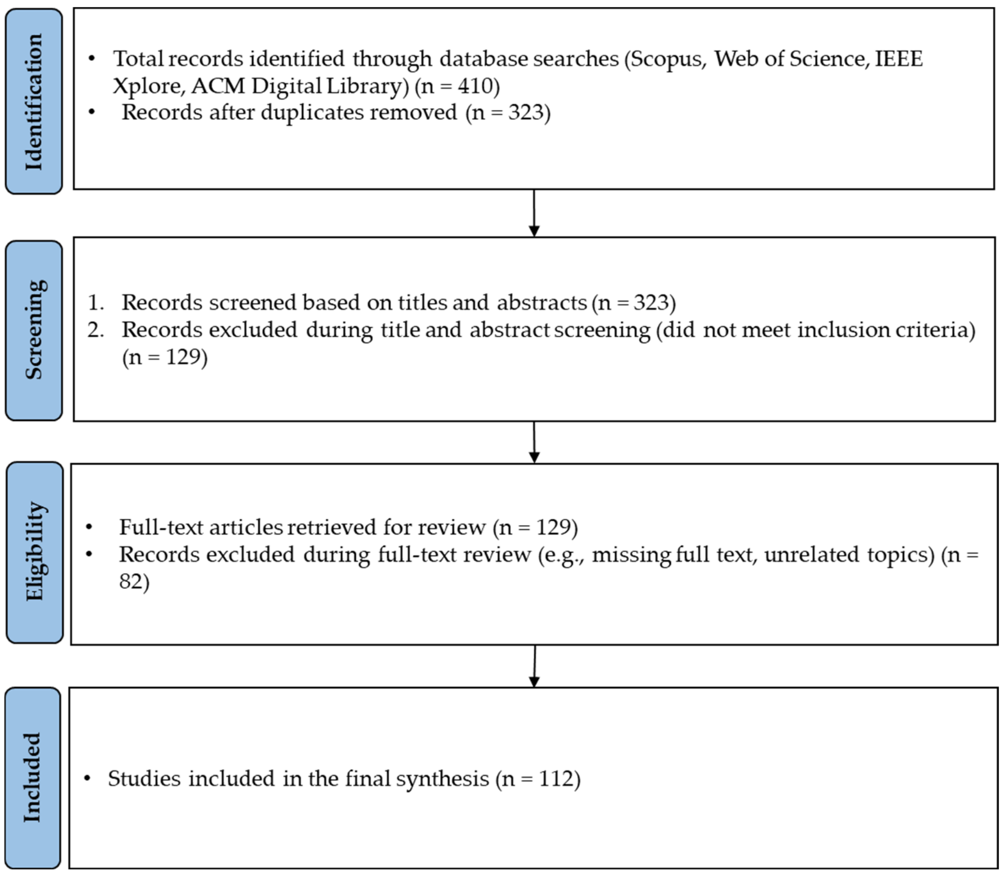

Figure 2. The PRISMA flow diagram.

3.6. Data Charting, Management, and Items

Data extraction and management were conducted systematically to ensure comprehensive and accurate synthesis. All 112 articles, including their abstracts and full texts, were imported into EndNote 21 for efficient organization, annotation, and retrieval. A standardized data extraction form (Table A3, Appendix B.3. Data Charting, Management, and Items) was developed to record the study focus, methodologies, key findings, and contextual details. The process involved independent charting by two reviewers, iterative refinement, and final quality assurance.

Key data items were systematically charted (Table A4, Appendix B.3. Data Charting, Management, and Items), including publication details, study classifications, geographic context, targeted building types, technologies, adoption factors, and key findings. These elements provided the foundation for categorizing and analyzing the studies to address the research objectives and highlight gaps and opportunities for further investigation.

3.7. Data Synthesis

The synthesis of the included studies followed a structured process involving categorization, thematic analysis, contextual examination, and alignment with the research questions to systematically present findings. A total of 112 studies were analyzed and categorized into 33 review articles (Table A1, Appendix A) and 79 research articles (Table A5, Appendix C). These studies explored diverse aspects of data-driven technologies in building and energy systems, providing insights into energy optimization, smart building management, and data-driven decision-making processes.

To further refine the analysis, Table 2 categorizes the studies into three primary aspects—energy, building, and data/AI—along with their subcategories. Among the included studies, 11 specifically addressed adoption barriers such as high costs, security concerns, and technical complexities. Additionally, three studies focused on business models, exploring innovative practices for commercialization and the sustainable integration of data-driven technologies.

Table 2. The three aspects and related sub-categories of the reviewed studies.

Energy Aspect	Building Aspect	Data and AI Aspect
Building energy modeling Energy consumption Energy cost or saving Energy efficiency Energy Management system Fault detection and diagnose Renewable energy Smart grid integration	Building in general Commercial building Industrial building Residential building	Artificial Intelligence Big data Blockchain Cloud Computing Digital Twin and simulation Edge computing Information system Internet of Things Machine Learning Sensor network

Thematic analysis identified recurring patterns, including energy optimization strategies, advancements in technologies such as IoT and AI, and factors influencing adoption. Studies addressing business models revealed innovative frameworks that support the scaling of these technologies. Contextual examination highlighted research gaps across building types, including residential, commercial, and industrial buildings, as well as energy systems such as renewable integration and smart grids. Synthesized findings were mapped to the research questions to evaluate the role of data-driven technologies, identify adoption barriers, and examine trends in supporting business models. This integration of findings revealed key contributions to the field and emphasized areas requiring further investigation.

4. Fundamental Technologies and System Integration in Smart Buildings

This section provides a comprehensive overview of the fundamental technologies and system integration approaches adopted in smart buildings. It covers data-driven technologies, energy resources, energy management systems, and the integration of these components to enhance building performance and sustainability.

4.1. Data-Driven Technologies in Smart Buildings

Data-driven technologies drive innovation and efficiency across buildings and energy systems. These technologies include big data analytics, Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), Wireless Sensor Networks, Edge and Cloud Computing, Blockchain, Digital Twins, Information Systems, and Geographic Information Systems (GIS), as shown in Table 3.

Table 3. Overview of data-driven technologies in smart buildings.

Data-Driven Technology	Description/Function	References
Big Data Analytics	Collection, processing, and analysis of large complex datasets to identify patterns.	[28,30,57,58]
Artificial Intelligence (AI)	Automates tasks, detects energy anomalies, optimizes energy use, predicts patterns, and forecasts costs.	[2,27,29,33,35,38,42,49,51,59]
Machine Learning	Subset of AI-enabling systems to learn from data, improving prediction and optimization over time.	[3,14,25,41,51,60,61]
Internet of Things (IoT) and Wireless Sensor Networks	Real-time data collection on energy usage and environmental conditions, enabling data communication among devices.	[1,8,14,16,20,21,27,36,37,39,41,45,47–49,51,52,62–64]
Edge and Cloud Computing	Local data processing to minimize energy consumption (Edge computing); cost-effective off-site data storage and services (Cloud Computing).	[2,16,36,52,61]
Blockchain Technologies	Secure and transparent transactions and trusted data sharing across distributed networks.	[23,62,65]
Digital Twin Technologies	Virtual representations of physical systems for real-time monitoring and optimization.	[62,66]
Information Systems and Geographic Information Systems (GIS)	Storage, visualization, analysis, and interpretation of data and managing energy distribution networks.	[19,29,32,67]

4.1.1. Big Data Analytics

Big data analytics involves the collection, processing, and analysis of large and complex datasets to extract meaningful insights and identify patterns that inform decision-making [57,58]. Characterized by the three Vs—volume, velocity, and variety—big data technologies enable the handling of datasets that are too large or complex for traditional data-processing applications.

In the context of smart buildings, methodologies such as data mining, clustering, and regression analysis are frequently employed to uncover patterns and relationships within energy consumption data. For example, data mining techniques, including association rules and decision trees, help identify anomalies and predict future energy demands [28]. These tools allow facility managers to gain insights into usage patterns, predict maintenance needs, and improve operational efficiency. These tools support applications, including energy forecasting, anomaly detection, and predictive maintenance.

In the context of smart buildings, big data analytics play a pivotal role in optimizing building operations and enhancing energy efficiency. For instance, Koseleva and Ropaite (2017) proposed a big data-based architecture for building management systems (BMS) to effectively manage daily operations [57]. By analyzing the vast amounts of data generated from sensors and systems within a building, facility managers could gain insights into usage patterns, predict maintenance needs, and improve overall operational efficiency. The methodologies applied include supervised and unsupervised Machine Learning algorithms. Supervised learning techniques such as Random Forest and Gradient-Boosted Trees are used to forecast energy consumption and identify anomalies in usage patterns. Unsupervised learning methods, like k-means clustering, help segment energy usage behaviors across different building zones. Additionally, predictive maintenance models often integrate time-series analysis using algorithms like ARIMA (Auto-Regressive Integrated Moving Average) and Long Short-Term Memory (LSTM) networks for enhanced fault detection and maintenance scheduling. These methods ensure proactive energy management and system reliability.

Big data are classified based on their size into small (kilobytes to gigabytes), medium (gigabytes to terabytes), and large (terabytes and beyond) datasets (as shown in Table 4). This classification guides the choice of tools and frameworks used for data processing. For small-to-medium datasets, Python (with libraries like Pandas, NumPy, and Scikit-learn) and R are widely employed due to their robust capabilities for data manipulation and statistical analysis [58,68]. For large-scale datasets, distributed frameworks like Apache Spark and Hadoop are essential, providing the scalability needed to handle high-volume data processing in real time [58,67]. These tools support advanced analytics applications such as energy consumption forecasting, anomaly detection, and predictive maintenance in smart building systems.

Table 4. Overview of big data in smart buildings.

Aspect	**Details**
Data Classification	Small (kilobytes to gigabytes), medium (gigabytes to terabytes), and large (terabytes and beyond) datasets.
Programming Languages	Python (Pandas, NumPy, Scikit-learn) and R, Java.
Frameworks/Libraries	Apache Spark, Hadoop, and TensorFlow.
Applications	Anomaly detection, energy consumption forecasting, and predictive maintenance.
Key Algorithms	Random Forest, Gradient-Boosted Trees, k-means clustering, ARIMA, and Long Short-Term Memory (LSTM).
Limitations	Hardware constraints, integration with legacy BMS, and high computational requirements for real-time tasks.

However, integrating data-driven technologies requires significant technical expertise and careful planning. A key limitation in this area is the difficulty of ensuring interoperability between new systems and legacy building technologies. Incompatibility often arises, requiring substantial customization efforts that increase both costs and complexity. Many smart building systems rely on seamless integration, and overcoming these technical barriers is essential to achieving widespread adoption. Furthermore, many existing BMS lack the hardware capabilities needed to process large-scale datasets in real time, necessitating the use of external data infrastructures. This adds complexity in terms of data integration, standardization, and compatibility with distributed frameworks [57,67].

Hardware constraints, coupled with high computational requirements, further limit the real-time analytics potential of embedded systems.

In the energy sector, big data analytics is utilized to understand individual and collective energy consumption behaviors, leading to strategies that enhance energy efficiency [57]. For instance, [69] highlights the use of automated data mining methods on whole-building electricity data to uncover insights related to energy efficiency opportunities. By identifying consumption trends and anomalies, stakeholders can implement targeted measures to reduce energy waste and promote sustainability.

Beyond smart buildings and energy, big data analytics has broad applications across various industries, including automotive, telecommunications, healthcare, media, travel, social media, and more [57]. In the domain of Automatic Test Equipment (ATE), the application of big data and advanced analytics has resulted in cost reductions, process improvements, faster decision-making, and enhanced customer offerings [58].

By leveraging big data tools and frameworks tailored to specific use cases, smart buildings can achieve real-time monitoring, proactive anomaly detection, and predictive maintenance. This integration enhances energy optimization, operational cost reduction, and occupant comfort while overcoming traditional limitations.

4.1.2. Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) refers to the development of computer systems that are capable of performing tasks that typically require human intelligence, such as reasoning, learning, and decision-making [42]. Within the broader domain of AI, Machine Learning (ML) is a specialized subset that focuses on algorithms allowing systems to learn and improve from data without explicit programming [3,14,25,41,51,60,61]. This distinction is critical, as AI encompasses a wide array of techniques, while ML focuses on data-driven algorithmic learning.

In smart buildings, AI automates tasks and adapts to user preferences, enhancing functionality and convenience. For example, AI algorithms can optimize energy consumption by adjusting lighting, HVAC systems, and renewable energy integration [2,33,49]. AI also supports anomaly detection in energy usage, enabling proactive maintenance and energy-saving strategies [38].

ML techniques further advance these capabilities by predicting future energy consumption patterns, forecasting costs, and improving the efficiency of energy systems [38]. Specific ML methods employed in smart buildings include the following:

- Ensemble Learning Methods: techniques like Boosted Trees and Random Forests are used to predict and analyze energy performance in individual buildings and clusters [2,3].
- Support Vector Machines (SVMs): SVM methods, including Linear, Quadratic, and Cubic SVMs, are utilized for energy consumption prediction and anomaly detection [3,29].
- Artificial Neural Networks (ANNs) and Deep Learning: ANNs and Deep Learning models, such as Deep Neural Networks (DNNs) and Deep Reinforcement Learning, are applied for complex pattern recognition and predictive analytics in energy management.
- Deep Neural Networks (DNNs)**:** DNNs build on ANNs by incorporating multiple hidden layers and enabling the modeling of complex patterns and relationships in high-dimensional datasets. They are especially effective for advanced applications like image recognition, non-linear energy demand forecasting, and natural language processing [2,41,52,67].

For example, DNNs have been applied in smart building systems to forecast peak demand, optimize HVAC operations, and manage energy storage systems, utilizing features like temperature, occupancy rates, and historical consumption patterns.

Detailed methodologies include feature engineering (e.g., selecting relevant data inputs like temperature and occupancy), model training on historical data using cross-validation techniques, and performance evaluation with metrics such as Mean Absolute Error (MAE) and R-squared (R^2). These practices ensure that models are robust and generalizable to unseen scenarios.

4.1.3. Internet of Things (IoT) and Wireless Sensor Networks

The Internet of Things (IoT) refers to a network of interconnected devices and objects that communicate and exchange data over the Internet or other communication networks [37,39]. In smart buildings, IoT technologies play a pivotal role in collecting real-time data on energy usage, environmental conditions, and occupant behaviors, enabling more efficient and responsive building management systems [1,7,8,14,16,20,21,27,36,37,39,41,45,47–49,51,62,70].

IoT systems in smart buildings typically consist of various components:

- Sensors and Actuators: These devices detect and measure environmental parameters such as temperature, humidity, light levels, and occupancy. Actuators execute physical actions based on control signals, such as adjusting thermostats or lighting [18,34,36,39,47,70].
- Controllers and Gateways: microprocessors and microcontrollers (e.g., Arduino, Raspberry Pi) process data from sensors and manage communication between devices and networks [1,40,50].
- Communication Modules: these technologies facilitate data transmission, such as Wi-Fi, Zigbee, Bluetooth, and MQTT protocols, ensuring seamless connectivity within the IoT ecosystem [15,19,21,46,71].

Methodologies involve the integration of protocols like MQTT and Zigbee for secure and efficient data exchange between devices. Tools such as Arduino and Raspberry Pi are used to prototype IoT-based solutions, while cloud platforms like AWS IoT Core support data storage and advanced analytics. Wireless Sensor Networks (WSNs) are specialized networks that utilize wireless communication to connect multiple sensor nodes for data collection and monitoring [36,64,71]. In smart buildings, WSNs enable the deployment of distributed sensing capabilities without the need for extensive wiring, reducing installation costs and enhancing scalability.

Applications of IoT and WSNs in smart buildings include the following:

- Energy Monitoring and Management: the real-time tracking of energy consumption to identify inefficiencies and optimize usage [18,34,41].
- Environmental Control: the automated adjustment of heating, ventilation, and air conditioning (HVAC) systems based on occupancy and environmental conditions [47,70].
- Smart Lighting Systems: the dynamic control of lighting based on occupancy and natural light availability to reduce energy consumption [8,70].
- By integrating IoT and WSN technologies, smart buildings can achieve enhanced operational efficiency, improved occupant comfort, and reduced energy consumption through data-driven decision-making and automation.

4.1.4. Edge and Cloud Computing

Edge and Cloud Computing complement each other in processing and storing building data. Edge computing processes data locally near the source, reducing latency and bandwidth usage. This is particularly useful for time-sensitive applications, such as security and occupancy-based HVAC adjustments [2,36,61]. In smart buildings, edge computing enables real-time data analysis and decision-making, which is critical for applications like security systems, energy management, and occupant comfort adjustments.

For example, ref. [61] utilized edge computing with a Raspberry Pi as an edge IoT device to perform facial recognition locally, enhancing security while minimizing data transmission to external servers. Edge computing also contributes to energy savings by reducing the energy consumption associated with data transmission and remote processing [2].

Cloud Computing provides scalable, cost-effective off-site data storage and processing services over the internet [2,16,52]. In smart buildings, Cloud Computing facilitates centralized data management, analytics, and access to advanced computational resources.

An example is the integration of cloud services in Home Energy Management Systems (HEMS). Reference [16] demonstrated the use of Amazon Web Services (AWS IoT Core) to manage incoming data messages and deliver data-driven services and applications, enhancing the capabilities of HEMS without the need for extensive on-site infrastructure. Methodologies for integration often include secure APIs to transfer data from Edge nodes to the cloud and the leveraging of cloud-native tools for predictive analytics and visualization.

By leveraging both Edge and Cloud Computing, smart buildings can optimize performance by processing critical data locally while utilizing cloud resources for more extensive data analytics, storage, and services.

4.1.5. Blockchain Technologies

Blockchain technology provides a decentralized, secure, and transparent method for recording transactions and data sharing across distributed networks. Applications include peer-to-peer energy trading and the secure storage of IoT sensor data [23,62,65]. In smart buildings, Blockchain can enhance security, trust, and efficiency in energy transactions and data management.

Applications of Blockchain in smart buildings include the following:

- Secure Energy Transactions: peer-to-peer energy trading is facilitated among building occupants or between buildings, allowing for the efficient distribution and use of renewable energy resources [62,65].
- Data Integrity and Security: the authenticity and immutability of data collected from IoT devices and sensors are ensured, enhancing trust among stakeholders [23,62].

For instance, ref. [62] proposed a Trusted Digital Building Logbook architecture using Blockchain and Digital Twin technologies to safeguard privacy and ensure secure data transactions. By minimizing information disparities and fostering trustworthy relationships, Blockchain technology can contribute to more efficient and secure building management systems.

The methodology involves creating smart contracts to automate transactions and validate data authenticity. For example, Ethereum-based frameworks are commonly used in Blockchain implementations for energy systems, ensuring the tamper-proof recording of energy usage or trading activity. Challenges such as computational overhead and scalability are addressed using lightweight consensus algorithms like Proof of Authority (PoA) or Delegated Proof of Stake (DPoS).

4.1.6. Digital Twin Technologies

Digital Twin (DT) technologies involve creating virtual replicas of physical systems that integrate real-time sensor data, simulations, and historical information [62,66]. In smart buildings, Digital Twins enable the real-time monitoring, predictive maintenance, and optimization of building performance.

Applications of Digital Twins in smart buildings include the following:

- Real-Time Monitoring: this provides a comprehensive view of building systems' status, allowing the immediate detection of issues and informed decision-making [62,66]. Methodologies for real-time monitoring often leverage IoT sensors and data acquisition tools to feed accurate and continuous updates into Digital Twin platforms, ensuring up-to-date system representations.
- Predictive Maintenance: data analytics are utilized to predict equipment failures or maintenance needs, reducing downtime and maintenance costs [66]. Machine Learning algorithms such as Long Short-Term Memory (LSTM) networks or ARIMA models are commonly used for forecasting failures, enabling proactive interventions.
- Optimization of Building Performance: Different scenarios are simulated to improve energy efficiency, occupant comfort, and operational strategies [62]. Simulation tools, such as MATLAB Simulink or EnergyPlus, are often integrated with Digital Twins to test and refine system responses under varying conditions.

For example, ref. [66] developed a Digital Twin prototype for HVAC systems, integrating sensor data and simulations to predict system behavior and optimize performance. Similarly, ref. [62] presented an architecture combining Blockchain and Digital Twin technologies to enhance data security and building management. This integration ensures that the data that are driving decisions are both accurate and tamper-proof, addressing key concerns around trust and reliability in data-driven systems.

4.1.7. Information Systems and Geographic Information Systems (GIS)

Information Systems (IS) and Geographic Information Systems (GIS) are critical tools for storing, visualizing, analyzing, and interpreting data related to smart buildings and energy management.

Geographic Information Systems (GIS) provide spatial analysis capabilities that are essential for the following:

- Energy Distribution Management: energy distribution networks are managed by performing real-time monitoring, maintenance, and outage response [19]. Advanced GIS platforms integrate real-time sensor data with spatial models to enhance the accuracy of monitoring and facilitate automated responses during outages.
- Energy Consumption Mapping: visual representations are created of energy consumption across buildings or regions, facilitating the identification of high-consumption areas and opportunities for efficiency improvements [32,67]. These visualizations often rely on heatmaps or choropleth maps generated through tools like ArcGIS, which allow for the easy identification of energy usage patterns.
- Solar Energy Potential Analysis: the solar energy that rooftops can capture is estimated while considering shading effects from nearby structures [67]. Methodologies for this analysis frequently include 3D-GIS modeling and LiDAR-based data integration to enhance accuracy.

For instance, ref. [32] used GIS to create maps representing buildings with color-coded blocks corresponding to their energy performance grades. Additionally, ref. [67] proposed a 3D-GIS approach to predict solar energy potential in urban areas. Such tools provide actionable insights for energy planners and policymakers, enabling the optimized deployment of solar infrastructure.

Information Systems such as EnerGis, a GIS designed for modeling energy service requirements, provide platforms for integrating various data sources and supporting decision-making processes in energy management [29]. These systems often integrate IoT-generated data with historical and forecasted datasets, allowing for dynamic simulations of energy management scenarios. By incorporating multi-criteria decision-making tools, IS and GIS platforms can optimize resource allocation and project planning.

By leveraging IS and GIS technologies, smart buildings and urban planners can utilize data-driven decisions to enhance energy efficiency, plan infrastructure, and promote sustainable development. These technologies support long-term urban planning efforts by aligning sustainability goals with operational strategies, ensuring that energy systems meet future demands effectively.

4.2. Energy Resources and Systems in Smart Buildings

This subsection presents the energy resources, technologies, and management systems employed in smart buildings to enhance energy efficiency and sustainability.

4.2.1. Renewable Energy Resources and Technologies

Renewable energy resources and technologies are fundamental to the development of sustainable smart buildings. By integrating these resources, smart buildings can generate, store, and utilize energy more efficiently, reducing reliance on non-renewable energy sources and minimizing environmental impact.

- Solar Photovoltaic (PV) Systems: Solar PV panels convert sunlight directly into electricity, providing a clean and renewable energy source for buildings. They are widely adopted in smart buildings to reduce grid dependency and lower energy costs [21,24,38,43,55,67].
- Solar Thermal Systems with Storage: These systems capture solar energy for heating applications, such as water heating and space heating. Incorporating thermal storage allows excess heat to be stored for use during periods without sunlight, enhancing energy availability and efficiency [24].
- Ground-Source Heat Pump (GSHP) Systems: GSHPs utilize the stable temperatures beneath the Earth's surface to provide heating and cooling for buildings. By exchanging heat with the ground, these systems offer higher efficiency compared to traditional HVAC systems [24].
- Energy Storage Systems (ESS) and Batteries: ESS, including batteries, store excess energy generated from renewable sources like solar PV. Stored energy can be used during peak demand times or when renewable generation is low, improving energy reliability and reducing costs [21,38].
- Electric Vehicles (EVs) and Charging Infrastructure: Integrating EV charging stations into smart buildings supports the adoption of electric mobility. EVs can also act as mobile energy storage units, and vehicle-to-grid (V2G) technologies enable energy exchange between EVs and buildings [38,43].
- Mechanical Ventilation with Heat Recovery (MVHR): MVHR systems improve energy efficiency by recovering heat from outgoing stale air and transferring it to incoming fresh air. This process reduces the energy required for heating or cooling incoming air, enhancing indoor air quality and comfort [24].

4.2.2. Energy Management and Automation Systems

Energy management and automation systems are critical components of data-driven smart buildings, enabling the efficient monitoring, control, and optimization of energy consumption. These systems leverage advanced technologies to enhance operational efficiency, reduce energy costs, and improve occupant comfort. Table 5 provides an overview of the various energy management and automation systems implemented in smart buildings.

Table 5. Overview of the energy management and automation systems in the data-driven smart buildings.

Technology	Sub-Types	References
Home Energy Management and Monitoring Systems	Home Energy Management System	[16,18,19,34,41,51,52]
	Intelligent Home Energy Management System (AIHEMS)	[72]
	Smart home power management	[47]
	Home energy monitoring system	[20]
	IoT-based energy monitoring system	[50]
	Standby-power management system	[30]
Building Energy Management and Monitoring Systems	Energy management systems (EMSS)	[43,49]
	Building Energy Management Systems	[28,68]
	Building energy monitoring and management system	[71]
	Building management systems (BMS)	[7]
	Building automation system (BAS)	[26]
Smart and Automated Systems for Homes and Offices	Home automation system	[21,39]
	Smart home and building automation applications	[46]
	Wireless home automation systems	[54]
	Smart office system	[61]
	Smart office lighting control system	[70]
Specialized Control and Data Management Systems	Versatile sensor data acquisition and control system (VSDACS)	[15]
	Building Information Modeling (BIM)-based intelligent illumination system	[8]
	Energy-aware data gathering techniques (EDGE)	[64]

Home Energy Management and Monitoring Systems

Home Energy Management Systems (HEMS) are designed to empower homeowners with real-time insights into their energy consumption patterns. By providing detailed information on energy usage, HEMS can enable users to make informed decisions to reduce costs and improve efficiency. For example, standard HEMS platforms [16,18,19,34,41,51,52] allow users to monitor energy consumption through mobile apps or web interfaces, schedule appliance operations during off-peak hours, and receive alerts about unusual energy usage.

Building on this foundation, Intelligent Home Energy Management Systems (AiHEMS) incorporate artificial intelligence to learn from user behaviors and environmental data such as temperature, humidity, and occupancy [72]. By dynamically adjusting settings based on this information, AiHEMS can optimize energy consumption without compromising comfort. For instance, they might lower the amount of energy spent on heating or cooling when the occupants are away from home or adjust lighting based on natural light availability.

Other specialized systems include Smart Home Power Management solutions [47], which automate the control of appliances and electrical systems, often integrating with smart grids to manage power consumption more efficiently. Home Energy Monitoring Systems [20] focus on providing detailed real-time data to help users identify high-consumption devices and implement energy-saving measures. IoT-based Energy Monitoring Systems [50] utilize connected sensors to collect granular data, enabling remote monitoring and control via smartphones or other devices. Additionally, Standby-Power Management Systems [30] aim to reduce energy waste by automatically cutting power to devices in standby mode.

Building Energy Management and Monitoring Systems

In commercial and large-scale buildings, Building Energy Management Systems (BEMS) are crucial for overseeing energy consumption across various systems such as heating, ventilation, air conditioning (HVAC), lighting, and security. Energy Management Systems (EMS [43,49]) provide centralized control, employing strategies for energy conservation and cost reduction. By integrating data from multiple sources, these systems allow facility managers to monitor performance, identify inefficiencies, and implement corrective actions.

Building Energy Management Systems [28,68] take a holistic approach by integrating multiple building systems, enabling optimization across different energy domains. These systems can adjust HVAC operations based on occupancy patterns or optimize lighting levels according to daylight availability, thereby enhancing energy efficiency. Building Energy Monitoring and Management Systems [71] focus on detailed monitoring, providing tools to manage and optimize consumption effectively.

Building Management Systems (BMS) [7] facilitate the management of building operations, including energy usage, environmental conditions, and safety systems, enhancing both efficiency and occupant comfort. These systems often include features like real-time monitoring, automated control, and data analytics to support decision-making processes. Building Automation Systems (BAS) [26] automate the control of services like HVAC and lighting, adjusting settings based on real-time data from sensors and occupancy patterns, which can lead to significant energy savings and improved environmental conditions within the building.

Energy management systems (EMS) play a critical role in optimizing energy use in smart buildings. These systems leverage advanced technologies like IoT, Machine Learning, and Cloud Computing to monitor and control energy consumption. However, the scalability of these systems remains a challenge, particularly in larger buildings or multi-site deployments. Current EMS solutions often struggle to accommodate the growing volume of data generated by expanding sensor networks, highlighting the need for scalable architectures and robust processing capabilities.

Smart and Automated Systems for Homes and Offices

Automation systems enhance intelligence and convenience in residential and office environments, contributing to energy efficiency and user comfort. Home Automation Systems [21,39] automate functions such as lighting, climate control, security, and appliance management, often allowing control via mobile devices or voice commands. For example, a homeowner can remotely adjust the thermostat or turn off the lights using a smartphone app, reducing unnecessary energy consumption.

Smart Home and Building Automation Applications [46] integrate multiple devices and systems, providing seamless automation and enhanced user experience. These applications can coordinate the operation of various smart devices, enabling scenarios like automatically adjusting blinds and lighting depending on when the sun sets. Wireless Home Automation Systems [54] utilize wireless communication protocols to connect devices, simplifying installation and expanding flexibility, which is particularly beneficial in retrofit situations where running new wiring is impractical.

In office settings, smart office systems [61] automate operations, including environmental controls, lighting, and access systems, improving energy efficiency and employee productivity. For instance, smart systems can adjust ventilation and temperature based on occupancy levels, enhancing comfort while conserving energy. Smart Office Lighting Control Systems [70] adjust lighting based on occupancy and daylight availability, reducing energy consumption while maintaining a comfortable work environment.

Specialized Control and Data Management Systems

Specialized systems offer advanced functionalities for data acquisition and control in smart buildings. The Versatile Sensor Data Acquisition and Control System (VSDACS) ref. [15] manages data from various utility sensors, such as electricity, water, gas, air flow, and solar energy. By providing real-time data processing, storage, and alert generation, VSDACS supports decision-making processes and enhances operational efficiency. Facility managers can, for example, receive immediate notifications of anomalies like water leaks or unusual energy spikes.

Building Information Modeling (BIM)-based Intelligent Illumination Systems [8] utilize BIM to optimize lighting controls based on building design and occupancy patterns. By integrating design data with real-time occupancy information, these systems can adjust the lighting in different zones of a building, ensuring adequate illumination where needed while saving energy in unoccupied areas. Energy-aware data gathering techniques (EDGE) [64] focus on optimizing data collection in Wireless Sensor Networks, conserving energy in sensor nodes while ensuring accurate and reliable data transmission. This is particularly important for battery-powered sensors where energy efficiency extends the operational life of devices.

The integration of these energy management and automation systems in data-driven smart buildings significantly enhances energy efficiency, reduces operational costs, and promotes sustainability. These systems enable the proactive management of energy consumption and contribute to the overall performance and environmental impact of smart buildings by leveraging advanced technologies and data analytics. The synergy between energy management systems and data-driven technologies forms the backbone of modern smart buildings, paving the way for more sustainable and intelligent built environments.

4.2.3. Energy Modeling and Fault Detection

Accurate energy modeling and effective fault detection are essential for optimizing energy usage and maintaining the reliable operation of building systems.

Building Energy Modeling and Simulation

Building energy modeling involves creating digital representations of buildings to simulate and analyze energy consumption. This process helps in designing energy-efficient buildings and retrofitting existing structures. A comprehensive building energy simulation program is used to model heating, cooling, lighting, ventilation, and other energy flows within a building [14].

In our discussion, we focus on simulation methods relevant to walls, roofs, and indoor air (room temperature). Tools such as EnergyPlus (U.S. Department of Energy. https://energyplus.net, accessed 8 December 2024) and TRNSYS (Solar Energy Laboratory, University of Wisconsin-Madison. https://sel.me.wisc.edu/trnsys, accessed 8 December 2024) are widely employed, but each handles these components with the following distinct solvers:

- EnergyPlus
    - Conduction Transfer Function (CTF) Method for Opaque Walls and Roofs: by default, EnergyPlus uses a CTF-based approach for most conventional building

envelopes (walls and roofs). This method balances computational speed with acceptable accuracy for standard construction materials.
    - Finite Difference Method (FDM) for Advanced Materials: for walls or roofs incorporating complex materials (e.g., Phase Change Materials), EnergyPlus employs an FDM approach, allowing a more detailed layer-by-layer temperature profile.
    - Moisture Transfer and Room Air: some EnergyPlus modules incorporate additional solvers for moisture transfer within walls. Meanwhile, room air (zone) temperature is solved with iterative heat balance methods that couple radiative and convective processes in the zone air.
- TRNSYS
    - Differential-Algebraic Equation (DAE)-Based Approach with Modular Components: TRNSYS is known for its DAE-solving capabilities and its flexible, modular setup. However, for building simulations, TRNSYS employs specific approaches for each component, including the walls and zone air.
    - Component-Level Solvers for Walls: each wall, roof, or other envelope component (often referred to as a "Type" in TRNSYS) has its own solver strategy to handle heat conduction and sometimes mass transfer.
    - Room/Zone Air: the zone temperature is updated using a separate solver that couples convective, radiative, and (if necessary) latent (moisture) heat flows at the zone boundary.
    - Renewable or Specialized Systems: while TRNSYS can simultaneously solve renewable energy systems (e.g., solar thermal) in the same simulation environment, this flexibility lies outside the scope of the wall, roof, and room-air solvers discussed here.

Table 6 below summarizes the methodologies and features of EnergyPlus and TRNSYS.

Table 6. Methodologies and features of EnergyPlus and TRNSYS.

Tool	Key Features	Methodologies	Applications
EnergyPlus	Whole-building energy modeling for HVAC, lighting, and energy flows	Finite Difference Method (FDM) for thermal analysis; iterative solvers for energy balance; weather data integration	Evaluating energy performance of design choices, optimizing HVAC and lighting systems
TRNSYS	Modular simulation environment for transient systems, including renewable energy components	Component-based architecture; Ordinary Differential Equation (ODE) solvers for transient simulations	Renewable energy simulation (solar PV, thermal); the analysis of dynamic system behavior, thermal storage systems

Challenges in building energy modeling include accounting for diverse building types, climates, and occupancy behaviors and accurately predicting system interactions. For example, variations in weather patterns or unexpected changes in occupant behavior can introduce uncertainties into model outputs. To address these challenges, advanced tools like DesignBuilder (based on EnergyPlus) and IDA ICE incorporate Monte Carlo simulations to quantify uncertainties and provide probabilistic forecasts [73]. It is essential to understand how each solver handles heat transfer through walls, roofs, and indoor air to ensure modeling accuracy, as different solvers may be more suitable for specific configurations or material types. Continuous validation and calibration with real-world data enhance the reliability of simulation results, ensuring that models remain applicable to practical scenarios [74,75].

In addition to EnergyPlus and TRNSYS, other tools provide specialized functionalities but generally follow a similar philosophy: focusing on envelope heat conduction (walls, roofs, windows) and zone-level temperature simulation. This ensures that the core building envelope and indoor thermal environment are accurately represented before extending to additional features (e.g., advanced HVAC, humidity transfer, and specialized renewable systems):

- DesignBuilder: this provides a user-friendly interface for EnergyPlus, supporting parametric analyses to optimize energy performance.
- OpenStudio: this integrates with EnergyPlus and enables advanced customizations of simulation parameters for specialized projects.
- IDA ICE: this focuses on indoor climate and energy analysis, using modular simulations and advanced equation solvers for precise calculations.
- IES VE: this combines 3D modeling with dynamic simulations, supporting detailed environmental and energy assessments.

These tools employ various algorithms, including finite element analysis (FEA) for thermal modeling, ODE solvers for transient processes, and Monte Carlo simulations for uncertainty analysis [73,74]. By leveraging these diverse approaches, engineers and architects can select tools that best align with their project requirements, from simple energy efficiency assessments to complex renewable energy integrations.

Fault Detection and Diagnosis (FDD)

Fault detection and diagnosis (FDD) systems are essential components in smart buildings, serving to promptly identify anomalies or faults within building systems. By enabling timely interventions, FDD systems help prevent energy waste, avoid equipment failure, and ensure the optimal performance of building operations. These systems continuously monitor various building services, such as HVAC, lighting, and electrical systems, facilitating proactive maintenance and reducing downtime [2,68].

A critical aspect of modern FDD systems is the incorporation of Artificial Intelligence (AI)-based anomaly detection techniques. Machine Learning algorithms analyze energy consumption patterns and operational data to detect deviations that may indicate faults or inefficiencies [2]. These algorithms can operate under the following different learning paradigms:

- Supervised Learning involves training models on labeled datasets where known fault patterns are identified. The model learns to recognize these patterns and can detect similar faults in new, unlabeled data.
- Unsupervised Learning does not require labeled data. Instead, the algorithm identifies normal operational patterns and flags any deviations from these patterns as potential anomalies, making it effective for detecting new or unexpected faults.
- Semi-Supervised Learning combines elements of both supervised and Unsupervised Learning. It utilizes a small amount of labeled data along with a larger set of unlabeled data to improve detection accuracy, especially when labeled data are scarce.

Fault detection approaches are broadly classified into two categories: data-driven methods and knowledge-driven methods. Data-driven methods rely on statistical analysis and Machine Learning to identify patterns and anomalies directly from operational data without the need for explicit models of system behavior [26]. These methods are particularly useful when dealing with complex systems where modeling every component is impractical.

On the other hand, knowledge-driven methods utilize expert knowledge, predefined rules, and models of expected system behavior to detect deviations indicative of faults [76]. These methods are effective when the comprehensive understanding and modeling of the system are feasible, allowing for the precise identification of anomalies based on established criteria.

Implementing robust energy modeling and FDD systems brings several benefits to smart buildings:

- Energy Efficiency: By identifying and correcting inefficiencies, FDD systems reduce unnecessary energy consumption and lower operational costs. Detecting faults early prevents the wastage of energy that occurs when systems operate sub-optimally.
- System Reliability: The early detection of faults prevents minor issues from escalating into major equipment failures. This proactive approach extends the lifespan of building systems and minimizes disruptions to building operations.
- Occupant Comfort: Maintaining optimal system performance ensures that indoor environmental conditions remain within the desired comfort levels. Effective FDD contributes to consistent temperature control, air quality, and lighting, enhancing occupant satisfaction.

5. Influential Factors for the Adoption and Business Models of Data-Driven Technologies

5.1. Factors Influencing the Adoption of Data-Driven Technologies

The successful deployment of data-driven technologies in smart buildings largely depends on user acceptance and willingness to adopt these innovations. Failure to understand users' needs, preferences, and expectations is a significant reason why many projects do not succeed [77]. Among the most critical barriers is the high initial cost of implementation, particularly for retrofitting existing buildings with legacy systems. These costs can deter stakeholders from investing in necessary infrastructure upgrades, especially when the return on investment is not immediately evident. The literature identifies several key factors influencing the adoption of data-driven technologies in smart buildings, which can be categorized into social factors, individual perceptions, cost considerations, security and privacy concerns, and data quality and relevance. Table 7 summarizes these influential factors and their corresponding references.

Table 7. Literature on influential factors for the adoption of data-driven technologies in smart buildings.

Influential Factors	Sub-Types	References
Social factors	Trust	[78–80]
	Attractiveness of alternatives	[80]
	Social influence	[81]
	Behavioral intention	[80]
	Hedonic motivation	[80]
	Soft skills	[33]
	Well-being	[79]
Individual perceptions	Perceived innovation	[78]
	Perceived usefulness	[78,82]
	Life-quality expectations	[83]
	Relative advantage	[78]
	Risk perception	[80]
	Perceived value	[84]
	Perceived ease of use (PEOU)	[78]
	Compatibility	[82,85]
	Perceived simplicity	[82]
	Effort expectancy	[80]
	Human detachment concern	[83]
	Perceived connectedness	[85]

Table 7. *Cont.*

Influential Factors	Sub-Types	References
Cost	Cost	[83,85]
Security and Privacy	Security Security risks Privacy risks Privacy concerns Safety	[79] [86] [84] [83] [86]
Data Quality and Relevance	Inaccurate or irrelevant data Inaccurate outcomes	[87] [87]

5.1.1. Social Factors

Social factors significantly influence individuals' decisions to adopt new technologies, particularly in group or societal contexts. These factors encompass trust, social influence, behavioral intention, hedonic motivation, soft skills, and well-being.

Trust plays a crucial role in technological adoption. Users are more likely to embrace data-driven technologies when they trust the technology itself and the entities providing it [78–80]. Trust can be established through transparent communication, reliable performance, and robust security measures.

Social influence refers to the impact of others' opinions and behaviors on an individual's decision to adopt technology [81]. If peers, family members, or influential figures endorse or use a particular technology, individuals may feel more inclined to adopt it themselves.

Behavioral intention is the degree to which an individual plans to use technology, influenced by attitudes and subjective norms [80]. Positive behavioral intentions, shaped by favorable attitudes and perceived social pressure, often lead to higher adoption rates.

Hedonic motivation involves the enjoyment or pleasure derived from using technology [80]. When users find technology engaging or entertaining, they are more likely to adopt it due to the intrinsic satisfaction it provides.

Soft skills, such as interpersonal and intrapersonal abilities, can impact technology adoption. A lack of soft skills among users may hinder the adoption of data-driven technologies [51]. For instance, inadequate communication skills or resistance to change can impede the effective implementation of new systems.

Well-being considerations influence adoption when technologies are perceived to enhance users' quality of life [79]. Technologies that contribute to health, comfort, or convenience are more likely to be embraced by users seeking to improve their well-being.

5.1.2. Individual Perceptions

Individual perceptions about technology's attributes significantly affect decisions for its adoption. Factors such as perceived usefulness, ease of use, innovation, compatibility, perceived value, and risk perception are critical.

Perceived usefulness and ease of use are foundational elements in technology acceptance models [78,82]. Users are more inclined to adopt technologies that they believe will enhance their performance or efficiency and that are easy to learn and operate. For example, if a smart home system simplifies household management without requiring extensive effort when using it, adoption likelihood increases.

Perceived innovation reflects the degree to which technology is seen as new or novel [78]. Users may be attracted to innovative technologies that offer advanced features or capabilities beyond existing solutions.

Compatibility refers to how well a type of technology aligns with users' existing values, needs, and past experiences [82,85]. Technologies that fit seamlessly into users' lifestyles or work practices are more readily adopted. For instance, an energy management system that integrates with existing appliances and devices may be more appealing.

Perceived value involves the overall assessment of technology's benefits relative to its costs [84]. Users weigh the advantages, such as energy savings or convenience, against the financial expenses and effort required. A high perceived value enhances the likelihood of adoption.

Risk perception encompasses concerns about potential negative outcomes, such as security breaches, privacy violations, or technical failures [80]. High levels of perceived risk can deter users from adopting new technologies. Addressing these concerns through risk mitigation strategies is essential.

Effort expectancy is the perceived ease associated with using the technology [80]. Technologies requiring minimal effort and complexity are more attractive to users who may be reluctant to invest significant time and energy into learning new systems.

Human detachment concerns relate to worries about reduced human interaction or over-reliance on technology [83]. Users may fear that automation could lead to isolation or diminished personal connections, affecting their willingness to adopt such technologies.

5.1.3. Cost Considerations

Cost is a significant factor influencing the adoption of data-driven technologies. High initial investment costs, ongoing maintenance expenses, and the perceived affordability of technology can either facilitate or hinder adoption [83,85]. The cost of implementing Internet of Things (IoT)-enabled HVAC systems can vary significantly depending on factors such as the size of the building, the complexity of the system, and regional pricing. Estimates suggest that such systems may require substantial upfront investments, especially for large-scale commercial buildings [88]. Retrofitting older buildings further increases costs due to compatibility issues and the required infrastructure updates.

Studies indicate that the cost of implementing Internet of Things (IoT) technologies in smart homes can be a barrier [85]. Users may hesitate to invest in expensive systems without clear evidence of long-term benefits or return on investment. Conversely, advancements in technology, increased market competition, and economies of scale can reduce costs over time, making data-driven technologies more accessible. However, these expenses must be weighed against long-term savings in energy costs, which can range from 20% to 40% annually [89], enabling a return on investment within 5 to 10 years, depending on the scale of implementation and available subsidies [90].

The trade-offs between cost and comfort are particularly critical. For instance, adaptive HVAC systems dynamically balance energy efficiency with thermal comfort, which is assessed using metrics such as the Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD). Systems must also meet indoor air quality (IAQ) standards, which mandate minimum ventilation rates (e.g., 8.5 L per second per occupant in offices per the ASHRAE Standard 62.1) [91]. Perceived economic benefits, such as energy savings and operational efficiencies, can offset cost concerns. When users recognize that the long-term savings outweigh the initial expenses, they may be more willing to adopt the technology [83].

Additionally, regulatory compliance adds complexity to cost considerations. Many regions enforce stringent energy codes, such as the EU Energy Performance of Buildings Directive or the U.S. ASHRAE 90.1 standard [92], which mandate minimum energy performance levels while ensuring occupant health and comfort. HVAC systems are designed to optimize energy efficiency while adhering to these mandatory constraints, further emphasizing the cost–compliance–comfort trade-off.

5.1.4. Security and Privacy Concerns

Security and privacy are paramount in the adoption of data-driven technologies. Users must feel confident that their personal information is protected and that technology does not expose them to undue risks.

Security risks involve fears of cyber threats, hacking, and unauthorized access to systems [86]. Users may worry about the vulnerability of smart building systems to cyber-attacks, which could compromise safety or lead to data breaches.

Privacy risks pertain to concerns about how personal data are collected, stored, and used [83,84]. Users are cautious about technologies that may infringe on their privacy by sharing sensitive information without consent.

Safety concerns relate to the potential physical risks associated with technology use [86]. For example, malfunctioning automated systems could pose hazards within a smart building environment.

Addressing these concerns requires implementing robust security measures, transparent data policies, and compliance with regulations. Enhancing user education about how data are protected can build trust and facilitate adoption [79].

5.1.5. Data Quality and Relevance

The effectiveness and reliability of data-driven technologies depend on the quality and security of the data they utilize. However, increased connectivity and reliance on IoT devices expose smart buildings to cybersecurity threats. Unauthorized access or data breaches not only compromise sensitive information but also impact trust among users. Poor data management practices exacerbate these risks, potentially leading to inaccurate insights and reduced satisfaction with the technology [87].

Inaccurate or irrelevant data can result from faulty sensors, data entry errors, or inadequate data processing methods. When users receive incorrect information or insights, they may lose confidence in the technology's usefulness.

Inaccurate outcomes stemming from poor data can hinder decision-making processes and operational efficiency [87]. For instance, in Building Energy Management, inaccurate data analytics may lead to suboptimal energy usage recommendations, negating the benefits of technology.

Enhancing data quality involves ensuring accurate data collection, employing reliable data processing techniques, and providing transparent analytics. By improving data integrity, stakeholders can enhance the perceived usefulness of data-driven technologies, encouraging adoption.

5.2. Business Models Supporting the Adoption of Data-Driven Technologies

The successful adoption of data-driven technologies in smart buildings is not solely dependent on technological advancements but is also significantly influenced by the development of sustainable and effective business models. These business models provide frameworks that align technological innovations with market needs, ensuring that the value propositions meet the expectations of stakeholders such as building owners, operators, occupants, and technology providers. This section examines business models identified in the literature that support the adoption of data-driven technologies in smart buildings, focusing on their key components and how they facilitate implementation. Table 8 presents an overview of business models for data-driven smart buildings and energy, summarizing the main elements based on the Business Model Canvas framework for each study reviewed.

Table 8. Business models for data-driven smart buildings and energy.

Business Model Canvas Segment	Ref. [33]	Ref. [93]	Ref. [94]
Customer Segments	Government buildings	Building operators and real estate companies	Property managers, residents, and service providers
Value Propositions	Cost savings and efficiency improvements	Energy efficiency and operational performance optimization	Building management efficiency, cost reductions, enhanced user experience, and potential energy savings
Key Partners	Government bodies, educational institutions, and potential AI technology providers	Real estate and facility management operators, large international companies, and research institutions	Technology providers, construction companies, IoT companies, and real estate agencies
Key Activities	Researching AI applications in energy management, understanding barriers, and testing hypotheses related to AI deployment in government buildings	AI applications development and integration into existing building management systems	Continuous development and maintenance and the integration of various IoT devices and services
Key Resources	Intellectual resources (research data, AI technologies, and expert opinions) and survey data from government building occupants	AI technologies, platform infrastructure, research data, and expertise	IoT platforms and connected devices, expertise in IoT and building management, and data analytics capabilities
Cost Structure	Training and implementing AI systems	N/A	N/A
Customer Relationships	N/A	Co-development partnership	N/A
Channels	N/A	Digital platforms and conferences	Direct installations, online platforms for management, and possible mobile applications
Revenue Stream	N/A	N/A	N/A

The literature reveals that while technological innovations in data-driven smart buildings are well-documented, there is limited focus on the corresponding business models necessary for their adoption. The studies reviewed highlight the importance of aligning business models with technological advancements to facilitate their implementation and adoption.

5.2.1. Case Studies of Business Models

The following case studies illustrate different business models supporting the adoption of data-driven technologies in smart buildings, demonstrating how they address various components of the Business Model Canvas.

- AI in Energy Conservation for Government Buildings

Ref. [33] investigates the barriers to implementing Artificial Intelligence (AI) for energy conservation in government buildings in Sri Lanka. The primary customers are the entities managing government buildings and the public, who benefit from reduced operational costs and enhanced energy efficiency.

The value proposition emphasizes significant cost savings and efficiency improvements through AI-driven automation and decision-making systems. By integrating AI, government buildings can optimize energy usage, leading to substantial financial savings and reduced environmental impact.

Key partners include government bodies that are responsible for building management, educational institutions like the University of Moratuwa conducting research, and AI technology providers offering the necessary tools and expertise. Collaboration among these stakeholders is crucial for addressing the barriers to AI adoption.

Key activities involve researching AI applications in energy management, understanding the specific challenges faced by government buildings, and testing hypotheses related to AI deployment. This study highlights the importance of identifying and mitigating factors that hinder adoption, such as a lack of skills, technology acceptance issues, and financial constraints.

Key resources consist of intellectual assets like research data, AI technologies, and expert opinions, as well as survey data collected from building occupants. These resources are essential for developing tailored AI solutions that meet the unique needs of government buildings.

The cost structure includes expenses related to training personnel and implementing AI systems. Addressing the cost barrier is critical, as financial limitations are a significant hindrance to adoption.

- AI-Enabled Platform Business Models in Smart Buildings

Ref. [93] presents an analysis of AI-enabled platform business models within the context of smart buildings. The primary customers are building operators and real estate companies seeking to leverage AI for improved management and energy efficiency.

The value proposition centers on providing enhanced building management solutions through AI, leading to better energy efficiency and optimized operational performance. The platform-based business model allows for scalability and fosters an ecosystem where various stakeholders can collaborate.

Key partners include real estate and facility management operators, large international companies, and research institutions participating in a Finnish national innovation project. These partnerships facilitate the pooling of resources and expertise, promoting innovation and adoption.

Key activities involve developing AI applications tailored for smart buildings, integrating these solutions into existing building management systems, and fostering collaboration within the ecosystem. The focus is on creating scalable and sustainable business models that can adapt to evolving technological landscapes. Developing sustainable business models is crucial for the adoption of data-driven technologies in smart buildings. Effective models align technological innovations with market needs, ensuring that stakeholders recognize the value propositions. A significant limitation in this area is a lack of alignment among stakeholders, including building owners, technology providers, and end-users. Divergent priorities often lead to fragmented efforts, reducing the overall effectiveness of these business models. Collaborative frameworks are needed to bridge these gaps and ensure cohesive implementation strategies.

Key resources encompass AI technologies, platform infrastructure that supports integration and scalability, research data generated from collaborative projects, and expertise from participating institutions.

Customer relationships are managed through continuous engagement and co-development partnerships. By involving customers and partners in the development process, the business model ensures that the solutions meet market needs and foster long-term relationships.

Channels for delivering value include digital platforms that enable interaction and collaboration among ecosystem actors. Academic publications and conferences serve as channels for disseminating findings, attracting further participation, and promoting the business model.

- IoT-Driven Business Models for Smart Building Management Systems

Ref. [94] provides an overview of an Internet of Things (IoT)-driven business model for smart building management systems. The primary customers are property managers, residents, and service providers directly involved with building management.

The value proposition includes increased efficiency in building management, cost reductions, enhanced user experience for residents, and potential energy savings. The IoT solutions aim to create smarter, more responsive buildings that meet the needs of all stakeholders.

Key partners involve a broad spectrum of the IoT ecosystem, including technology providers, construction companies, IoT companies, real estate agencies, and financial institutions. These partnerships are essential for integrating diverse technologies and services into comprehensive solutions.

Key activities focus on the continuous development and maintenance of IoT solutions, integrating various devices and services, and fostering innovation to remain competitive. The business model emphasizes the importance of staying ahead in a rapidly evolving market by adopting the latest technologies and practices.

Key resources include technological infrastructure such as IoT platforms and connected devices, human resources with expertise in IoT and building management, and data analytics capabilities that enable the interpretation and utilization of vast amounts of data generated by IoT devices.

Channels for delivering the smart building management system comprise direct installations in buildings, online platforms for remote management, and mobile applications that provide users with convenient access and control.

5.2.2. Analysis of Business Model Components

The case studies reveal several commonalities and differences in how business models support the adoption of data-driven technologies in smart buildings.

Value Propositions: All models emphasize efficiency improvements, cost savings, and enhanced user experiences. These value propositions directly address some of the influential factors affecting adoption, such as perceived usefulness and value, as discussed in Section 4.1.

Customer Segments: Business models cater to different customer segments, including government entities, building operators, real estate companies, property managers, residents, and service providers. Understanding the specific needs of these segments is crucial for tailoring solutions that meet their expectations.

Key Partners and Activities: Collaboration with key partners is a recurring theme. Engaging with various stakeholders allows for pooling resources, expertise, and technologies, which is essential for developing sophisticated solutions like AI and IoT systems. Key activities revolve around research and development, the integration of technologies, and continuous innovation.

Key Resources: These include intellectual resources, technological infrastructure, and human expertise are vital components. Access to advanced technologies and skilled personnel enables the development of effective solutions that can drive adoption.

Cost Structure and Revenue Streams: While the studies highlight the importance of cost considerations, detailed information on cost structures and revenue streams is often lacking. However, addressing cost barriers through efficient resource utilization and demonstrating a clear return on investment is essential for adoption.

Channels and Customer Relationships: Effective channels for delivering value and maintaining customer relationships are integral to business models. Digital platforms, direct installations, and mobile applications enhance accessibility and user engagement.

5.2.3. Implications for Adoption

The case studies in the literature show that developing robust business models is instrumental in facilitating the adoption of data-driven technologies in smart buildings. By aligning value propositions with the needs of stakeholders and addressing influential factors such as cost, perceived usefulness, and trust, these models can overcome adoption barriers. For example, demonstrating tangible benefits like cost savings and efficiency improvements can mitigate concerns related to high initial investments. Collaborating with reputable partners enhances trust and credibility, which is crucial for technologies that involve significant changes to building operations. Moreover, focusing on user experience and continuous innovation ensures that technologies remain relevant and user-friendly, addressing individual perceptions related to ease of use and perceived value. By providing clear value propositions and engaging stakeholders throughout the development process, business models can create supportive environments for adoption.

6. Discussion

The integration of data-driven technologies and energy optimization strategies in smart buildings represents a significant advancement in the pursuit of sustainable and efficient built environments. This discussion synthesizes the key findings from the review, explores the implications these have for the industry, identifies challenges and limitations, and suggests directions for future research.

6.1. Key Findings

The review highlights a multifaceted ecosystem where data-driven technologies intersect with energy systems to enhance building performance and sustainability. Fundamental technologies such as big data analytics, Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), Wireless Sensor Networks (WSNs), Edge and Cloud Computing, Blockchain, Digital Twins, and Geographic Information Systems (GIS) form the backbone of smart building infrastructures.

Big data analytics enables the processing of vast datasets to uncover patterns that inform decision-making, leading to optimized operations and energy efficiency [28,30,57,58]. AI and ML contribute to automating tasks, predicting energy consumption patterns, and enhancing occupant comfort through intelligent automation [2,3,14,25,27,29,33,35,38,41,42,49,51,59–61] IoT, and WSNs facilitate real-time data collection and communication among devices, which are essential for responsive energy management systems [1,7,8,14,16,20,21,27,36,37,39,41,45,47–49,51,62,70].

Edge and Cloud Computing provide complementary solutions for data processing, with Edge computing enabling real-time analysis at the source and Cloud Computing offering scalable storage and advanced analytics [2,16,36,52,61]. Blockchain technologies enhance security and trust in energy transactions and data sharing, which is crucial for decentralized energy systems [23,62,65]. Digital Twin Technologies create virtual replicas of physical systems for real-time monitoring and optimization, leading to predictive maintenance and performance enhancement [62,66]. GIS offers spatial analysis capabilities for energy distribution management and planning [19,29,32,67].

The incorporation of renewable energy resources and technologies such as solar photovoltaic systems, solar thermal systems, ground-source heat pumps, energy storage systems, and electric vehicle integration underscores the commitment to sustainability [21,24,38,43,44,55,67]. Energy management and automation systems, including Home Energy Management Systems (HEMS), Building Energy Management Systems (BEMS), and specialized control systems, enable the efficient monitoring, control, and optimization of energy consumption [7,15,16,18–21,26,28,34,39–41,43,46,47,49–52,61,68,70–72].

Energy modeling and fault detection are critical for optimizing energy usage and maintaining system reliability. Building energy modeling assists in designing energy-efficient structures, while fault detection and diagnosis (FDD) systems leverage AI and ML to identify anomalies, prevent energy waste, and ensure optimal operation [2,14,26,68].

The adoption of these technologies is influenced by various factors. Social factors such as trust, social influence, and behavioral intention play significant roles in technology acceptance [33,78–81]. Individual perceptions regarding usefulness, ease of use, innovation, and risk impact adoption decisions [78,80,82–85]. Cost considerations, security and privacy concerns, and data quality and relevance are also critical factors affecting adoption [79,83–87].

Developing effective business models is essential for aligning technological innovations with market needs. The reviewed studies include business models focusing on value propositions like cost savings, efficiency improvements, and enhanced user experiences, catering to different customer segments, and leveraging key partnerships and activities [33,93,94].

6.2. Implications for the Smart Building Industry

The convergence of data-driven technologies with energy optimization strategies has profound implications for the smart building industry:

- Enhanced Energy Efficiency and Sustainability: Integrating advanced technologies enables buildings to consume energy more efficiently, reduce greenhouse gas emissions, and contribute to sustainability goals. Renewable energy integration and intelligent management systems support the transition to low-carbon buildings.
- Improved Operational Performance: Real-time monitoring, predictive analytics, and automated control systems enhance operational efficiency. Facility managers can make informed decisions, anticipate maintenance needs, and respond proactively to issues, reducing downtime and operational costs.
- Occupant Comfort and Well-being: Personalized and adaptive environments enhance occupant satisfaction. Technologies that adjust to user preferences and environmental conditions improve comfort and productivity, making buildings desirable spaces.
- Market Competitiveness: Buildings equipped with advanced technologies may have a competitive edge in the real estate market. Energy-efficient and intelligent buildings can attract tenants and buyers who prioritize sustainability and technological sophistication.
- Data-Driven Decision-Making: The abundance of data generated facilitates evidence-based decisions in building design, operation, and policymaking. Stakeholders can leverage insights to optimize resource allocation and strategic planning.

6.3. Challenges and Limitations

Despite these promising advancements, several challenges hinder the widespread adoption of data-driven technologies in smart buildings:

1. Cost Barriers: High initial investment costs for technology implementation and upgrades can deter stakeholders. Return on investment may not be immediately apparent, especially when retrofitting existing buildings.
2. Technical Complexity and Integration: Integrating diverse technologies requires technical expertise and may face interoperability issues. Legacy systems might not be compatible with new technologies, necessitating significant modifications.
3. Security and Privacy Risks: Increased connectivity and data exchange expose buildings to cybersecurity threats. Ensuring robust security measures and addressing privacy concerns are paramount to maintaining trust among users.
4. Data Quality and Management: Reliable operation depends on accurate and high-quality data. Challenges include sensor accuracy, data processing capabilities, and managing large volumes of data effectively.
5. User Acceptance and Behavior: Social factors and individual perceptions influence adoption. Resistance to change, a lack of awareness, or negative attitudes toward technology can impede implementation.
6. Regulatory and Standardization Issues: The absence of standardized protocols and regulations can create uncertainties. Compliance with varying regional regulations adds complexity to implementation.

6.4. Future Research Directions

To address the identified challenges and further advance the field, future research should focus on the following topics:

- Cost Reduction Strategies: Studies should investigate ways to lower the costs of technology adoption, such as scalable solutions, modular designs, and leveraging economies of scale. Research into financing models and incentives can also facilitate adoption.
- Interoperability and Standardization: Studies should develop standardized protocols and frameworks that enable the seamless integration of diverse technologies. Collaboration among industry stakeholders can promote interoperability.
- Enhanced Security Measures: Studies should advance cybersecurity solutions tailored for smart buildings, including encryption methods, intrusion detection systems, and secure communication protocols. Research into privacy-preserving data analytics can mitigate privacy concerns.
- Data Management and Analytics: Studies should improve data processing algorithms and storage solutions to handle big data efficiently. This includes emphasizing the development of AI and ML models that can operate with limited or imperfect data.
- User-Centric Design: Studies should incorporate user preferences and behaviors into technology design and conduct studies on user engagement strategies, training programs, and interfaces that enhance usability and acceptance.
- Policy and Regulatory Frameworks: Researchers should engage with policymakers to establish regulations that support technological innovation while protecting user interests. Research into the impact of regulations on the adoption of technology can inform policy development.
- Longitudinal Studies on Impact: Long-term studies should be conducted to assess the actual impact of data-driven technologies on energy consumption, operational costs, and occupant satisfaction. Empirical evidence can validate the benefits and guide future implementation.

Furthermore, aligning business models with technological advancements is crucial for the successful adoption of data-driven technologies. Future efforts should consider the following:

- Value Proposition Refinement: Studies should clearly articulate the benefits of technologies to different stakeholders. Value propositions can also be tailored to address specific needs and concerns, such as cost savings for building owners or enhanced comfort for occupants.
- Collaborative Ecosystems: Partnerships among technology providers should be fostered among building managers, researchers, and policymakers. Collaborative ecosystems can facilitate resource sharing, innovation, and market penetration.
- Flexible and Scalable Models: Business models should be developed that can adapt to changing technological landscapes and market conditions. Flexibility in offerings and scalability of solutions can cater to a broader range of customers.
- Emphasis on User Experience: User experience should be prioritized in service delivery. Providing seamless interfaces, responsive customer support, and continuous updates can enhance customer relationships and loyalty.
- Transparent Cost Structures and ROI: Clear information should be offered on costs and expected returns. Demonstrating tangible benefits and payback periods can alleviate financial concerns and justify investments.

7. Conclusions

This review provides a comprehensive examination of the integration of data-driven technologies and energy optimization strategies in smart buildings. By analyzing the current state of research, this paper identifies the fundamental technologies employed, the energy resources and systems utilized, and the factors influencing the adoption of these innovations. The findings highlight the pivotal role that data-driven technologies such as big data analytics, Artificial Intelligence, Machine Learning, the Internet of Things, and others play in enhancing building performance, energy efficiency, and sustainability.

The incorporation of renewable energy resources and advanced energy management systems demonstrates a significant shift toward more sustainable and efficient energy use within smart buildings. The utilization of technologies like solar photovoltaic systems, energy storage solutions, and intelligent energy management systems not only reduces reliance on non-renewable energy sources but also promotes operational efficiency and occupant comfort.

The analysis of the influential factors affecting the adoption of data-driven technologies reveals that social factors, individual perceptions, cost considerations, security and privacy concerns, and data quality are critical determinants. Understanding these factors is essential for stakeholders who aim to implement these technologies successfully. Furthermore, the examination of business models underscores the necessity of aligning technological advancements with market needs through sustainable and effective frameworks that support their adoption.

Despite the comprehensive approach employed, this review has certain limitations. Firstly, the search was limited to four databases and publications in English, which may have excluded relevant studies in other languages or from other sources, potentially introducing language and publication bias. Secondly, the dynamic nature of the field means that new developments may have emerged after the literature search was conducted, possibly affecting the currency of the findings. Thirdly, the diversity of methodologies and contexts among the included studies poses challenges in synthesizing the results uniformly. Some studies lacked detailed methodological information, which may affect the interpretation of their findings.

The implications of the findings are significant for the smart building industry. The integration of data-driven technologies in smart buildings offers significant opportunities for energy optimization and sustainability. However, the realization of these benefits is hindered by several key challenges, including high initial costs, technical complexities associated with system integration, cybersecurity risks, and misalignment among stakeholders. Addressing these limitations through cost-effective solutions, enhanced interoperability, and collaborative business models is essential for the widespread adoption of smart building technologies.

Future research should focus on developing cost-effective solutions, enhancing interoperability and standardization, improving cybersecurity measures, and fostering user-centric designs. Additionally, exploring innovative business models that facilitate adoption and align with stakeholder needs will be crucial in advancing the field. Furthermore, the limitations acknowledged in this study highlight the need for ongoing research and the continuous updating of knowledge in this rapidly evolving field.

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Appendix A

Table A1. Thirty-three review articles on smart building and energy.

Article Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Smart Building Skins for Urban Heat Island Mitigation: A Review	[95]	Energy efficiency	Building in general	N/A
Smart Home Energy Management Systems: A Systematic Review of Architecture, Communication, and Algorithmic Trends	[96]	Energy Management system; Energy consumption; Energy efficiency	Residential building	Internet of Things; Machine Learning; AI
Examining Energy Efficiency Practices in Office Buildings through the Lens of LEED, BREEAM, and DGNB Certifications	[97]	Energy efficiency	Commercial building (Office buildings)	N/A
An overview of reinforcement learning-based approaches for smart home energy management systems with energy storages	[98]	Energy Management system; Energy consumption; Energy efficiency	Residential building	Machine Learning (Reinforcement Learning); AI

Table A1. *Cont.*

Article Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Application of Deep Learning and Intelligent Sensing Analysis in Smart Home	[99]	Energy efficiency (implied)	Residential building	Artificial Intelligence; Machine Learning; Sensor network
Systematic review on capacity building through renewable energy enabled IoT-unmanned aerial vehicle for smart agroforestry	[76]	Renewable energy	Not directly related to buildings	Internet of Things
Smart home energy management systems in India: a socio-economic commitment towards a green future	[77]	Energy Management system; Energy efficiency	Residential building	N/A
Optimizing building energy consumption in office buildings: A review of building automation and control systems and factors influencing energy savings	[100]	Energy consumption; Energy efficiency; Energy Management system	Commercial building (Office buildings)	N/A
General Overview and Proof of Concept of a Smart Home Energy Management System Architecture	[101]	Energy Management system; Energy consumption	Residential building	Internet of Things
A review of data-driven smart building-integrated photovoltaic systems: Challenges and objectives	[102]	Renewable energy; Energy efficiency	Building in general	Big data; Artificial Intelligence; Digital Twin and simulation
A review on adaptive thermal comfort of office building for energy-saving building design	[103]	Energy efficiency; Energy consumption	Commercial building (Office buildings)	N/A
A review of non-residential building renovation and improvement of energy efficiency: Office buildings in Finland, Sweden, Norway, Denmark, and Germany	[104]	Energy efficiency	Commercial building (Office buildings)	N/A
Energy Efficiency Improvement and Strategies in Malaysian Office Buildings (Tropical Climate): A Review	[63]	Energy efficiency	Commercial building (Office buildings)	N/A
A survey of smart home energy conservation techniques	[105]	Energy consumption; Energy efficiency; Energy Management system	Residential building	Internet of Things; Artificial Intelligence
Building Occupants, Their Behavior and the Resulting Impact on Energy Use in Campus Buildings: A Literature Review with Focus on Smart Building Systems	[106]	Energy consumption; Energy efficiency	Building in general; Commercial buildings	N/A

Table A1. *Cont.*

Article Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Artificial Intelligence Based Smart Home Energy Management System: A Review	[107]	Energy Management system; Energy efficiency	Residential building	Artificial Intelligence
Performance and energy optimization of building automation and management systems: Towards smart sustainable carbon-neutral sports facilities	[108]	Energy efficiency; Energy Management system	Commercial building (Sports facilities)	N/A
Smart home tracking: A smart home architecture for smart energy consumption in a residence with multiple users	[109]	Energy consumption; Energy Management system	Residential building	Internet of Things; Information system
Closed-loop home energy management system with renewable energy sources in a smart grid: A comprehensive review	[110]	Energy Management system; Renewable energy; Smart grid integration	Residential building	N/A
A review of deep reinforcement learning for smart building energy management	[111]	Energy Management system; Energy efficiency	Building in general	Machine Learning (Deep Reinforcement Learning); Artificial Intelligence
Smart home energy management: state of the art	[112]	Energy Management system; Energy efficiency	Residential building	Internet of Things; Artificial Intelligence
Geothermal energy R&D: an overview of the US Department of Energy's geothermal technologies office	[113]	Renewable energy	Not specifically building-related	N/A
Smart Home Energy Management Systems in Internet of Things networks for green cities demands and services	[114]	Energy Management system; Energy efficiency	Residential building	Internet of Things
Systematic mapping study on energy optimization solutions in smart building structure: Opportunities and challenges	[115]	Energy efficiency; Energy consumption	Building in general	Internet of Things; Artificial Intelligence
Coordination of smart home energy management systems in neighborhood areas: A systematic review	[116]	Energy Management system; Energy efficiency	Residential building	Internet of Things; Information system
A review on intelligent process for smart home applications based on IoT: coherent taxonomy, motivation, open challenges, and recommendations	[117]	Energy efficiency (implied)	Residential building	Internet of Things; Artificial Intelligence

Table A1. *Cont.*

Article Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Home energy management system concepts, configurations, and technologies for the smart grid	[118]	Energy Management system; Smart grid integration	Residential building	Internet of Things
Analysing Smart-Home Energy Management under the Aspects of Organic Computing	[119]	Energy Management system; Energy efficiency	Residential building	Artificial Intelligence
An overview of the building energy management system considering the demand response programs, smart strategies and smart grid	[120]	Energy Management system; Energy efficiency; Smart grid integration	Building in general	N/A
Review on design strategies of energy saving office building with evaporative cooling in tropical region	[121]	Energy efficiency	Commercial building (Office buildings)	N/A
Atria, Roof-space Solar Collectors and Windows for Low-energy New and Renovated Office Buildings: a Review	[122]	Energy efficiency; Renewable energy	Commercial building (Office buildings)	N/A
Of impacts, agents, and functions: An interdisciplinary meta-review of smart home energy management systems research	[123]	Energy Management system; Energy efficiency	Residential building	N/A
Smart Home Energy Management-the Future of Energy Conservation: A Review	[124]	Energy Management system; Energy efficiency	Residential building	Internet of Things

Appendix B

Appendix B.1. Search Strategy

The search strategy was tailored for each of the selected databases (Scopus, Web of Science, IEEE Xplore, and ACM Digital Library) using the following principles:

- Keyword Selection: keywords reflected the review's focus areas, such as "smart buildings", "energy optimization", "Big Data", "Artificial Intelligence", and "adoption barriers."
- Boolean Operators: logical operators (e.g., AND, OR) were used to create structured and efficient search strings.
- Filters: language- (English) and document-type (journal articles and conference papers) filters were applied to ensure relevance and manageability.
- Database Syntax Adaptation: search strings were adapted to meet the requirements and functionalities of each database.

Domain experts reviewed the search strategy for coverage and scope. Pilot searches were conducted to assess the string's effectiveness and ensure relevant results. Adjustments were made based on the test results to improve precision and recall.

The following primary search string was used:

("smart" OR "intelligent" OR "connected" OR "automated" OR "energy" OR "load" OR "electricity" OR "district heating") AND ("building" OR "home" OR "office") AND ("Big Data" OR "data analytics" OR "data mining" OR "predictive analytics" OR "Artificial Intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "natural language processing" OR "Internet of Things" OR "IoT" OR "connected devices" OR "sensor networks" OR "digital twin" OR "virtual models" OR "cyber-physical systems" OR "blockchain" OR "cloud computing" OR "edge computing") AND ("adoption" OR "implementation" OR "utilization" OR "barrier" OR "challenge" OR "obstacle" OR "incentive" OR "motivation" OR "potential" OR "opportunit*" OR "business" OR "value" OR "innovation").

Each database's specific syntax and search functionalities were considered, and search filters were applied to include only publications in English and relevant document types (articles and conference papers).

Appendix B.2. Study Selection

The study selection process followed a structured, multi-step approach to ensure transparency, rigor, and alignment with the scoping following review's objectives:

(1) Identification

The automated search conducted using AutoResearch (see Search Strategy) yielded a total of 410 records from four databases: Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. References were exported into reference management software (EndNote), where duplicates were identified and removed, resulting in 323 unique records.

(2) Screening

Titles and abstracts of the remaining records were screened independently by two reviewers using the predefined inclusion and exclusion criteria, as shown in Table A2. During this phase, 129 records were excluded, leaving 194 studies for full-text assessment.

(3) Eligibility Assessment

The full texts of 129 studies were retrieved and assessed for eligibility. Twenty-one records were excluded due to missing full texts or a lack of relevance to the research scope.

In total, 61 additional records were excluded after full-text review because they did not meet the inclusion criteria (e.g., they focused on unrelated topics or included insufficient discussion of data-driven technologies). Among the included articles, 33 were identified as review articles, which are distinct in focus and type compared to other research papers. These review articles were analyzed separately due to their different objectives and methodologies, providing synthesized insights into overarching themes and research gaps rather than case-specific findings. In contrast, primary research papers were examined for specific results, methodologies, and contextual details.

(4) Final Inclusion:

A total of 112 studies were included in the final synthesis. These studies were categorized thematically based on energy optimization strategies, building types, and data-driven technologies.

(5) Reviewer Consensus:

The process was conducted collaboratively by two independent reviewers. Discrepancies between reviewers during the title, abstract, and full-text screening stages were resolved through discussion. If agreement could not be reached, a third reviewer was consulted to make the final decision.

Table A2. Inclusion criteria and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
- Studies focusing on data-driven technologies in smart buildings. - Research discussing energy optimization strategies or adoption factors. - Peer-reviewed journal articles and conference papers published in English.	- Studies unrelated to smart buildings or data-driven technologies. - Non-peer-reviewed literature (e.g., editorials, opinion pieces, abstracts without full texts). - Duplicates or inaccessible records.

The selection process was documented comprehensively, and a PRISMA flow diagram (Figure 2) was used to visually illustrate the number of records at each stage of the selection process, including the reasons for exclusion.

Appendix B.3. Data Charting, Management, and Items

Data extraction and management were conducted meticulously to ensure a comprehensive and accurate synthesis of the literature. All the reviewed articles, including their abstracts and full texts, were downloaded and imported into the reference management software EndNote. EndNote facilitated the organization, annotation, and retrieval of articles throughout the review process, enabling the efficient handling of a large volume of studies.

A standardized data extraction form was developed to systematically collect the relevant information from each included study (as shown in Table A3). The data extraction focused on the following key elements:

- Study focus: the main topics and objectives of the study were identified, such as specific data-driven technologies implemented in smart buildings, energy optimization strategies, or aspects of business models and adoption factors.
- Methodology: the research design and methods used were documented during the study, including data collection techniques (e.g., experiments, simulations, case studies, surveys), analytical approaches, and any models or frameworks applied.
- Key findings: the principal results, conclusions, and recommendations were extracted relating to data-driven technologies, energy optimization, business models, and influential factors affecting their adoption in smart buildings.

Table A3. Overview of the data charting process and management.

Stage	Details
Development of the Data Charting Form	- A standardized data charting form was created to capture the following key elements: • Study Focus: objectives and scope (e.g., specific data-driven technologies, energy optimization strategies, or adoption factors). • Methodology: research design and methods (e.g., case studies, experiments, simulations, surveys) and analytical approaches. • Key Findings: principal results, conclusions, and recommendations related to energy optimization, business models, or influential adoption factors. • Contextual Details: study context (e.g., region, building type, or technology type) and publication year.
	- The form was piloted on a subset of included studies, and adjustments were made to ensure clarity and comprehensiveness.

Table A3. *Cont.*

Stage	Details
Reviewer Preparation	- Two reviewers were prepared to use the data charting form consistently across studies.
	- This preparation focused on achieving alignment in data interpretation and minimizing discrepancies.
Charting Process	- Each study was charted independently by two reviewers using the standardized form.
	- Extracted data were compared between reviewers to identify and resolve discrepancies through discussion.
	- If disagreements persisted, a third reviewer was consulted to make the final decision.
Iterative Refinement	- The data charting form and process were iteratively refined based on feedback during the initial stages to address ambiguities or gaps in data extraction.
	- Additional categories were added as needed to capture emerging themes or information relevant to the review objectives.
Data Management	- All charted data were organized and stored in a central database using reference management software (e.g., EndNote) and spreadsheet software for analysis.
	- Meta-data, including notes on methodological rigor or study limitations, were recorded to provide context during synthesis.
Quality Assurance	- A final round of the review was conducted to ensure the completeness and accuracy of the extracted data across all included studies.

This scoping review identified and extracted key data items from the included studies to address research objectives and provide a comprehensive overview of the field. The data items shown in Table A4 were systematically charted.

Table A4. Overview of data items extracted from included studies.

Category	Sub-Category	Details
Study Characteristics	Publication Details	Author(s), year of publication, and journal or conference title.
	Type of Study	Classification of studies as review articles or primary research papers.
	Geographical Context	The region or country where the study was conducted or focused.
Focus of the Study	Targeted Building Types	Categorization of buildings (e.g., residential, commercial, industrial).
	Data-Driven Technologies	Types of technologies: the types of technologies discussed (e.g., big data analytics, Artificial Intelligence, Internet of Things, Digital Twins).
		Integration approaches: integration approaches and specific use cases in smart building systems.

Table A4. *Cont.*

Category	Sub-Category	Details
Focus of the Study	Adoption Factors	Influencing factors: social, technical, and economic factors influencing the adoption of data-driven technologies.
		Barriers: the identification of barriers (e.g., high costs, security concerns, technical complexities).
Key Findings	Principal Results	Principal results and conclusions, including the observed benefits and limitations of data-driven technologies in energy optimization.
	Research Gaps	Highlighted research gaps and future directions.
Methodological Details	Research Design	Research design and methods (e.g., case studies, experiments, or surveys).
	Analytical Frameworks	Analytical frameworks and the models employed.

Appendix C

Table A5. Overview of reviewed studies for data-driven technologies in buildings and energy systems.

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Effective power utilization and conservation in smart homes using IoT	[1]	Energy consumption; Energy cost or saving; Energy efficiency	Residential building	Internet of Things
Anomaly Detection of Energy Consumption in Cloud Computing and Buildings Using Artificial Intelligence as a Tool of Sustainability: A Systematic Review of Current Trends, Applications, and Challenges	[2]	Energy consumption; Fault detection and diagnosis; Energy efficiency	Building in general	Artificial Intelligence; Cloud Computing; Machine Learning
Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings	[3]	Building energy modeling; Energy consumption; Energy efficiency	Commercial building	Machine Learning
Energy-efficiency-oriented occupancy space optimization in buildings: A data-driven approach based on multi-sensor fusion considering behavior–environment integration	[4]	Energy efficiency	Building in general	Sensor network; Big data
An End-to-End Implementation of a Service-Oriented Architecture for Data-Driven Smart Buildings	[5]	Energy Management system (implied)	Building in general	Information system; Big data; Cloud Computing

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Facilitating Energy-Efficient Operation of Smart Building using Data-driven Approaches	[6]	Energy efficiency; Energy Management system	Building in general	Big data; Machine Learning
Collaborative data analytics for smart buildings: opportunities and models	[7]	Energy Management system (implied)	Building in general	Big data; Cloud Computing; Information system
Analysis of the opportunities and costs of energy saving in lighting system of library buildings with the aid of building information modelling and Internet of things	[8]	Energy cost or saving; Energy efficiency	Building in general; Commercial building	Digital twin and simulation; Internet of Things
Application of Digital Twin Technology in Intelligent Building Energy Efficiency Management System	[9]	Energy efficiency; Energy Management system	Building in general	Digital twin and simulation
The Contribution of Data-Driven Technologies in Achieving the Sustainable Development Goals	[10]	Energy efficiency (implied)	Building in general (implied)	Big data
Simulation and big data challenges in tuning building energy models	[14]	Building energy modeling	Building in general	Big data; Digital twin and simulation
IoT—An intelligent design and implementation of agent based versatile sensor data acquisition and control system for industries and buildings	[15]	Energy Management system (implied)	Industrial building; Building in general	Internet of Things; Sensor network
Design and Implementation of a Cloud-IoT-Based Home Energy Management System	[16]	Energy Management system	Residential building	Internet of Things; Cloud Computing
A comparative analysis of patterns of electricity use and flexibility potential of domestic and non-domestic building archetypes through data mining techniques	[17]	Energy consumption; Energy efficiency	Residential building; Commercial building	Big data; Machine Learning
IoT-Based Home Energy Management System to Minimize Energy Consumption Cost in Peak Demand Hours	[18]	Energy consumption; Energy cost or saving; Energy Management system	Residential building	Internet of Things
Design and Implementation of an Internet-of-Things-Enabled Smart Meter and Smart Plug for Home-Energy-Management System	[19]	Energy Management system; Energy consumption	Residential building	Internet of Things; Sensor network
Design and Implementation of an IoT-Based Home Energy Monitoring System	[20]	Energy consumption; Energy Management system	Residential building	Internet of Things

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Design and Prototype Implementation of a Renewable Energy-Powered Home with Home Automation System Using Internet of Things (IoT)	[21]	Renewable energy; Energy Management system	Residential building	Internet of Things
Implementation of Realtime Database for IoT Home Automation and Energy Monitoring Apps based on Android	[22]	Energy consumption; Energy Management system	Residential building	Internet of Things; Cloud Computing; Information system
Communication challenges and blockchain in building energy efficiency retrofits: Croatia case	[23]	Energy efficiency	Building in general	Blockchain
Data-driven building energy modelling—An analysis of the potential for generalisation through interpretable machine learning	[24]	Building energy modeling	Building in general	Machine Learning; Big data
Creating a Dataset Used for Applying Machine Learning Techniques to Accurately Forecast the Energy Cost in Home-Based Small Businesses	[25]	Energy cost or saving; Energy consumption	Residential building	Machine Learning; Big data
Deploying data driven applications in smart buildings: Overcoming the initial onboarding barrier using machine learning	[26]	Energy Management system (implied)	Building in general	Machine Learning; Big data
Issues concerning IoT adoption for energy and comfort management in intelligent buildings in India	[27]	Energy Management system; Energy efficiency	Building in general	Internet of Things
Big Data Architecture for Building Energy Management Systems	[28]	Energy Management system	Building in general	Big data; Information system
Artificial intelligence implementation framework development for building energy saving	[29]	Energy cost or saving; Energy efficiency	Building in general	Artificial Intelligence
Design and implementation of an office standby-power management system through physical and virtual management by user-device habitual pattern analysis in energy-Internet of Things environments	[30]	Energy Management system; Energy consumption; Energy efficiency	Commercial building	Internet of Things; Sensor network; Machine Learning
Self-updating machine learning system for building load forecasting-method, implementation and case-study on COVID-19 impact	[31]	Energy consumption; Energy Management system (implied)	Building in general	Machine Learning

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Identifying buildings with rising electricity consumption and those with high energy-saving potential for government's management by data mining approaches	[32]	Energy consumption; Energy cost or saving; Energy efficiency	Building in general	Big data; Machine Learning
Barriers to use of artificial intelligence on energy conservation in government buildings: Awareness as a moderating function of technology acceptance	[33]	Energy cost or saving; Energy efficiency	Building in general	Artificial Intelligence
Design and implementation of an AI-based & IoT-enabled Home Energy Management System: A case study in Benguerir—Morocco	[34]	Energy Management system; Energy consumption; Energy efficiency	Residential building	Artificial Intelligence; Internet of Things
Application of Computer Artificial Intelligence Control Technology in the Comprehensive Utilization of Green Building Energy	[35]	Energy efficiency; Renewable energy; Energy Management system	Building in general	Artificial Intelligence
Integration of IoT in building energy infrastructure: A critical review on challenges and solutions	[36]	Building energy modeling; Energy consumption; Energy efficiency; Energy Management system	Building in general	Internet of Things
Implementation of M2M-IoT Smart Building System Using Blynk App	[37]	Energy Management system (implied)	Building in general	Internet of Things; Information system
Energy Community Management Based on Artificial Intelligence for the Implementation of Renewable Energy Systems in Smart Homes	[38]	Renewable energy; Energy Management system	Residential building	Artificial Intelligence
Design and Implementation RESTful API for IoT Based Smart Home Systems	[39]	Energy Management system (implied)	Residential building	Internet of Things; Information system
Design and Implementation of an IoT-based Smart Home with the Ability to Communicate with the Smart Grid	[40]	Smart grid integration; Energy Management system	Residential building	Internet of Things
Design and Implementation of a Smart Home Energy Management System Using IoT and Machine Learning	[41]	Energy Management system; Energy efficiency	Residential building	Internet of Things; Machine Learning
Enhancing Smart Home Design with AI Models: A Case Study of Living Spaces Implementation Review	[42]	Energy efficiency	Residential building	Artificial Intelligence

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Energy Management of Smart Homes with Electric Vehicles Using Deep Reinforcement Learning	[43]	Energy Management system; Energy consumption; Energy cost or saving	Residential building	Machine Learning
Real time implementation of Demand Side Management scheme for IoT enabled PV integrated smart residential building	[44]	Energy Management system; Renewable energy; Smart grid integration	Residential building	Internet of Things
The challenge for energy saving in smart homes: Exploring the interest for IoT devices acquisition in Romania	[45]	Energy cost or saving; Energy efficiency	Residential building	Internet of Things
A Multi-Protocol IoT Gateway and WiFi/BLE Sensor Nodes for Smart Home and Building Automation: Design and Implementation	[46]	Energy Management system (implied)	Residential building; Building in general	Internet of Things; Sensor network
The Implementation of Smart Home Power Management: Integration of Internet of Things and Cloud Computing	[47]	Energy Management system; Energy consumption	Residential building	Internet of Things; Cloud Computing
Design, development and implementation of an iot-based intelligent ambient controller for lvdc enabled green buildings	[48]	Energy efficiency; Energy Management system	Building in general	Internet of Things
Design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes	[49]	Energy consumption; Energy Management system; Energy efficiency	Residential building	Artificial Intelligence; Cloud Computing; Edge computing; Internet of Things
Design and implementation of an iot-based energy monitoring system for managing smart homes	[50]	Energy consumption; Energy Management system	Residential building	Internet of Things; Edge computing
Design and implementation of an IoT-oriented energy management system based on non-intrusive and self-organizing neuro-fuzzy classification as an electrical energy audit in smart homes	[51]	Energy Management system; Energy consumption; Energy efficiency	Residential building	Internet of Things; Artificial Intelligence; Machine Learning
Design and Implementation of a Power Consumption Management System for Smart Home Over Fog cloud Computing	[52]	Energy consumption; Energy Management system	Residential building	Cloud Computing; Edge computing; Internet of Things
Implementation of Smart Optimal and Automatic Control of Electrical Home Appliances (IoT)	[53]	Energy consumption; Energy Management system; Smart grid integration	Residential building	Internet of Things

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
An IoT Ecosystem for the Implementation of Scalable Wireless Home Automation Systems at Smart City Level	[54]	Energy Management system (implied); Energy efficiency (implied)	Residential building; Building in general	Internet of Things; Sensor network; Information system
Design and implementation of a cloud-based IoT platform for data acquisition and device supply management in smart buildings	[55]	Energy consumption; Energy Management system	Building in general	Internet of Things; Cloud Computing; Information system
Big Data in Building Energy Efficiency: Understanding of Big Data and Main Challenges	[57]	Energy efficiency	Building in general	Big data
Unlocking the potential of "big data" and advanced analytics in ATE	[58]	Not directly related	Not specified	Big data; Machine Learning
AI-driven smart homes: Challenges and opportunities	[59]	Energy consumption (implied); Energy efficiency (implied)	Residential building	Artificial Intelligence; Internet of Things
Practical issues in implementing machine-learning models for building energy efficiency: Moving beyond obstacles	[60]	Energy efficiency	Building in general	Machine Learning
Smart Office System with Face Detection at the Edge	[61]	Not directly related	Commercial building	Artificial Intelligence; Edge computing
Trusted DBL: A Blockchain-based Digital Twin for Sustainable and Interoperable Building Performance Evaluation	[62]	Energy efficiency; Building energy modeling	Building in general	Blockchain; Digital twin and simulation
The design and implementation of energy-aware data gathering techniques (EDGE) for in-building wireless sensor networks	[64]	Energy consumption; Energy efficiency	Building in general	Sensor network; Edge computing
Blockchain enhanced price incentive demand response for building user energy network in sustainable society	[65]	Energy consumption; Energy cost or saving; Energy Management system; Smart grid integration	Building in general	Blockchain; Information system
Unlocking potentials of building energy systems' operational efficiency: Application of digital twin design for HVAC systems	[66]	Energy efficiency; Fault detection and diagnosis; Energy Management system	Building in general	Digital twin and simulation
A novel 3D-geographic information system and deep learning integrated approach for high-accuracy building rooftop solar energy potential characterization of high-density cities	[67]	Renewable energy; Energy efficiency	Building in general; Residential building; Commercial building	Artificial Intelligence; Machine Learning; Digital twin and simulation

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Automated Data Mining Methods for Identifying Energy Efficiency Opportunities Using Whole-Building Electricity Data	[69]	Energy efficiency; Energy consumption	Building in general	Big data; Machine Learning
Design and Implementation of a Leader–Follower Smart Office Lighting Control System Based on IoT Technology	[70]	Energy consumption; Energy efficiency; Energy Management system	Commercial building	Internet of Things; Sensor network; Edge computing
Design and Implementation of Building Energy Monitoring and Management System based on Wireless Sensor Networks	[71]	Energy consumption; Energy Management system	Building in general	Sensor network; Internet of Things
Implementation of an adaptive intelligent home energy management system using a wireless ad-hoc and sensor network in pervasive environments	[72]	Energy consumption; Energy Management system; Energy efficiency	Residential building	Sensor network; Internet of Things; Artificial Intelligence
Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future	[68]	Fault detection and diagnosis; Energy efficiency	Building in general	Artificial Intelligence; Machine Learning
Consumer Readiness for Adoption of IOT-Smart Homes (CRA-IOT-SH) in South Africa Gauteng	[78]	Energy efficiency (implied)	Residential building	Internet of Things
Home, sweet home: How well-being shapes the adoption of artificial intelligence-powered apartments in smart cities	[79]	Energy efficiency (implied)	Residential building	Artificial Intelligence
Analysis of Affecting Technology Adoption Factors for Smart Home Services in Jabodetabek, Indonesia	[80]	Energy efficiency (implied)	Residential building	Internet of Things
Patients' Behavioral Intentions toward Using WSN Based Smart Home Healthcare Systems: An Empirical Investigation	[81]	Not directly related	Residential building	Sensor network; Internet of Things
An Empirical Assessment of Wireless Communication Technology Issues in the Smart Home	[82]	Energy efficiency (implied)	Residential building	Sensor network; Internet of Things
Patients' Adoption of WSN-Based Smart Home Healthcare Systems: An Integrated Model of Facilitators and Barriers	[83]	Not directly related	Residential building	Sensor network; Internet of Things
A study on the adoption of IoT smart home service: using Value-based Adoption Model	[84]	Energy efficiency (implied)	Residential building	Internet of Things

Table A5. *Cont.*

Title	Ref.	Energy Aspect Elements	Building Aspect Elements	Data and AI Aspect Elements
Comprehensive Approaches to User Acceptance of Internet of Things in a Smart Home Environment	[85]	Energy efficiency (implied)	Residential building	Internet of Things
IoTFuzz: Automated Discovery of Violations in Smart Homes With Real Environment	[86]	Not directly related	Residential building	Internet of Things
Understanding the adoption and usage of data analytics and simulation among building energy management professionals: A nationwide survey	[87]	Energy Management system; Energy efficiency	Building in general	Big data; Digital twin and simulation; Information system
Platform-Based Business Models: Insights from an Emerging AI-Enabled Smart Building Ecosystem	[93]	Energy efficiency (implied)	Building in general	Artificial Intelligence; Internet of Things; Information system
Smart-building management system: An Internet-of-Things (IoT) application business model in Vietnam	[94]	Energy Management system; Energy efficiency	Building in general	Internet of Things; Information system

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