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Review

Leveraging Digital Twins for Enhancing Building Energy Efficiency: A Literature Review of Applications, Technologies, and Challenges

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Abstract: Amid global efforts to mitigate greenhouse gas emissions, improving the energy efficiency of buildings has emerged as a strategic priority. Buildings account for approximately 40% of global energy consumption and a significant share of CO_2 emissions, making them key targets for sustainable practices. This study employs a systematic literature review combined with a bibliometric analysis to explore the transformative potential of digital twins in building energy efficiency. The review synthesizes key contributions of digital twins in real-time monitoring, predictive modeling, renewable energy integration, and proactive maintenance while addressing critical challenges such as interoperability, scalability, and privacy. The originality of this work lies in its integrated approach, which identifies emerging trends and research gaps, providing actionable insights to guide the future adoption of digital twins in the building sector. These findings highlight the pivotal role of digital twins in fostering sustainable and intelligent energy practices.

Keywords: digital twin; energy efficiency; energy; energy management; energy system optimization; building; smart buildings; building information modeling; BIM

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1. Introduction

In the global effort to mitigate greenhouse gas emissions, buildings have emerged as a strategic priority, accounting for approximately 40% of global energy consumption and contributing significantly to greenhouse gas emissions [1,2]. According to the UNEP Global Status Report for Buildings and Construction, the building sector represents a critical opportunity for achieving sustainability goals [3]. Optimizing energy management in buildings is essential for addressing climate challenges, particularly in alignment with the European Union's Green Deal, which targets a 55% reduction in greenhouse gas emissions by 2030 [4,5]. These efforts align closely with the Paris Agreement, which calls for transformative changes in energy management practices worldwide [6].

Despite significant advancements in passive energy management approaches, these methods are increasingly constrained by the complexity of modern infrastructure [7]. Often static in nature, they struggle to meet the dynamic, real-time demands of contemporary buildings [8]. To address these challenges, intelligent solutions capable of anticipating, optimizing, and actively controlling energy consumption have become essential [9]. Heating, ventilation, and air conditioning (HVAC) systems, which represent a large share of a building's energy consumption, exemplify this need [10,11]. Similarly, optimizing the management of lighting systems and other energy-intensive infrastructures remains a significant challenge, especially in large and complex facilities [12–14]. Emerging technologies, particularly digital twins, offer a transformative approach to overcoming these challenges [15]. A digital twin creates a precise virtual model of a physical structure [16], integrating static data from building information modeling (BIM), which provides a structured and detailed foundation for a building's geometry, materials, and systems [17,18], with dynamic data collected in real time via Internet of Things (IoT) sensors that monitor parameters such as temperature, energy consumption, and occupancy patterns [19]. By leveraging artificial intelligence algorithms, digital twins enable the simulation, analysis, and prediction of a building's energy performance, providing in-depth insights into energy flows and potential sources of inefficiency [20,21]. These capabilities pave the way for data-driven decision-making and energy optimization strategies that rely on real-time insights [22].

Accordingly, these solutions, particularly digital twins, are garnering increasing interest within the scientific community [23]. The evolution of scientific publications, as depicted in Figure 1, highlights an exponential growth in research on this technology since 2018. These studies span a broad range of disciplines, including industry, healthcare, and smart infrastructure [23]. However, in the building sector, while interest in digital twins is rising, their adoption remains limited compared to other industries. Current studies predominantly focus on applications such as simulation, predictive maintenance, and operational performance optimization [24]. The integration of digital twins into building energy optimization, in particular, remains an emerging field. Although some research explores their potential applications, deployment is still relatively moderate, suggesting significant opportunities for further exploration.

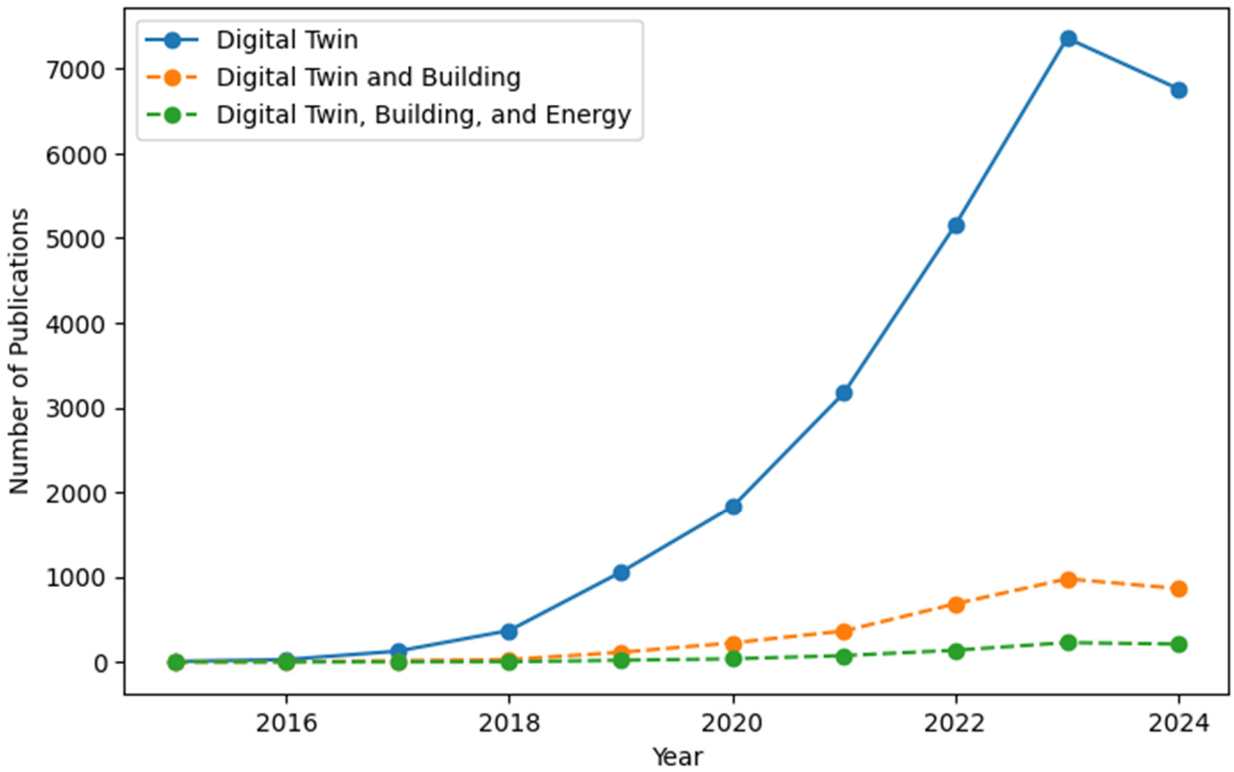

Figure 1. Trends in publications on digital twin, building, and energy over the years.

This study is motivated by the lack of a consolidated and systematic analysis of the roles, technologies, and challenges associated with digital twins in the field of building energy efficiency. While the existing literature often focuses on specific aspects such as individual technological tools or isolated applications, there is a need for a comprehensive perspective to better understand their potential and limitations in this critical area. To address this gap, this study adopts a dual-method approach, combining bibliometric analysis and a systematic literature review to provide a robust and structured understanding of the topic. The primary objective of this study is to explore the roles and applications of digital twins in optimizing building energy efficiency, identify the key technologies used in their implementation (including BIM, IoT, and artificial intelligence), analyze major challenges (such as interoperability, scalability, and data privacy), and propose future directions to promote broader and more effective adoption of digital twins in energy management. To guide this effort, the following research questions (RQs) are formulated:

- RQ1: What are the primary roles and applications of digital twins in improving building energy efficiency?
- RQ2: What emerging technologies are integrated into digital twins for buildings?
- RQ3: What are the main challenges in implementing digital twins, and how can they be overcome?

This study makes a significant contribution by consolidating and analyzing current knowledge on digital twins in the context of building energy efficiency. The study stands out for its systematic and interdisciplinary approach, combining a systematic literature review and an analysis of technological challenges. The results highlight the roles of digital twins, their associated technologies, and barriers to their adoption.

The organization of this article is as follows: Section 2 describes the research methodology; Section 3 details the results from the bibliometric analysis and the systematic content review; Section 4 provides a synthesis and discussion of the findings; and Section 5 concludes by summarizing the key outcomes and proposing directions for future research.

2. Materials and Methods

A rigorous and thorough systematic review was carried out using a methodology that integrated bibliometric and content analyses. The process adhered to the PRISMA (preferred reporting items for systematic reviews and meta-analyses) guidelines, a well-established framework designed to ensure transparency and methodological rigor in systematic reviews [25,26]. This framework provides a structured approach to study selection, quality evaluation, and result reporting, guaranteeing the reproducibility of the analysis [26].

Two major databases, Scopus and Web of Science (WOS), were chosen for this study due to their extensive multidisciplinary coverage [27,28] and their relevance in the fields of energy efficiency and digital technologies [29]. Scopus is recognized for its diversity of academic journals [30] and its effectiveness in bibliometric analysis, offering robust coverage in applied sciences and engineering [31], and Web of Science (WOS) is valued for its academic rigor and its ability to identify high-quality publications in interdisciplinary research [28,32].

An exhaustive search was conducted using specific keywords related to the adoption of digital twins in optimizing energy efficiency in buildings. The search query used was: (“Digital Twin” AND (“Energy Efficiency” OR “Energy” OR “Energy Management” OR “Energy System Optimization”) AND (“Buildings” OR “Smart Buildings” OR “Building Information Modeling” OR “BIM”)). Before 2018, digital twins were primarily adopted in sectors such as aerospace and manufacturing, while their application in the building sector remained scarce and largely exploratory [33,34]. This limitation was due to the lack of mature technologies, such as affordable IoT sensors, advanced artificial intelligence (AI) algorithms, and standardized building information modeling (BIM) tools, as well as challenges related to data fragmentation and high implementation costs [35,36].

The post-2018 period marks a significant turning point with the maturation of these enabling technologies, which facilitated real-time data integration and predictive analysis tailored to the challenges of the building sector [37,38]. The emergence of smart buildings, characterized by connected systems designed to optimize energy efficiency and infrastructure management, further accelerated the adoption of digital twins [39]. Moreover, international commitments such as the Paris Agreement (2015) [6] and the United Nations Sustainable Development Goals (SDGs) intensified efforts to promote innovative solutions like digital twins [5]. Finally, this period coincides with a notable increase in scientific publications (Figure 1), reflecting the growing interest in this technology within the building sector. These factors collectively justify the selection of 2018 as the starting point for this study. Table 1 summarizes the criteria used for article selection.

Table 1. Criteria for paper selection.

Criteria	Details
Timeframe	2018–2024
Databases	Scopus; Web of Science
Keywords	digital twin; energy efficiency; energy management; energy system optimization; buildings; smart buildings; building; information modeling BIM
Document Type	Journal; conference paper

A total of 1045 articles were initially identified for this study. The selection process adhered to the PRISMA methodology, ensuring a rigorous and transparent approach. During the identification phase, duplicates and irrelevant articles were removed, reducing the total to 786 articles. A detailed review of the titles and abstracts of the remaining articles was then conducted, excluding studies that did not meet the inclusion criteria—specifically, those unrelated to digital twins or outside the building context, as outlined in Table 2. At the end of this phase, 155 articles were selected for bibliometric analysis. This stage focused on the metadata of the articles, regardless of full-text accessibility. During the inclusion phase, which required a full-text review of the articles, 51 articles were excluded due to lack of access to their full text. The remaining articles were then thoroughly analyzed to ensure their relevance and alignment with the study objectives. This rigorous process led to the exclusion of certain articles that did not meet the defined criteria. First, four literature reviews, while interesting and relevant, were analyzed separately and therefore excluded from the main analysis. Additionally, 55 articles that mentioned digital twins only in the abstract or keywords, without providing technical details on architecture or implementation within the methodology and discussion sections, were also removed. Following this phase, only the most relevant and detailed studies were retained, forming a robust foundation for the content analysis.

Figure 2 provides a graphical representation of the article selection procedure. It illustrates the various stages of the methodology employed, from the identification of articles in the databases to the final selection, including the filtering of results and the evaluation of inclusion and exclusion criteria.

Table 2. Inclusion and exclusion criteria.

Exclusion Criteria	Inclusion Criteria
Articles not in English	Articles in English
Non-journal articles, non-conference papers	Journal, conference paper
Studies on energy management without digital twins	Research focused on energy optimization through digital twins
Research on digital twins in other sectors (e.g., automotive, nuclear, etc.)	Studies on energy optimization in buildings using digital twins
Studies focused on non-energy aspects of buildings (e.g., design, maintenance, and smart cities)	Research addressing energy-related aspects of buildings with digital twins
Articles without full-text access	Articles with full-text access

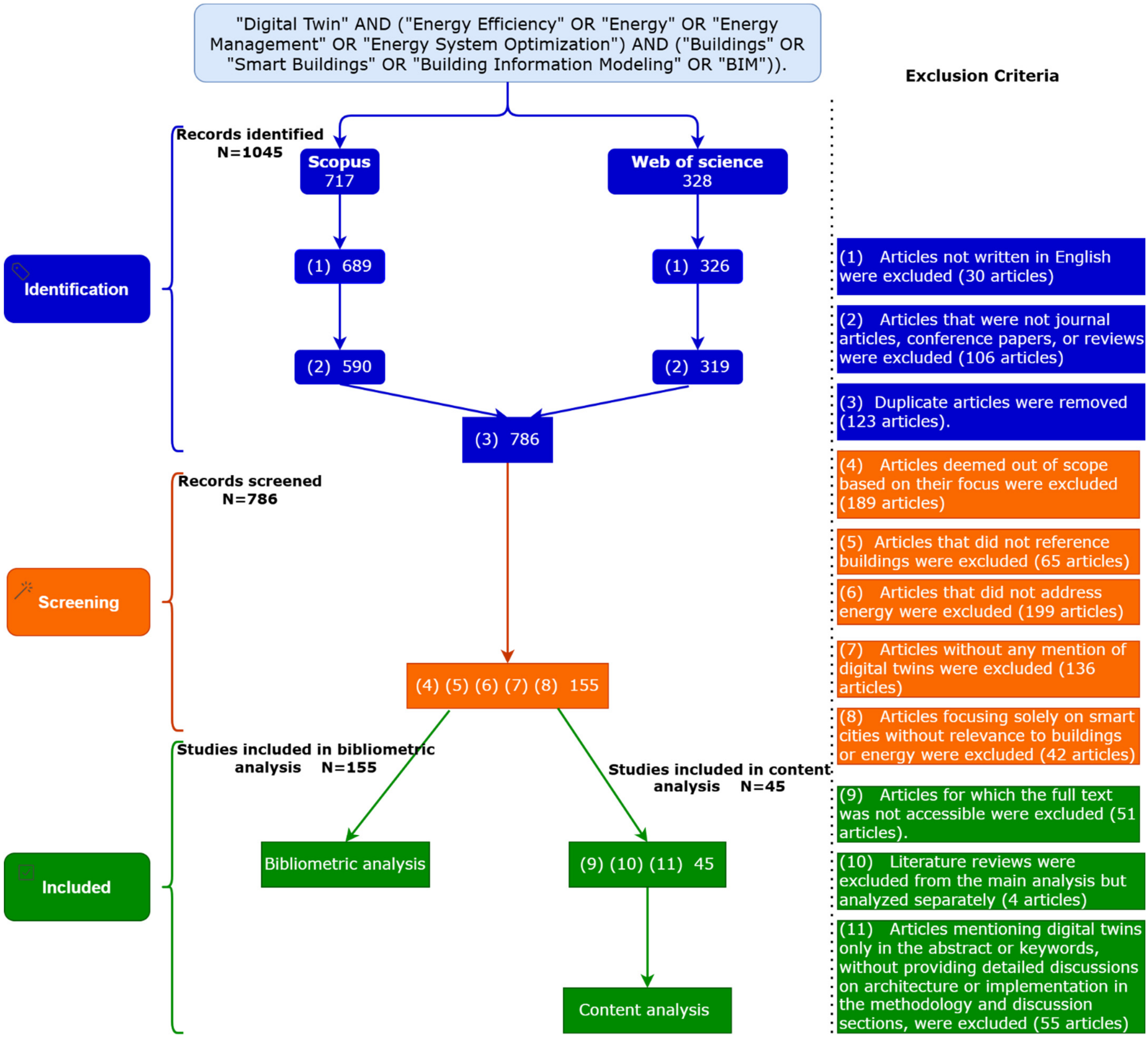

Figure 2. PRISMA methodological process of the literature review.

3. Results

3.1. Bibliometric Analysis

Bibliometric analysis provides a systematic approach to explore and understand research trends related to the integration of digital twins in optimizing building energy efficiency. By examining publication trends, author contributions, collaborations, and research themes, this analysis highlights the major directions shaping the field. This section offers a comprehensive overview, detailing the temporal evolution of publications, their geographical distribution, collaboration networks, as well as key citations and primary sources. It also includes a thematic analysis of keywords to uncover future research directions. These insights help identify emerging trends, key contributors, and technological innovations driving the energy transition in the building sector [40,41]. Python was employed as the primary tool for this analysis due to its advanced capabilities in processing and visualizing bibliometric data [42].

3.1.1. Descriptive Analysis of Publications

Evolution of Publications by Year

Figure 3 illustrates the trend in the number of publications per year, analyzed in a bibliometric study on the application of digital twins for building energy efficiency. A marked growth trend in publications is observed between 2018 and 2023. During the initial years, particularly in 2018 and 2020, the number of publications remained relatively low. However, starting in 2021, a significant increase is evident, peaking in 2023 with a sharp rise, reflecting growing interest in this research area.

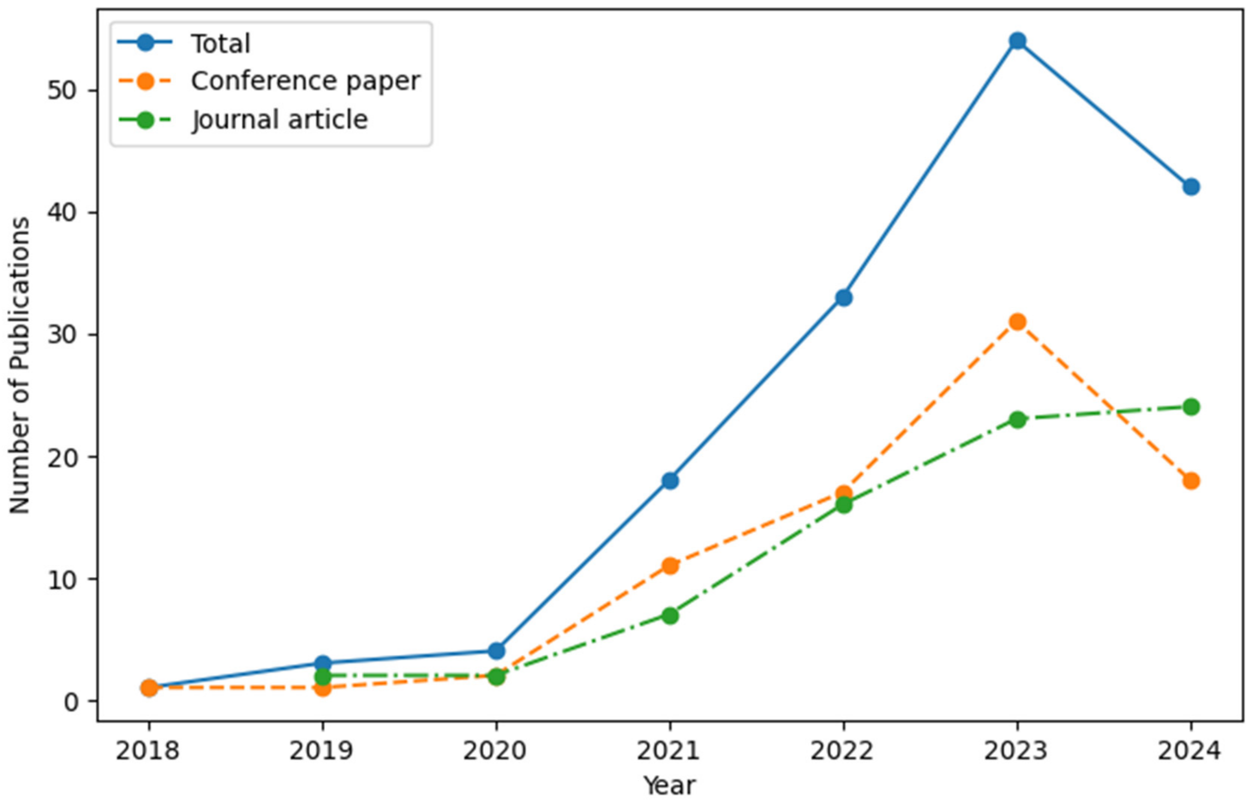

Figure 3. Annual trends in publications.

This trend underscores the increasing importance attributed to emerging technologies such as digital twins, especially in recent years, to address energy efficiency challenges. The rapid growth in publications between 2022 and 2023 indicates an intensification of research efforts in this field, likely driven by heightened global awareness of energy issues and increasingly ambitious sustainability goals.

Geographical Distribution of Publications

Figure 4 highlights the geographical distribution of publications on digital twins applied to building energy efficiency, revealing a significant concentration in a few leading countries. China emerges as the dominant contributor, reflecting substantial investments in digital technologies and the need to optimize energy management in a rapidly urbanizing context. European countries, such as Italy, Germany, and Spain, also play a pivotal role, driven by their strong focus on sustainability and compliance with strict EU regulations.

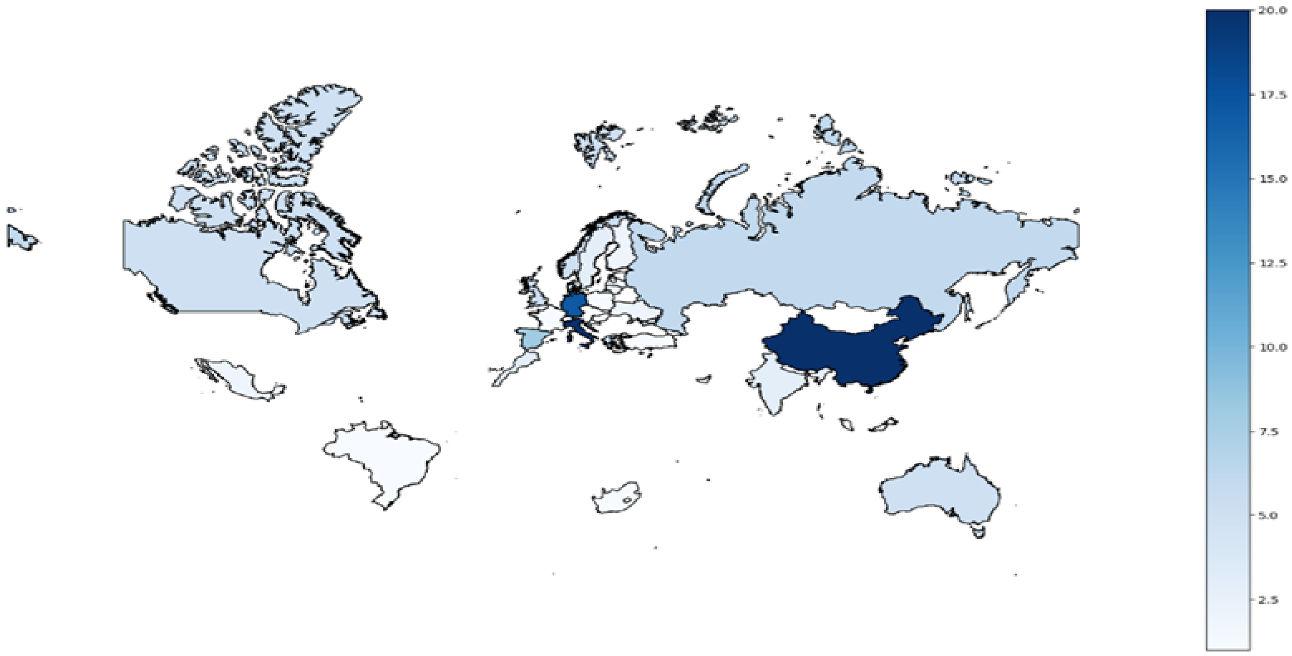

Figure 4. Geographical distribution by country.

North America, particularly Canada, demonstrates moderate research activity, emphasizing innovation-oriented approaches. Meanwhile, Russia shows a growing interest in integrating digital technologies into its building sector. However, the figure also reveals underrepresentation in regions such as Africa and parts of the Middle East, pointing to significant opportunities for future research and development.

This geographical analysis underscores the need for more balanced global research efforts, particularly in underrepresented regions. Promoting international collaboration and knowledge transfer could help bridge these gaps, enabling emerging economies to develop their research capabilities and contribute more significantly to the global energy transition.

3.1.2. Citation and Source Analysis

Citation Analysis

Table 3 provides an analysis of article citations in the field of digital twins applied to building energy efficiency, highlighting several key aspects. First, the most cited articles, such as Agostinelli et al. (2021), published in *Energies* with 164 citations, and Tagliabue et al. (2021) in *Sustainability* with 145 citations, reflect significant contributions, establishing these works as key references in the field.

Table 3. Most cited publications.

Ref	Authors	Title	Publication Title	Citation	Year
[43]	Kaewunruen S, Rungskunroch P, Welsh J	"A digital-twin evaluation of net zero energy building for existing buildings"	*Sustainability*	218	2018
[22]	Agostinelli S, Cumo F, Guidi G, Tomazzoli C	"Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence"	*Energies*	164	2021
[44]	Tagliabue LC, Cecconi FR, Maltese S, Rinaldi S, Ciribini ALC, Flammini A	"Leveraging digital twin for sustainability assessment of an educational building"	*Sustainability*	145	2021
[45]	Lydon GP, Caranovic S, Hischier I, Schlueter A	"Coupled simulation of thermally active building systems to support a digital twin"	*Energy and Buildings*	135	2019
[46]	Porsani GB, de Lersundi KDV, Gutiérrez AS-O, Bandera CF	"Interoperability between Building Information Modelling (BIM) and Building Energy Model (BEM)	*Applied Sciences*	116	2021
[47]	Bortolini R, Rodrigues R, Alavi H, Dalla Vecchia LF, Forcada N	"Digital Twins' Applications for Building Energy Efficiency: A Review"	*Energies*	85	2022
[48]	Zhao L, Zhang H, Wang Q, Wang HN	"Digital-Twin-Based Evaluation of Nearly Zero-Energy Building for Existing Buildings Based on Scan-to-BIM"	*Advances in Civil Engineering*	80	2021
[49]	Clausen A, Arendt K, Johansen A, Sangogboye FC, Kjærgaard, MB, Veje CT, Jørgensen BN	"A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings"	*Energy Informatics*	71	2021
[50]	Tan Y, Chen PL, Shou WC, Sadick AM	"Digital Twin-driven approach to improving energy efficiency of indoor lighting based on computer vision and dynamic BIM"	*Energy and Buildings*	62	2022
[51]	Arowoiya VA, Moehler RC, Fang Y	"Digital twin technology for thermal comfort and energy efficiency in buildings: A state-of-the-art and future directions"	*Energy and Built Environment*	57	2024
[52]	Agouzoul A, Tabaa M, Chegari B, Simeu E, Dandache A, Alami K	"Towards a Digital Twin model for Building Energy Management: Case of Morocco"	(ANT)/(EDI40)	56	2021

The diversity of sources, including journals such as *Energies*, *Sustainability*, *Energy and Buildings*, and *Applied Sciences*, underscores the interdisciplinary nature of the topic, spanning fields such as energy, sustainability, engineering, and building management. Additionally, temporal trends indicate a recent and growing interest in this application of digital twins, with a concentration of influential publications in 2021 and 2022. This peak in activity may be linked to the increased focus on sustainability goals and technological advancements that facilitate the adoption of digital twins in the energy and building sectors.

Source Analysis

Analyzing publication sources is crucial to identifying the platforms that play a key role in disseminating research on digital twins applied to building energy efficiency. Table 4 shows that scientific journals are the primary sources of influential publications. *Energy and*

Buildings stands out with the highest number of articles (15) and the largest total number of citations (537), reflecting its major impact in this field. Other journals, such as *Energies* (eight articles, 373 citations) and *Sustainability* (seven articles, 231 citations), also contribute significantly, demonstrating the interdisciplinary nature of the topic and its relevance across fields like energy and sustainability.

Table 4. Most cited source.

Source	**Number of Articles**	**Total Number of Citations**
Journal		
Energy and Buildings	15	537
Sustainability	8	449
Energies	8	373
Applied Sciences	4	148
Energy Informatics	3	110
Buildings	10	84
Advances in Civil Engineering	1	80
Energy and Built Environment	1	57
Building and Environment	1	49
Journal of Manufacturing and Materials Processing	1	43
Advances in Building Energy Research	1	39
Conference	Number of Articles	Total Number of Citations
"12th International Conference on Ambient Systems, Networks and Technologies (ANT)/4th International Conference on Emerging Data and Industry 4.0 (EDI40)"	1	56
"International Society for Photogrammetry and Remote Sensing"	1	28
"Building Performance Analysis Conference and SimBuild co-organized by ASHRAE and IBPSA-USA"	1	23
"IEEE International Smart Cities Conference (ISC2)"	1	7
"Fifth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA)"	1	6
"International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency (SUMMA)"	1	6

Concurrently, while less prolific, conferences play a notable role in emerging research. For instance, the "12th International Conference on Ambient Systems, Networks, and Technologies (ANT)", in conjunction with the "4th International Conference on Emerging Data and Industry 4.0 (EDI40)", produced a paper that garnered 56 citations, highlighting the importance of conferences for the rapid dissemination of innovations.

These findings reveal a clear preference among researchers for journals as platforms for long-term and in-depth dissemination of their work while emphasizing the role of conferences as venues for sharing ongoing or emerging studies. This contrast between journals and conferences illustrates a publication dynamic where journals provide enduring scientific recognition, whereas conferences enable the immediate communication of advancements in the field.

3.1.3. Thematic Analysis

VOSviewer, a free tool developed for the analysis and visualization of research networks, was used to depict the co-occurrence of keywords from the selected articles [53,54]. By applying clustering algorithms, the tool groups related keywords, enabling the identification of key research themes. In this analysis, keywords are represented as nodes, with the line thickness and distance between nodes indicating the strength of their associations [55,56].

Figure 5, generated using VOSviewer, illustrates the thematic relationships and the evolution of priorities in research on digital twins applied to building energy efficiency. "Digital twin" occupies a central position, reflecting its key role, and is closely linked to fundamental concepts such as "energy efficiency", "building energy consumption", and "performance", which represent initial priorities in energy management. Over time, emerging themes, such as "renewable energy", "energy storage", "electric load dispatching", and "zero energy buildings", have gained prominence, highlighting a shift toward sustainable and decarbonized solutions. At the same time, the integration of advanced technologies such as artificial intelligence, the Internet of Things, BIM modeling, big data, prediction, and real-time control plays a crucial role in automating and connecting building energy systems. This visualization also highlights opportunities for future research, particularly the interconnection of emerging technologies with sustainable solutions to create intelligent and autonomous buildings. Finally, the clusters identified in this figure provide a critical framework for structuring an in-depth content analysis, exploring the practical applications of these concepts, the technologies that support them, and the challenges to overcome in complex energy environments.

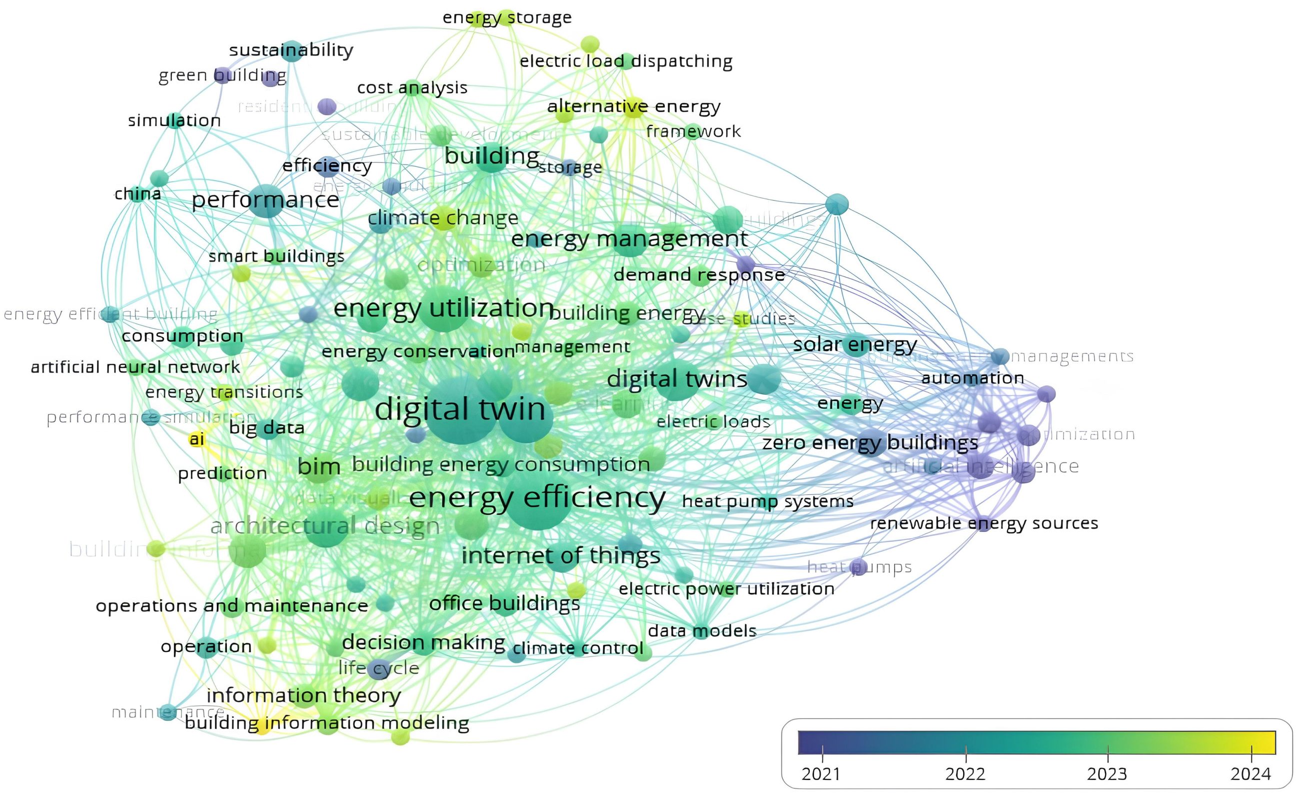

Figure 5. Overlay visualization map of keyword occurrence.

3.2. *Systematic Content Analysis*

3.2.1. Analysis of Literature Reviews on the Integration of Digital Twins for Building Energy Efficiency

This section analyzes existing systematic literature reviews on the use of digital twins to optimize building energy efficiency. By examining methodologies and the number of articles reviewed, this critical assessment highlights key contributions and gaps in the scientific literature. It also provides a foundation for justifying the relevance of our study while identifying future research directions.

For instance, [57] examines how digital twins can enhance building energy efficiency based on an analysis of 21 articles and six enterprise-level digital twin solutions. The analysis is structured around three main themes: real-time system monitoring, energy optimization, and predictive maintenance. This review also highlights technical challenges related to the integration of IoT and BIM while proposing future research pathways. Similarly, [51] explores the applications of digital twins in thermal management and energy efficiency in buildings. This analysis focuses on different phases of the building lifecycle (design, development, operation, and management), with an emphasis on optimizing energy consumption and thermal comfort. The study includes 118 articles, of which 27 specifically address energy optimization using digital twins, while the remainder focus on complementary energy-related aspects. Likewise, [47] offers a comprehensive analysis of digital twin applications for improving building energy efficiency. This review identifies current research trends, existing gaps, and proposes future research directions. The 95 reviewed articles are categorized into four themes: optimized design, occupant well-being, building functionality and maintenance, and energy usage simulation. However, some of the articles reviewed address complementary technologies, such as BIM and IoT, rather than digital twins directly. Finally, refs. [58,59] explore energy simulation technologies and advanced architectures for smart energy systems (SESs). These studies highlight the opportunities provided by emerging technologies while emphasizing limitations such as system integration complexity, the need for high-quality data, and challenges related to end-user acceptance.

The analysis of previous reviews reveals that, although they provide valuable insights into the use of digital twins for energy efficiency, they often focus on specific technologies, limited datasets, or narrow applications. Most reviews emphasize certain themes, such as real-time monitoring or thermal management, without adopting a comprehensive perspective that integrates the entire lifecycle of building energy optimization. Additionally, some reviews include articles that primarily address complementary technologies rather than focusing exclusively on digital twins. In contrast, our study adopts a systematic literature review methodology that combines bibliometric analysis and in-depth content evaluation, covering the period from 2018 to 2024, since the emergence of the first studies on the deployment of digital twins for building energy efficiency (as shown in Figure 1). Unlike previous studies, our analysis focuses exclusively on the role of digital twins in optimizing building energy efficiency while adopting a holistic perspective that integrates essential dimensions, such as the technologies and software used. This comprehensive approach positions our review as a significant contribution to the field, offering both a detailed understanding of current research trends and actionable insights for future investigations. Table 5 below summarizes the characteristics of the analyzed reviews.

Table 5. Synthesis of reviews.

Ref	Year	Journal	Type of Review	Number of Articles Analyzed	Time Interval
[57]	2024	*Energy Informatics*	Systematic literature review	21 articles and six enterprise-level digital twin solutions	2010 => 2022
[51]	2024	*Energy and Built Environment*	Scientometric analysis and critical review	24 + 4 published in 2023	2012 => 2022
[47]	2022	*Energies*	Systematic review	95 (not all focused on digital twins)	2010 => 2022
[58]	2023	*Applied Sciences*	Review	54 (not all focused on digital twins)	Not specified
[59]	2024	*Energy Informatics*	Systematic review	66 articles	2018 => 2024

3.2.2. Analysis of Empirical Studies on the Integration of Digital Twins for Building Energy Efficiency

The increasing digitization of the construction and building management sectors has led to the rise of digital twins, which are emerging as a strategic solution for enhancing energy efficiency. This innovative technology allows the creation of dynamic, real-time virtual representations of buildings and their systems. This analysis explores how these digital replicas facilitate proactive and optimized resource management, contributing to reducing energy consumption and improving occupant comfort.

Real-Time Monitoring and Control

Digital twins serve a key function in real-time monitoring and control of building energy systems by leveraging data collected through IoT sensors to optimize HVAC systems, lighting, and other critical equipment. For HVAC system optimization, ref. [60] focuses on real-time monitoring and control of energy consumption and HVAC performance in non-residential buildings using IoT sensors, enabling proactive management of energy retrofits. Similarly, ref. [61] applies a real-time monitoring approach in a hospital in China, optimizing HVAC systems, lighting, and medical equipment while maximizing occupant comfort.

In intelligent lighting management, ref. [62] investigates real-time monitoring and control in educational centers by utilizing sensors to measure environmental parameters such as humidity, temperature, and CO_2. These data are analyzed using a convolutional neural networks (CNNs) model to adjust energy systems. In a related study, ref. [63] proposes a real-time control approach in university classrooms, where passive infrared sensors (PIRs) detect occupant presence to automate light switching and adjust LED intensity, achieving a 60% reduction in energy consumption.

In terms of integrated multi-system management, ref. [64] implements a real-time monitoring platform connecting physical building spaces to a virtual model, enabling monitoring of HVAC systems, lighting, and air quality. However, this solution faces challenges related to sensor costs and managing large volumes of data. Furthermore, ref. [65] combines real-time monitoring with BIM and smart sensors to evaluate energy performance in mixed-use buildings, enabling occupants to make informed decisions, though the study identifies limitations in IoT and BIM integration.

Among innovations in energy monitoring, ref. [66] emphasizes real-time monitoring and control of energy resources across multiple residential buildings, combining IoT with deep learning models like CNN and LSTM (long short-term memory) to tailor systems to occupant needs. Meanwhile, ref. [67] employs a real-time approach to monitor environmental conditions using phase change materials (PCM), though this solution is limited by insufficient consideration of climate fluctuations. Lastly, ref. [68] explores the optimization of energy and climate management, leveraging IoT sensors, BIM models, and AI-based analyses to monitor, control, and simulate energy performance in real time.

Table 6 provides a summary of digital twin applications for real-time monitoring and control of energy systems, highlighting various building types, data sources, and software solutions used.

These studies demonstrate that real-time monitoring and control represent a primary application of digital twins, enabling proactive optimization and management of building energy systems while also highlighting persistent challenges related to sensor costs, real-time data management, and the incorporation of BIM, IoT, and AI technologies.

Predictive Modeling and Simulation

Table 6. Summary of digital twin applications for real-time monitoring and control of energy system.

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[60]	HVAC	Non-residential	√	√	None	None	Machine learning	ReCalc, AUSTRET
[62]	Lighting	Educational	√	√	None	None	CNN	Not specified
[61]	Multi-systems	Hospital	√	√	None	None	√	Not specified
[66]	Multi-systems	Residential	√	√	None	None	LSTM/CNN	Not specified
[64]	Multi-systems	Business district	√	None	None	UWB positioning system	√	Unity 3D Engine
[65]	Multi-systems	Mixed-use building	√	√	None	None	None	Not specified
[63]	Lighting	University building	√	None	None	University computing systems	None	Not specified
[67]	Thermal wall management	Not specified	√	√	None	None	Not specified	PyCharm, Linux
[68]	Multi-systems	Public buildings	√	√	√	None	Machine learning	Autodesk Revit/Insight, Energy Plus

Digital twins serve a pivotal role in predictive modeling and simulation of building energy consumption, anticipating energy needs and optimizing systems based on future conditions. The primary objective of these studies is to leverage real-time data and advanced algorithms to proactively adjust energy systems. For predictive modeling and HVAC system management, ref. [69] integrates CNN and LSTM models to forecast real-time energy loads while ensuring data privacy through thermal noise injection. Similarly, ref. [70] combines an LSTM model with a microgrid and a real-time simulator to adjust energy systems based on load predictions. By implementing model predictive control (MPC), ref. [49] applies a digital twin to public and commercial buildings to dynamically adjust HVAC systems according to weather forecasts and occupancy behavior. Ref. [71] combines historical and real-time data using neural networks to optimize HVAC system performance in an office building in Norway, while [72] proposes a digital twin framework for HVAC system management in commercial buildings, combining BIM data and real-time measurements with ANN (artificial neural network) and MOGA (multi-objective genetic algorithm) algorithms. For advanced energy demand simulations, [73] proposes an optimization algorithm (whale IWOA) combined with an LSTM model to simulate appliance operations, considering historical consumption and weather conditions in a smart building. Ref. [74] compares various predictive models (LSTM, regression, Prophet) to optimize energy resources in residential buildings. Additionally, ref. [75] uses OpenModelica and machine learning algorithms to simulate and optimize HVAC systems in real time within a test environment. In terms of occupant–building interactions, ref. [76] introduces a digital twin based on a deep learning GNN (graph neural network) model to analyze interactions between occupants and HVAC systems, integrating environmental and physiological data to optimize indoor comfort in real time. For thermal modeling, ref. [77] combines measured parameters (thermal inertia, thermal bridges) with genetic algorithms (NSGA-II) and tools like EnergyPlus to simulate building energy performance. Similarly, ref. [78] utilizes EnergyPlus to refine energy models using data collected from IoT sensors. Ref. [52] develops a digital twin based on Autodesk Revit and Insight to optimize HVAC and lighting systems in residential buildings, accounting for thermal envelope considerations. In specific contexts, ref. [79] simulates a virtual pigsty environment to study feeding conditions and apply the results to real-world scenarios. Ref. [80] uses data collected from a university building in Spain to train an ANN model capable of optimizing thermal and energy management in real time, although this study is limited to a single building.

Table 7 summarizes the applications of digital twins for predictive modeling and simulation, providing details on building types, IoT and BIM data usage, weather data, AI models, and software solutions utilized across various studies.

Table 7. Summary of digital twin applications for predictive modeling and simulation.

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[69]	Renewable energy	Not specified	√	None	√	None	CNN-LSTM	Not specified
[70]	Renewable energy	Not specified	None	None	√	Cooling system temperatures	LSTM	OPAL-RT Siemens Microgrid Controller
[49]	HVAC	Not specified	√	√	√	Current occupancy/ environmental state	Genetic algorithm	Controleum, sMAP, ModestPy
[71]	HVAC	Office building	√	None	None	None	Machine Learning	Unity 3D Engine, FIWARE Context Broker
[73]	Lighting	Residential (smart homes)	√	none	None	Historical energy consumption data and home appliances	LSTM IWOA	Not specified
[74]	Multi-systems	Residential	None	None	√	Building-wide energy consumption data	Naïve, linear regression, LSTM, Prophet	Not specified
[76]	HVAC	Educational	√	√	None	Occupant surveys on comfort perception	GNN	Neo4j
[77]	HVAC	Residential (twin prototype homes)	√	None	√	None	NSGA-II	Energy Plus Open Studio JePlus+ EA
[78]	HVAC, thermal performance	Not specified	√	None	None	Historical building energy consumption data	None	Not specified
[52]	HVAC	Residential buildings	None	√	√	None	None	Insight, Autodesk REVIT
[79]	Simulation of energy performance	Commercial (pigsty)	√	None	√	None	None	Not specified
[80]	Energy performance simulation and modeling	Educational	√	None	None	None	ANN	Power BI MATLAB SketchUp TRNSYS
[75]	Thermal management	Test building, single room ($25m^2$), Singapore	√	None	None	Physical measurements from the test environment	Machine Learning	OpenModelica, Functional Mockup Interface, Python
[81]	HVAC	Smart buildings	√	None	√	Geometric and material properties created	Algorithm not specified	Not specified

Table 7. *Cont.*

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[82]	HVAC	Commercial (office building)	√	None	None	None	None	Not specified
[72]	Renewable energy	Commercial (office building)	√	√	None	Thermal comfort survey data	ANN/MOGA	Revit C # Simulink MATLAB

These studies demonstrate that digital twins, through predictive modeling and simulation, enable the anticipation of energy needs and proactive optimization of systems. However, they also highlight challenges such as scalability, real-time data management, and the high costs associated with certain infrastructures or the density of required sensors.

Management of Renewable Energy Integration

Digital twins are crucial in managing and integrating renewable energy by simulating and optimizing energy utilization resources such as wind and solar. They enhance the energy self-sufficiency of buildings, reduce reliance on fossil fuels, and support the achievement of net zero energy buildings (NZEB) goals.

For adaptation to NZEB standards, ref. [43] proposes a digital twin coupled with BIM modeling to integrate renewable energy technologies, such as solar systems and heat pumps, while simulating energy costs and performance. This approach reduces energy consumption without relying on AI algorithms. At a larger scale, ref. [83] utilizes a digital twin integrating IoT and AI to manage renewable energy in a residential neighborhood in Rome. Using a 3D model coupled with environmental sensors, this solution tests various scenarios to maximize solar energy production and efficiency.

In predictive energy system management, ref. [69] employs CNN and LSTM networks to optimize HVAC systems and integrate renewable energy while ensuring occupant privacy through data noise injection. Similarly, ref. [84] combines LSTM, TCN (temporal convolutional neural networks), and transformer models with a real-time simulator to forecast energy loads and facilitate the integration of renewable energy into a microgrid.

For improving energy efficiency based on the thermal envelopes of historic buildings, ref. [85] introduces a digital twin applying an ANN model to predict energy consumption using parameters such as wall, window, and insulation characteristics. Simulations conducted with eQuest optimize energy design. Likewise, ref. [86] focuses on vertical greening systems to enhance the thermal insulation of buildings in China. Using Revit and DeST, this solution simulates the impact of green systems on façades and roofs to reduce energy consumption.

At the building and district scales, ref. [22] proposes a method to analyze the efficiency of renewable energy systems, primarily solar, to maximize self-energy production in NZEBs. Additionally, ref. [87] applies digital twins at multiple scales (buildings, campuses, districts) to optimize energy systems such as heat pumps, relying on IoT sensor data and dynamic simulations.

Table 8 provides a summary of digital twin applications for managing and integrating renewable energy. It highlights various application areas, building types, data sources, and AI models used to enhance energy efficiency and support NZEB goals.

Table 8. Summary of digital twin applications for renewable energy integration management.

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[43]	Renewable energy	Residential	√	None	None	None	None	Revit, Insight
[83]	Renewable energy	Residential	√	√	None	None	machine learning, Naïve Bayes classification,	MC4 Suite pour Revit, termus BIM, Archi Energy
[69]	Renewable energy	Not specified	√	None	√	None	CNN-LSTM	Not specified
[84]	HVAC	Historic public building	√	None	√	Electricity consumption and heating load history	Comparison: LSTM, TCN, Transformer	Microsoft Azure, Ontology Models (Brick), PyTorch, scikit-learn
[85]	Thermal management	Residential building	None	None	√	Building envelope design data (walls, roof, windows), energy simulation data	ANN	MATLAB (Simulink NFTOOL)
[86]	Greening systems	Traditional arcade buildings in China (commercial and residential spaces)	None	√	√	None	None	DeST, Revit
[88]	HVAC, lighting, and household appliances	Residential	√	√	None	None	√	CityGML, MC4 pour Revit, Autodesk InfraWorks
[87]	Integrated multi-systems	Residential neighborhoods, university campuses	√	none	None	None	√	Oemof-solph

These examples demonstrate that digital twins enable the integration of renewable energy and the real-time optimization of energy systems by combining BIM, IoT, and AI technologies. By enabling proactive management of renewable energy resources, digital twins contribute to energy sustainability and the achievement of NZEB goals across various types of infrastructure. However, challenges remain, particularly concerning sensor accuracy and the quality of real-time data collected.

Predictive Maintenance and Proactive Management

Digital twins are central to predictive maintenance and proactive management, enabling continuous monitoring of energy systems and identifying early warning signs of potential failures. By combining the analysis of historical and real-time data, these technologies optimize maintenance costs, extend equipment lifespan, and reduce operational disruptions.

For HVAC systems, ref. [88] focuses on predictive maintenance in an educational campus. Using BIM data and IoT sensors, this digital twin detects faults and anticipates component conditions to plan maintenance proactively. The APAR (Automated Performance Assessment Rules) algorithm improves prediction accuracy and generates significant energy savings. Similarly, ref. [45] proposes a predictive maintenance solution throughout the lifecycle of HVAC systems, leveraging high-resolution simulations and parametric BIM models enhanced with real-time IoT data. This approach rapidly identifies malfunctions and adjusts systems before failures occur.

For overall energy sustainability, ref. [44] highlights proactive building management using a digital twin integrated with BIM. By monitoring energy and environmental performance through IoT sensors, this solution helps achieve environmental certifications such as LEED (leadership in energy and environmental design) while preventing potential failures through continuous monitoring. A similar approach is adopted in [89], where non-residential buildings in Norway use Bayesian networks, ANN, and SVM (support vector machine) to predict HVAC system failures. This framework enables advanced maintenance management by targeting necessary interventions and optimizing energy efficiency. For lighting systems, ref. [50] applies a proactive maintenance approach in an office building. Using computer vision sensors and the YOLOv4 (You Only Look Once version 4) algorithm, this digital twin detects pedestrian presence in real-time, automatically adjusting lighting to prevent unnecessary overconsumption while ensuring targeted maintenance of lighting equipment. In the broader context of smart building maintenance, ref. [90] proposes an integrated platform to replace traditional static models with dynamic ones, these models leverage real-time data to improve energy efficiency, optimize occupant comfort, and anticipate maintenance needs, thereby reducing unplanned interruptions of critical systems.

Table 9 provides a summary of digital twin applications for predictive maintenance and proactive management, detailing various application areas, building types, data sources, AI models, and software solutions.

Table 9. Summary of digital twin applications for predictive maintenance and proactive management.

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[88]	HVAC	Educational	√	√	None	None	Machine mearning APAR	Autodesk Revit/c sharp BACnet
[45]	HVAC and thermal management	Multifunctional building	√	√	None	None	None	Grafana Autodesk, Revit iTwin
[44]	Lighting	Educational	√	√	None	None	None	NoSQL (Influx DB), Odoo ERP
[89]	HVAC	Non-residential buildings	√	√	None	None	ANN, SVM, Bayesian networks	Autodesk Revit, Dynamo
[50]	Lighting	Commercial (Office building)	√	√	None	None	Deep learning	YOLOv4, BIM Dynamic, WebGL
[90]	Integrated multi-systems	Smart and energy-efficient buildings	√	√	√	Historical and forecast data	Machine learning/deep learning	Not specified

These studies demonstrate that digital twins, through the integration of technologies like IoT sensors, BIM, and AI algorithms, enable a shift from reactive to proactive management of energy systems. They optimize maintenance by identifying faults before they occur, thereby reducing operational costs, extending equipment lifespan, and ensuring more efficient energy use.

Conservation and Adaptation in Historic Buildings

In historic buildings, digital twins play a vital role by combining architectural preservation with energy performance optimization. Through thermal and energy simulations, they identify potential improvements without altering the structure, enabling modernization while respecting heritage integrity. Ref. [91] proposes a digital twin for historic buildings in Sweden, based on IoT sensors collecting real-time data on humidity, temperature, and other environmental parameters. These data are analyzed using AI models to predict energy consumption and adjust systems for optimized operation. This approach balances energy efficiency with the preservation of heritage characteristics. Similarly, ref. [84] utilizes a digital twin combined with deep learning models, including LSTM, TCN (temporal convolutional neural networks), and Transformer, to monitor and optimize energy consumption in public historic buildings. By leveraging historical records of electricity and heating loads, this framework provides accurate forecasts for proactive and sustainable resource management.

Regarding renovation, [37–42] offers a solution to adapt existing buildings to NZEB standards. This digital twin integrates BIM and uses energy simulations to assess building needs while incorporating technologies such as enhanced insulation, solar systems, and heat pumps. However, this approach primarily focuses on modern buildings and faces limitations in large-scale energy retrofits of historic buildings due to a lack of standardization. Similarly [60], focuses on energy retrofits in non-residential buildings by combining IoT sensors and machine learning techniques to monitor real-time energy consumption. While this solution improves energy performance and comfort for occupants, it is limited by the absence of digital models specifically tailored to historic buildings.

Table 10 summarizes digital twin applications for historic buildings, focusing on energy optimization and heritage preservation. It details building types, data sources, AI models, and software solutions.

Table 10. Summary of digital twin applications for conservation and adaptation in historic buildings.

Ref	Application Area	Building Type	IoT Data	BIM Data	Weather Data	Other Data Sources	AI	Software
[91]	Lighting	historic buildings	√	None	√	Building management systems (BMS)	Machine learning	Microsoft Azure
[43]	Renewable energy	Residential	√	None	None	None	None	Revit, Insight
[60]	HVAC and thermal management	Non-residential	√	√	None	None	Machine learning	ReCalc AUSTRET
[84]	HVAC	Historic public building	√	None	√	Electricity consumption and heating load history	Comparison: LSTM, TCN, transformer	Microsoft Azure, Ontology Models (Brick), PyTorch, scikit-learn

These approaches demonstrate that digital twins help preserve historical value while enhancing energy sustainability. However, their large-scale adoption is hindered by a lack of standardization and a frequent focus on modern constructions.

4. Discussion

4.1. Role and Application of Digital Twins to Enhance Building Energy Efficiency

Digital twins are emerging as a key technology for improving energy efficiency in buildings by integrating advanced approaches for proactive resource management. This subsection addresses the first research question (RQ1) by analyzing how these technologies optimize building energy performance through various practical applications. The findings highlight significant contributions, including:

Real-Time Monitoring and Control: By leveraging IoT sensors, digital twins enable the proactive management of energy systems, including HVAC and lighting, optimizing infrastructure performance while reducing energy consumption. These capabilities have been effectively demonstrated in non-residential [60] and educational buildings [46,47], achieving significant energy cost reductions while maintaining optimal occupant comfort. The effectiveness of digital twin integration varies notably between residential and commercial buildings due to differences in energy demands, scale, and operational complexity. In residential buildings, digital twins prioritize occupant-centric optimizations, dynamically adjusting HVAC and lighting systems based on individual behavior and preferences. While this enhances comfort and personalization, the variability in occupant behavior can present challenges for consistent energy optimization strategies. In contrast, commercial buildings benefit from the centralized management of large-scale systems, where digital twins excel in optimizing energy use. Predictive models, supported by consistent occupancy patterns, enable precise energy demand forecasting and dynamic system adjustments. Furthermore, economies of scale amplify the impact of energy-saving measures in commercial contexts, making digital twins a particularly effective solution for large and complex infrastructures.

Predictive Modeling and Simulation: Digital twins utilize advanced algorithms, such as convolutional neural networks (CNNs), long short-term memory (LSTM), and artificial neural networks (ANNs), to forecast energy needs and simulate future scenarios. These simulations enable dynamic adjustments to energy systems, optimizing their performance ([53,54]). Additionally, they enhance occupant–building interactions to ensure both comfort and energy efficiency ([61,62]). A critical extension of predictive modeling in digital twins is the incorporation of occupant behavior variability. By leveraging data from occupancy sensors, IoT devices, and surveys, digital twins capture patterns in occupant behavior, which significantly influence energy consumption. Advanced AI models, such as graph neural networks (GNNs) and LSTM, are instrumental in predicting changes in occupancy and behavioral trends over time. These models enable dynamic adjustments to key building systems, such as HVAC and lighting, ensuring optimal energy efficiency without compromising occupant comfort. This approach is particularly advantageous in large and complex buildings, where variability in occupant behavior can result in significant fluctuations in energy demand. Incorporating such predictive capabilities allows digital twins to adapt in real-time, addressing both operational and behavioral challenges effectively.

Integration of Renewable Energy: Digital twins facilitate the adoption of renewable energy by optimizing the use of solar and wind resources, particularly in near-zero energy buildings (NZEBs). Virtual models coupled with BIM simulations test various energy scenarios to maximize production and reduce dependence on fossil fuels ([69,70]).

Predictive Maintenance: By leveraging real-time and historical data, digital twins detect potential failures before they impact system performance ([76–79]). This extends equipment lifespan, minimizes costly interruptions, and makes maintenance more reliable and sustainable.

Preservation of Historic Buildings: In heritage buildings, digital twins combine modernization with respect for architectural constraints. They enable energy efficiency improvements without compromising structural integrity, ensuring the sustainable management of historic infrastructures ([71–82]).

These diverse roles, illustrated in Figure 6, underscore the versatility of digital twins as powerful tools for energy efficiency and integrated management in smart buildings.

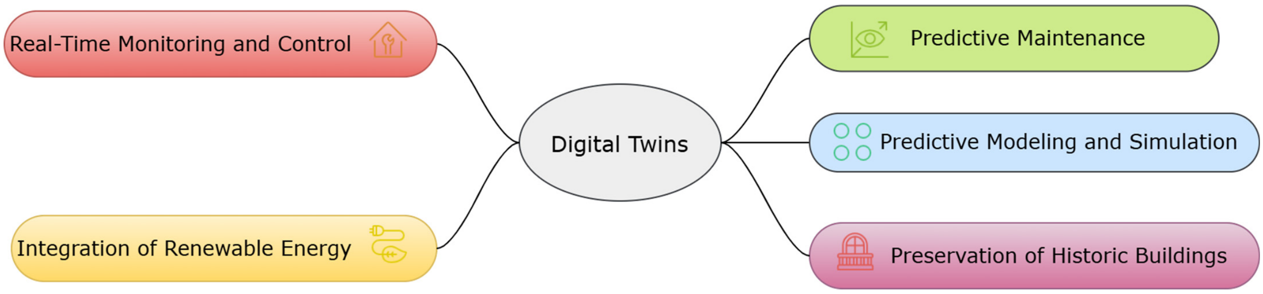

Figure 6. Roles and applications of digital twins in enhancing energy efficiency in buildings.

4.2. Technologies and Software Associated with Digital Twins for Energy Efficiency in Buildings

Digital twins rely on an advanced technological ecosystem, integrating various software and tools that enable the acquisition, analysis, and optimization of data essential to their functionality. This subsection addresses the second research question (RQ2) by detailing the key technologies that support the deployment of digital twins for building energy efficiency. These technologies include IoT, BIM, AI, data storage and processing infrastructures, as well as thermal and energy simulation software. Figure 7 provides a concise illustration of these elements.

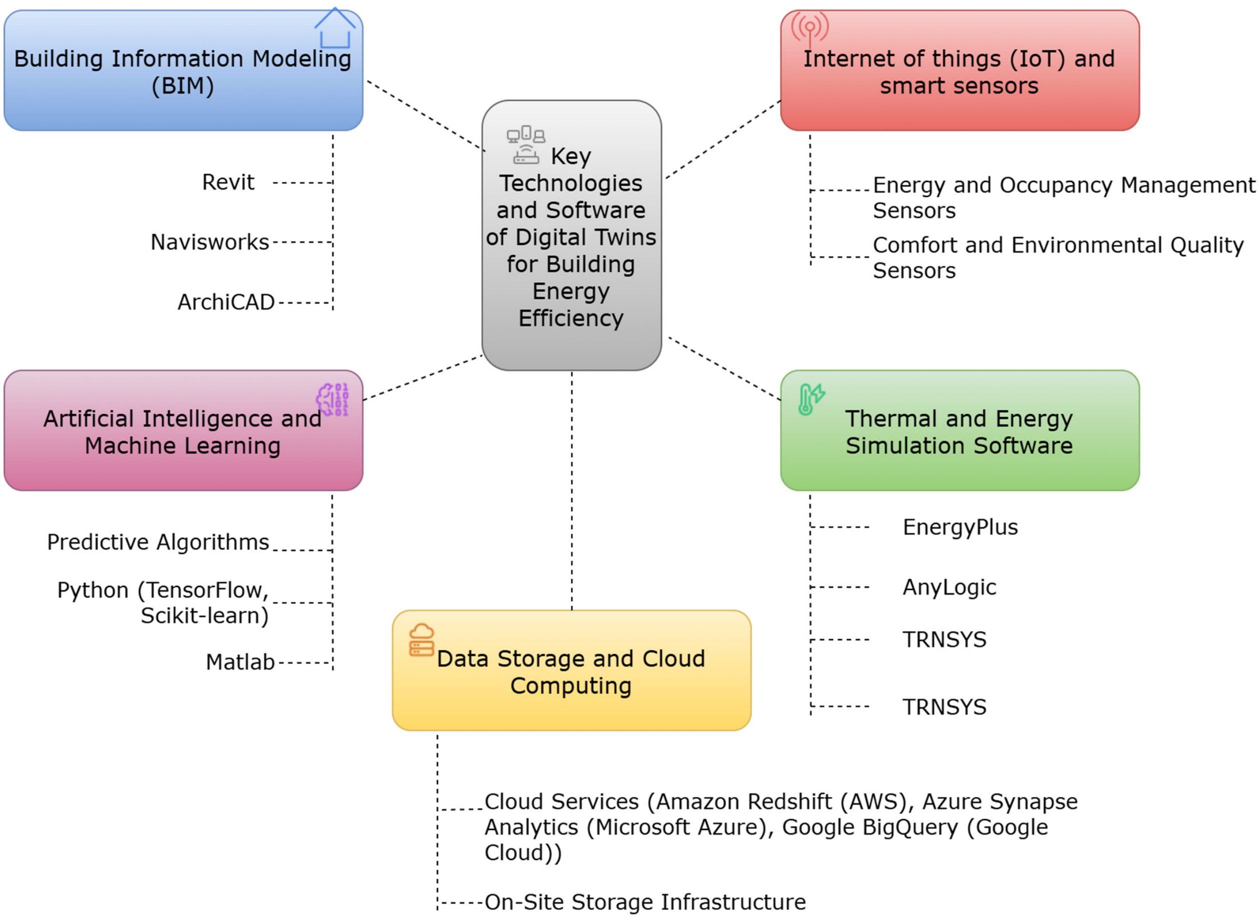

Figure 7. Technologies and software associated with digital twins for energy efficiency in buildings.

4.2.1. Internet of Things (IoT) and Smart Sensors

IoT and smart sensors are central to the operation of digital twins for energy efficiency in buildings, facilitating real-time data collection essential for continuous monitoring and dynamic adjustments. IoT sensors capture detailed information on various environmental and energy parameters, providing the data required to create an accurate and up-to-date virtual model of the building [18,58]. This connected infrastructure is fundamental for ensuring real-time control of energy systems and proactively detecting inefficiencies [43,65].

The IoT sensors used include temperature sensors, which measure thermal variations across different building zones to regulate HVAC systems [11,89]; air quality sensors (e.g., for monitoring CO_2 levels), which ensure a healthy environment for occupants while optimizing ventilation [12]; and motion or occupancy sensors, which automatically regulate air conditioning and lighting based on actual presence in spaces [49,67]. These sensors can also measure humidity, brightness, and other environmental factors that directly affect energy consumption [7,43].

To manage and analyze this data in real-time, digital twins integrate IoT platforms capable of processing large volumes of sensor data [46,88]. IoT management systems such as Microsoft Azure IoT, AWS IoT, and Google Cloud IoT provide solutions for connecting and monitoring sensors, enabling centralized data collection and real-time access to information [18,88]. These platforms also play a critical role in implementing predictive algorithms and machine learning, which are used to optimize energy systems by anticipating needs and variations [9,21,58].

4.2.2. Building Information Modeling (BIM)

BIM is a critical technology for digital twins, serving as a centralized 3D database that consolidates detailed information on a building's dimensions, materials, technical systems, and functionalities [70,88]. BIM applications are diverse and directly contribute to building energy efficiency. While BIM is primarily a static 3D model, it provides precise data on the geometric, material, and technical characteristics of buildings, including structure, energy systems, and spatial orientation [46,58]. These data form an essential foundation for advanced analyses.

When coupled with dynamic data, such as those collected by IoT sensors (real-time environmental data), weather forecasts, or occupancy scenarios, BIM enables sophisticated energy simulations and predictions [18,67]. Several BIM software tools are utilized to develop and leverage these digital models. For instance, Autodesk Revit is widely recognized for its capabilities in creating detailed and integrated models while supporting energy analysis through associated tools like Autodesk Insight [70]. ArchiCAD stands out for its user-friendliness and efficiency in developing complex architectural models, with a focus on integrating energy scenarios during the early design phases [46]. Meanwhile, Navisworks is employed for system coordination and clash detection between different building systems [58].

4.2.3. Artificial Intelligence and Machine Learning

Artificial intelligence (AI) and machine learning (ML) play a key role in improving the predictive, optimization, and dynamic management potential of digital twins in energy systems. These technologies facilitate the analysis of massive real-time data streams collected through IoT sensors and provide tailored solutions to anticipate building energy needs, adjust systems such as HVAC, and optimize operations based on current and future conditions [88,89]. Machine learning models encompass a wide range of algorithms, each suited to specific tasks. Artificial neural networks (ANNs) and deep learning techniques are commonly used to identify patterns in complex data and predict energy behaviors [9].

However, these models have limitations when dealing with real-time data complexities, such as their high computational requirements and sensitivity to noisy or incomplete data. Long short-term memory (LSTM) models, although well suited for time-series data, can face challenges in scalability and training efficiency when applied to large-scale dynamic systems [21]. In contrast, algorithms like support vector machines (SVMs) are more efficient for tasks such as data classification and anomaly detection, offering lower computational costs and better generalization on smaller datasets [57]. Genetic algorithms excel in solving multi-objective optimization problems, but their stochastic nature can lead to longer processing times compared to deterministic methods [67]. Random forests and Bayesian networks, on the other hand, provide robust predictive analyses, even with incomplete or uncertain data, ensuring reliable decision-making in real-world applications [58].

The choice of algorithm often depends on the specific requirements of the system being modeled. For example, ANN and LSTM are advantageous in capturing non-linear relationships and temporal dependencies, while SVM and random forests are preferred for simpler, interpretable models requiring faster computation. These trade-offs highlight the importance of algorithm selection based on the energy management objectives and the nature of the data being analyzed.

To develop and implement these AI models, Python libraries such as TensorFlow, PyTorch, Keras, and Scikit-learn are commonly used for training and deploying algorithms [88]. Additionally, environments like MATLAB, known for dynamic modeling, and PyCharm, a Python-specific IDE, are frequently utilized in academic and industrial contexts [58].

4.2.4. Data Storage and Cloud Computing

Databases and storage platforms have a pivotal role in the functioning of digital twins by providing solutions to store, organize, and analyze the massive and heterogeneous real-time data they collect. Data from IoT sensors, BIM models, weather conditions, and occupant behavior are often voluminous, unstructured, and generated at high frequencies [46,58]. A robust storage infrastructure is essential for efficiently processing this Big Data and enabling digital twins to perform advanced analyses and dynamic optimizations [67].

NoSQL databases, such as MongoDB and Cassandra, are particularly well suited for digital twins due to their ability to manage unstructured or semi-structured data, such as time series, IoT streams, or BIM documents. Unlike relational databases, NoSQL databases offer flexibility in data storage and horizontal scalability, essential for handling ever-increasing data volumes [18]. For example, they can store real-time IoT data, such as temperatures, CO_2 levels, or occupancy rates, while ensuring rapid and efficient retrieval for predictive analyses [58].

Additionally, cloud computing platforms such as AWS (Amazon Web Services), Microsoft Azure, and Google Cloud provide robust solutions for storing and processing large-scale data. These platforms enable elastic scalability, ensuring that storage and computing resources can adapt to data growth without requiring additional physical infrastructure [88]. They also provide remote data access, allowing digital twins to remain connected at all times and perform real-time analyses [46].

For specific applications, hybrid storage solutions that combine on-premise databases with cloud services are also relevant. These configurations allow critical or sensitive data to be retained locally while leveraging the cloud's capabilities for large-scale analyses. This approach is particularly useful in environments where data security or latency restrictions are prioritized [67,88].

4.2.5. Thermal and Energy Simulation Software

Thermal and energy simulation software are crucial tools for analyzing and optimizing the energy performance of buildings, complementing BIM models. These software solutions utilize static data from BIM models, such as geometric characteristics, materials, and building orientation, and enrich them with dynamic data, including climate conditions, occupancy scenarios, and real-time data collected by IoT sensors [46,67]. They enable simulations of the overall performance of energy systems, including HVAC needs, thermal losses, solar gains, and artificial lighting consumption, while testing various scenarios to determine the most high-performance solutions [58].

For instance, EnergyPlus uses data exported in gbXML or IFC formats to model thermal transfers, natural ventilation, and solar gains, providing a comprehensive analysis of energy performance [90]. Similarly, Autodesk Insight, integrated with Revit, allows architects and engineers to evaluate the impact of architectural and technical decisions on energy consumption early in the design phase [18].

Additionally, tools like DesignBuilder and TRNSYS offer features for graphically visualizing results, analyzing natural ventilation, and evaluating occupant comfort conditions while simulating the impact of renewable energy systems [48,92].

4.3. Limitations and Challenges in the Adoption of Digital Twins for Building Energy Efficiency

This subsection highlights the key limitations to the adoption of digital twins, addressing the third research question (RQ3). Several limitations have been identified in the analyzed studies. Despite their promising potential, digital twins in the field of building energy efficiency face several significant challenges that hinder their large-scale adoption. These limitations encompass technical, behavioral, and organizational aspects, directly impacting the energy performance of buildings.

The interoperability of heterogeneous systems, such as heating, ventilation, and air conditioning (HVAC); lighting; and building management systems, remains a major challenge. The lack of standardized communication protocols and shared frameworks limits the efficiency of their integration. For example, [46] highlighted that poor interoperability between BIM and building energy modeling (BEM) hinders energy management efficiency. Ontologies like Brick or middleware platforms could address these issues by standardizing data exchange.

Scalability and large-scale data management are other significant obstacles. Digital twins generate massive volumes of data from IoT sensors and BIM models, requiring advanced solutions for real-time processing. Ref. [48] demonstrated that integrating scan-to-BIM can improve the capture and processing of data from existing buildings, but such approaches require robust IT infrastructures to operate effectively at scale. Technologies such as edge computing and microservices, as discussed by [58], offer promising solutions to tackle these challenges.

The accuracy and reliability of predictive models also pose a critical limitation. Poorly calibrated models or insufficient data inputs can lead to erroneous predictions, reducing overall energy efficiency. Ref. [9] proposed neural ordinary differential equations (neural ODEs)-based models to enhance predictive accuracy in energy management, paving the way for more robust approaches.

The behavioral variability of occupants adds another layer of complexity to energy optimization. Unpredictable behaviors and individual preferences necessitate systems that can dynamically adapt. Ref. [13] emphasized the importance of incorporating user responses to improve energy efficiency, particularly in lighting systems. IoT sensors and adaptive algorithms could be integrated to personalize energy settings based on individual needs.

Data security and privacy are also critical challenges. Digital twins collect vast amounts of data, including sensitive information about occupants, exposing systems to potential cyberattacks. [88] explored the use of blockchain technology to ensure data security and integrity in energy management systems, but practical validation on a larger scale remains necessary.

Finally, digitalizing existing buildings is a significant limitation. Unlike new constructions, older infrastructures, which are often energy-intensive, are challenging to integrate into modern digital systems due to structural constraints and high costs. [43] demonstrated that the use of digital twins for energy retrofitting of existing buildings can yield substantial benefits but requires tailored methodologies such as scan-to-BIM.

These challenges highlight the need for in-depth research on interoperability, scalability, personalized energy strategies, data security, and the integration of existing buildings.

Our study helps to address these gaps by adopting an integrated approach that identifies key trends and critical challenges. Unlike previous studies, which often focus on isolated aspects of digital twins or associated technologies, we propose strategic research directions, including the following:

- The development of interoperable frameworks to integrate heterogeneous systems.
- The exploration of scalable solutions adapted to complex infrastructures.
- The adoption of practices that respect data confidentiality and security.

By aligning this analysis with global sustainability objectives, such as the 2030 Agenda for Sustainable Development [5] and the Paris Agreement [6], our study provides a solid foundation to guide future research and maximize the impact of digital twins in the energy transition of buildings.

These research directions are summarized in Table 11 below, which highlights the main identified limitations, their importance, and the associated research questions.

Table 11. Major challenges for integrating digital twins in energy efficiency in buildings.

Challenge	Description	Importance	Research Question
Interoperability and System Integration	One of the main obstacles remains the integration of multiple heterogeneous systems in buildings (HVAC, lighting, renewable energy, BMS, etc.). These systems are often developed by different manufacturers with varied and sometimes incompatible communication protocols.	To achieve optimal energy management, these systems must "communicate" effectively. Without proper interoperability, efficiency gains may be limited.	How can standardized frameworks and ontologies, such as Brick, be developed to ensure seamless interoperability among systems?
Scalability and Large-Scale Data Management	Digital twins generate and utilize massive amounts of data from IoT sensors and BIM models. Collecting, processing, and analyzing such data at scale, especially in complex buildings, remains challenging.	Real-time data is essential for effective optimization. Poor data management may result in inefficiencies or erroneous outcomes.	What mechanisms, such as edge computing and microservices, can improve the scalability and real-time data handling capabilities of digital twin architectures?
Accuracy of Predictive Models	The algorithms used in digital twins, such as AI models and machine learning algorithms, can struggle to accurately predict energy needs due to incorrect, insufficient, or poorly calibrated data.	Inaccurate modeling or simulation can lead to suboptimal decisions in energy system management.	How can predictive models be enhanced using hybrid approaches that combine historical and real-time data to ensure robust energy predictions?

Table 11. *Cont.*

Challenge	Description	Importance	Research Question
Occupant Impact and Behavioral Variability	Energy management systems must not only optimize consumption but also ensure occupant comfort, which can vary greatly due to diverse behaviors and preferences.	Considering occupant behavior is essential for solutions to be well accepted and to avoid operational issues.	How can adaptive algorithms and IoT sensors be integrated to dynamically tailor energy strategies to occupant preferences and behaviors?
Data Security and Privacy	With the extensive integration of IoT sensors and continuous data collection on buildings and occupants, data security and privacy concerns become critical.	System security breaches can lead to cyberattacks or violations of occupant privacy.	How can blockchain technology and advanced encryption protocols ensure data security and privacy while maintaining system performance?
Limited Adoption in Existing Buildings	Most current digital twin projects are deployed in new constructions, while existing infrastructures are more challenging to digitize and equip with advanced technologies.	A significant portion of the building stock consists of older, often energy-intensive buildings where potential gains could be substantial.	What specific methodologies, such as scan-to-BIM, can facilitate the cost-effective and efficient integration of digital twins into existing buildings?

5. Conclusions and Perspectives

This study has explored the pivotal role of digital twins in enhancing building energy efficiency, focusing on their applications, enabling technologies, and associated challenges. Through a rigorous literature review combining bibliometric and content analyses, key contributions of digital twins to energy management were identified and thoroughly examined. The bibliometric analysis demonstrated a notable growth in research interest, reflecting the increasing global focus on this transformative technology. It highlighted key themes such as renewable energy integration, predictive applications for energy systems, and the use of digital technologies for real-time monitoring and optimization. Geographical disparities in research activity were also observed, underlining the need for broader adoption and collaboration in underrepresented regions. The systematic content analysis provided a detailed understanding of the roles and applications of digital twins. These include real-time energy system monitoring and control, predictive modeling and simulation, proactive maintenance, integration of renewable energy sources, and conservation in historic buildings. By connecting dynamic IoT sensor data, static BIM models, and AI algorithms, digital twins facilitate integrated, data-driven, and sustainable energy management solutions.

Despite these advancements, several challenges persist, such as system interoperability, standardization, scalability, large-scale data management, predictive model accuracy, and issues related to data privacy and security. Addressing these barriers is crucial to unlocking the full potential of digital twins in the building sector. Future research should focus on developing modular and adaptable solutions for integrating digital twins into existing infrastructures, enabling their application across diverse building systems. Establishing universal technological standards will be key to ensuring seamless interoperability among IoT devices, BIM platforms, and AI algorithms. Additionally, advancing predictive models using cutting-edge machine learning techniques will enhance accuracy and scalability. Data security must also be prioritized, with technologies like blockchain offering promising solutions to ensure privacy and traceability. Looking ahead, the large-scale adoption of digital twins will require a multidisciplinary approach involving researchers, industry professionals, and policymakers. By addressing the technical and organizational challenges identified, digital twins can significantly contribute to the energy transition, supporting the global push for sustainability and decarbonization in the building sector.

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