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Review

Digital Twins' Applications for Building Energy Efficiency: A Review

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Abstract: Over the last few decades, energy efficiency has received increasing attention from the Architecture, Engineering, Construction and Operation (AECO) industry. Digital Twins have the potential to advance the Operation and Maintenance (O&M) phase in different application fields. With the increasing industry interest, there is a need to review the current status of research developments in Digital Twins for building energy efficiency. This paper aims to provide a comprehensive review of the applications of digital twins for building energy efficiency, analyze research trends and identify research gaps and potential future research directions. In this review, *Sustainability* and *Energy and Buildings* are among the most frequently cited sources of publications. Literature reviewed was classified into four different topics: topic 1. Optimization design; topic 2. Occupants' comfort; topic 3. Building operation and maintenance; and topic 4. Energy consumption simulation.

Keywords: digital twin; energy efficiency; occupants' comfort; energy performance; buildings

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1. Introduction

The Architecture, Engineering, Construction and Operations (AECO) sector is responsible for a large percentage of the world's energy consumption, which has a negative environmental impact on its day-to-day operations [1–3]. There has been a continuous increase in the contribution of buildings to global energy use, including both residential and commercial buildings, with estimations ranging from 20 to 40% [4]. Developing countries are likely to use more energy and, consequently, emit more greenhouse gases (GHG) as a result of economic growth [5]. The concept of energy efficiency refers to the ratio between the output of performance, service, good, or energy, and the input of energy, according to the European Parliament [6]. In other words, energy efficiency in building operations refers to the actual operational performance of various systems within a building. Currently, the AECO sector faces a great deal of pressure to reduce polluting emissions and to develop more energy-efficient methods of operation (materials, processes, equipment, buildings) [7,8].

Building Information Modelling (BIM) has been emerging as a potential solution to improve energy efficiency [9–11]. BIM is "an approach to design, construction, and facilities management, in which a digital representation of the building process is used to facilitate the exchange and interoperability of information in digital format" [12]. BIM constitutes an effective platform by which to depict high-quality information and integrate different platforms. BIM utilizes 3D, parametric and object-based models to create, store and use coordinated and compatible data throughout the life cycle of a facility [13]. Acting as a central resource for decision-makers, BIM has the ability to provide better documentation, improved collaboration and work flexibility, and updated information through the building life cycle [3,14]. Researchers focus on implementing BIM for different aspects, such as: sustainability [15–17]; strategy planning [13,18]; retrofit planning [19]; preventive maintenance planning [8,13,20,21]; building systems analysis [13,22,23]; commissioning processes [13,24]; and energy management [25,26].

Similarly, technological advances in recent decades have initiated the emergence of Digital Twins (DT), which are commonly thought of as the digital version of physical products. Singh et al. [27] suggest the following definition: "A DT is a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data. It is not just the DT which mimics its physical twin but any changes in the DT are mimicked by the physical twin too." In this sense, three main elements are required: a physical twin (a real-world entity), a digital twin (the digital representation that can mirror the physical twin in real time), and a linking mechanism, which allows the flow of data between the twins in both directions and in real time automatically [28]. These definitions and requirements apply for any product or entity. More specifically for the construction industry, Opoku et al. [29] define digital twins as a "real-time representation of the building or structure that is fully or partially completed and developed for the purpose of representing the status and character of the building or structure it mirrors." Thus, it allows the seamless synchronization and monitoring of energy systems via computerized and virtual world simulations based on data, information and consumer behavior [30].

Interest in DT and energy efficiency has been growing through the years [31] and has led to an increase in the yearly output of articles in the related domain. Deng et al. [32] present a review paper focused on identifying the emerging technologies that facilitate the evolution of BIM to DT in built environment applications. A total of 100 related papers including 23 review papers were selected and reviewed. This paper developed a five-level ladder taxonomy to reflect the evolution from BIM to DTs. The majority of past studies in the literature fall into Levels 2 and 3, which are BIM-supported simulations and BIM–IoT integration for built environment management. Teisserenc and Sepasgozar [33] also present a review paper, but with the aim to develop a technological framework for the integration of blockchain technology (BCT) with DT for projects of the BECOM industry 4.0. This model promotes ecosystems of trusted, decentralized, and sustainable DTs where BCT secures information sharing for the data value chain of projects. Marocco and Garofolo [34] also reviewed studies, but focusing on disruptive technologies for Facility Management (FM). Their findings revealed that a promising starting point for enhancing FM includes developing DT platforms by integrating BIM, cloud computing, and IoT. Casini [35] reviewed studies on extended reality technologies such as virtual reality, augmented reality, and mixed reality technologies and applications for smart building operation and maintenance. He argues that the future of O&M is represented by digital twin technology and concluded that the use of extended reality technologies in building and city management is demonstrating promising outcomes in terms of improving human performance in technical O&M tasks, understanding and managing the energy efficiency, comfort, and safety of buildings and infrastructures, and assisting in strategic decision-making. Opoku et al. [36] conducted a literature review focusing on the DT application in the construction industry. They analyzed 22 papers sorting the applications into the four phases of the life cycle of the objects in the construction industry: design and engineering, construction, operation and maintenance, and demolition and recovery. In this approach, energy efficiency features mainly in the operation and maintenance phase to inform decision-making through simulations and energy consumption optimization. In some cases, energy simulations were also present in the design and engineering phase. These authors identify energy simulation as one of six key applications of DT in the construction industry.

There is often confusion between BIM and DT, so it is important to clarify that BIM is a process of creating a 3D model extension of a real-world item, while a DT is designed to emulate the thing it represents [37]. DTs are "a digital representation of a unique active product (real device, object, machine, service, or intangible asset) or unique product service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors through models, information, and data within a single or even across multiple life cycle phases" [38]. DT provides insights into the life and features of individual products and it is possible to optimize its sustainability. Moreover, it contributes to the improvement of future product generations, for example through measures such as the Ecological Footprint or the Life Cycle Assessment (LCA) [39]. Few specific use cases describe how DT can be used to optimize energy use or monitor it using the Internet of Things (IoT) [40,41].

As shown, previous review papers on the use of DT in the construction industry and its enabling technologies have been identified [32–36]. However, these papers only mention the potential of applying DT to building energy efficiency as one of many possibilities. None of the review papers analyze specifically the current state of implementing DT to building energy efficiency. On the other hand, published research papers include case studies and methods to enable DT for different types of buildings and at different scales [40–42]. Although the body of literature about the use of DT specifically for building energy efficiency has grown over the past few years, the current state of implementing DT for building energy efficiency has still not been addressed in the form of literature review. Therefore, this paper presents a comprehensive review of the current status and insights of digital twins' applications focused on building energy efficiency. This study contributes to the field, identifying the main uses and methods for applying DT to building energy efficiency while also identifying gaps in the literature and paving the directions for future research.

This paper is structured as follows: Section 2 focuses on the research methodology, Section 3 provides the results of the scientometric analysis, Section 4 presents a discussion of the results from the review and groups the reviewed articles into four main application fields, and Section 5 further discusses research gaps and future directions and the conclusion.

2. Methodology

The methodology applied to develop the current paper was a systematic literature review. A systematic literature review identifies, evaluates and interprets relevant research on a specific topic, issue or area [43]. This method is well-known as an effective way of identifying important recurring themes and useful for structuring the data, being used by most review papers [29,32]. Unlike traditional review research methods, it allows the researcher to obtain data about a phenomenon and summarize the existing evidence concerning the specific topic in a thorough and unbiased manner. For that, systematic reviews must be undertaken in accordance with a predefined search strategy. First, the research question must be defined. Therefore, this review wants to answer the following research question:

"How can digital twins be applied to energy efficiency in buildings?"

To answers it, a specific strategy was followed. The first stage comprised the search for publications regarding the topic. The second stage included the definitions and application of exclusion criteria, and finally, the third stage comprised the execution of a scientometric analysis followed by the synthesis of the publications. Figure 1 delineates the overall procedure of this methodology. Three databases were used for searching the publications, the well-known scientific meta-search engines (1) Scopus, (2) Web of Science and (3) MDPI.

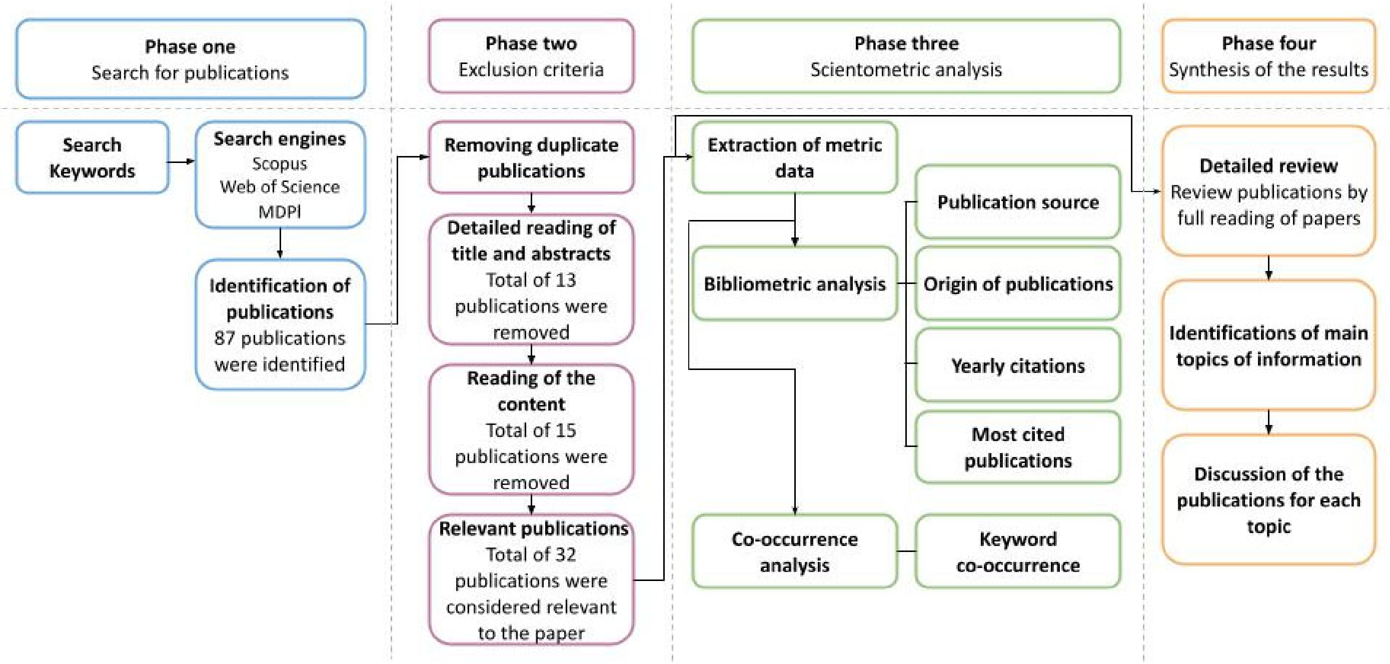

Figure 1. Research methodology.

2.1. Phase One: Search for Publications

First, three different search terms were defined to gather the most relevant information related to digital twins used to improve building energy efficiency. The Boolean operators OR and AND were used for the keyword-based search on title–abstract–keyword of each publication: "Digital twin" AND "Building" AND "Energy Efficiency" OR "Energy Performance". Considering the type of publications, the selected ones included published journal articles, book chapters, and conference papers, to give a thorough overview of extant research and guarantying a wide diversity of information sources. As a result, 87 publications were gathered. The search results were saved in Scopus, Web of Science and MDPI and the publications were downloaded and imported to Mendeley reference manager.

2.2. Phase Two: Exclusion Criteria

Firstly, the duplicate publications found in common in the three databases were excluded, resulting in 60 publications to be analyzed. Secondly, all the titles and abstracts of the publications were carefully reviewed to select the studies relevant to the subject of the present paper. Through this reading, thirteen publications were excluded from the database. Publications that were not related to the use of digital twins for buildings and those duplicate publications were excluded. After reading the content, fourteen publications were removed.

2.3. Phase Three: Scientometric Analysis

Several kinds of measurable bibliometric data were examined using statistics-based methodologies, including the evolution of publications per year, and the number of citations. The metric data was exported from the databases to Microsoft Excel, then processed and graphed to aid in the interpretation of this type of data. Additionally, co-occurrence analysis on the databases' information was carried out using VOSviewer software, which consists of a visualization application that uses natural language processing methods and text mining techniques to help analyze networks. Moreover, citation links between articles or journals, cooperation ties between researchers, and co-occurrence interactions between scientific terms were explored using the software. These are the types of analyses that are most closely related with the concept of scientometric analysis, with VOSviewer being frequently used in scientific research [44].

2.4. Phase Four: Synthesis of the Results

Finally, a careful analysis of the publications was conducted to synthetize the results. First, the main topics of information of the publications were identified totaling four main topics. This analysis and resulting groups of publications allowed a structured presentation of information. The state of the art for each of the four main topics was established by a rigorous literature review. The methods for creating digital twins for each publication were also identified. As a result, research gaps, findings, conclusions, and present shortcomings were found for each publication connected to each topic.

3. Results

3.1. Study Characteristics

The evolution of publications per year and the respective types are shown in Figure 2. The number of publications on journal papers increased in 2021 and 2022. Therefore, the topic discussed in this paper is of current and high interest in the scientific community. From the total of 32 publications, four were review papers, which were already presented in the introduction section.

Figure 3 shows the distribution of publications on digital twins for energy efficiency by country. As shown, Italy has published the majority of the studies, accounting for 19.3% of total publications in this research field. Italy is followed by the United Sates with 12.9% of the publications, and by the United Kingdom, Mexico and Australia which each have 9.6% of the publications.

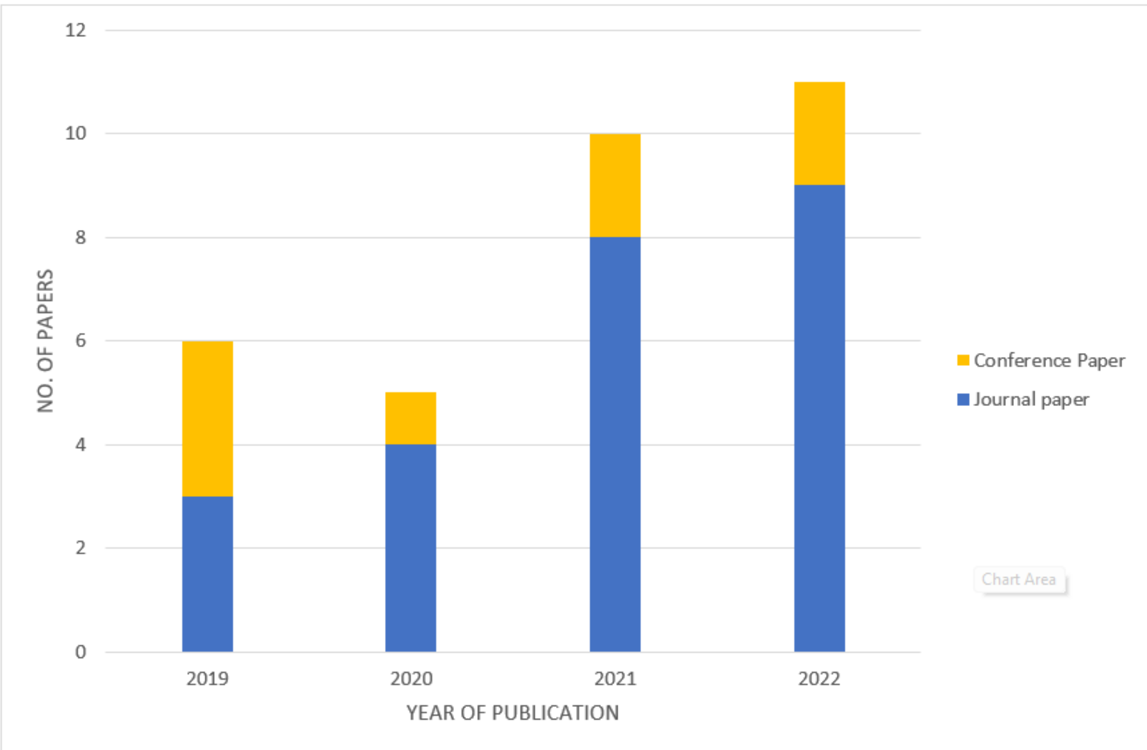

Figure 2. Global yearly publications on digital twins for energy efficiency.

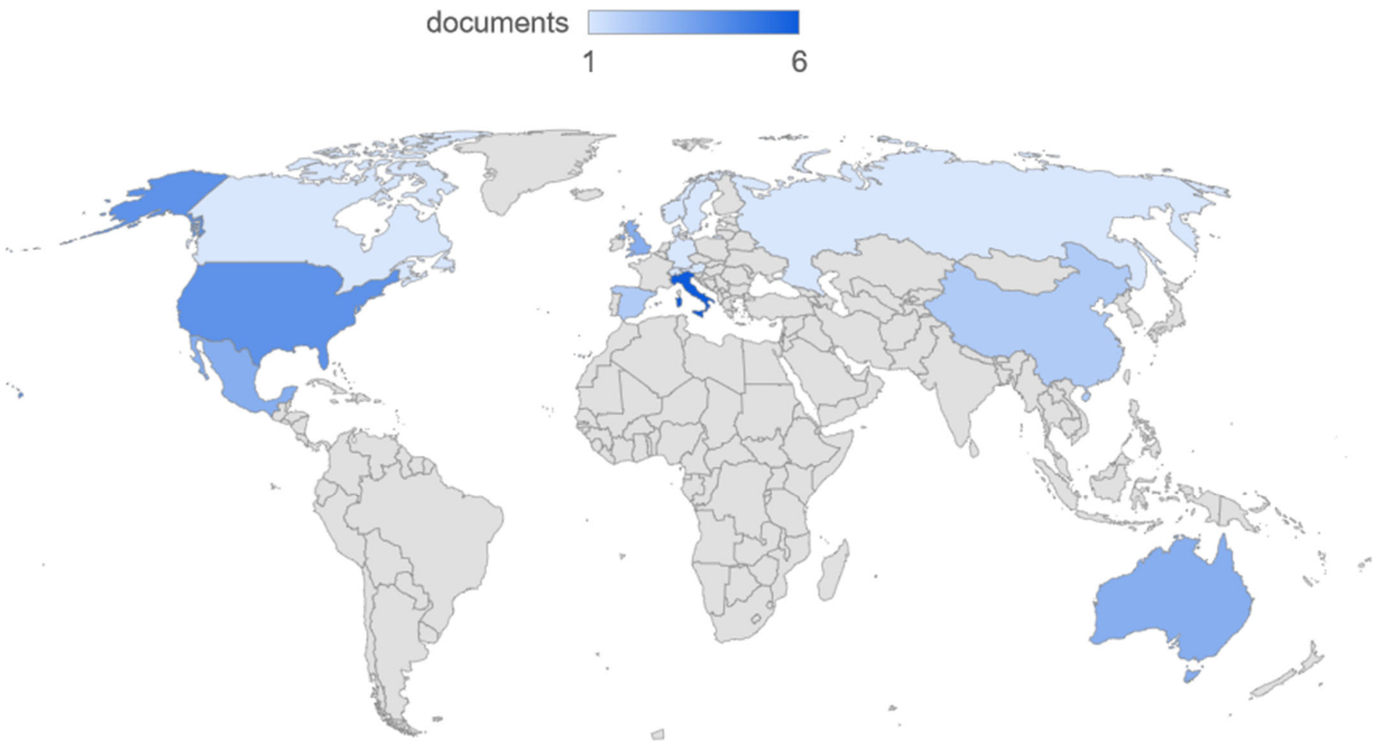

Figure 3. Distribution of publications by country.

The absolute number of citations for each publication was also analyzed. The ten most cited articles are presented in Table 1.

Table 1. Top 10 cited articles.

Order	No. of Cites	Authors	Title	Year	Source Title
1	67	Francisco A., Mohammadi N., Taylor J.E.	Smart City Digital Twin-Enabled Energy Management: Toward Real-Time Urban Building Energy Benchmarking	2020	Journal of Management in Engineering
2	53	Kaewunruen S., Rungskunroch P., Welsh J.	A digital-twin evaluation of Net Zero Energy Building for existing buildings	2019	Sustainability
3	32	Lydon G.P., Caranovic S., Hischier I., Schlueter A.	Coupled simulation of thermally active building systems to support a digital twin	2019	Energy and Buildings
4	30	Deng M., Menassa C.C., Kamat V.R.	From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry	2021	Journal of Information Technology in Construction
5	19	Zaballos A., Briones A., Massa A., Centelles P., Caballero V.	A smart campus' digital twin for sustainable comfort monitoring	2020	Sustainability
6	13	Agostinelli S., Cumo F., Guidi G., Tomazzoli C.	Cyber-physical systems improving building energy management: digital twin and artificial intelligence	2021	Energies
7	11	Blume C., Blume S., Thiede S., Herrmann C.	Data-driven digital twin for technical building services operation in factories: A cooling tower case study	2020	Journal of Manufacturing and Materials Processing
8	10	Kaewunruen S., Sresakoolchai J., Kerinnonta L.	Potential reconstruction design of an existing townhouse in Washington DC for approaching net zero energy building goal	2019	Sustainability
9	9	Teisserenc B., Sepasgozar S.	Adoption of blockchain technology through digital twin in the construction industry 4.0: A PESTELS approach	2021	Building

10	6	Trancossi M., Cannistraro G., Pascoa J.	Thermoelectric and solar heat pump use toward self-sufficient building: The case of a container house	2020	Thermal Science and Engineering Progress

Regarding the source of publications, only the two highest forms of publications, journal articles and conference papers, were considered. A total of 14 journals were identified. *Sustainability* and *Energy and Buildings* were found to be the most frequent sources of publication for this topic. These journals and the conference papers resulted in 32 articles published between 2019 and 2022.

3.2. Keywords Co-Occurrence

For conducting this analysis, initially a normalization of ambiguous keywords was necessary. For example, keywords in plural ("buildings") were adjusted to singular ("building"), to avoid the creation of different clusters of keyword frequency. The keywords with a minimum co-occurrence of two are exhibited in a network map (Figure 4), created using the VOSviewer software after reading through the literature's keywords. The weight of nodes and words in Figure 4 is represented by their size. The weight of a node and a word is proportional to their size. The strength of two nodes is determined by the distance between them. A stronger relationship is revealed by a shorter distance. The line that connects two keywords denotes that they appeared together. The thicker the line, the more likely they are to appear together. A cluster is formed by nodes of the same color.

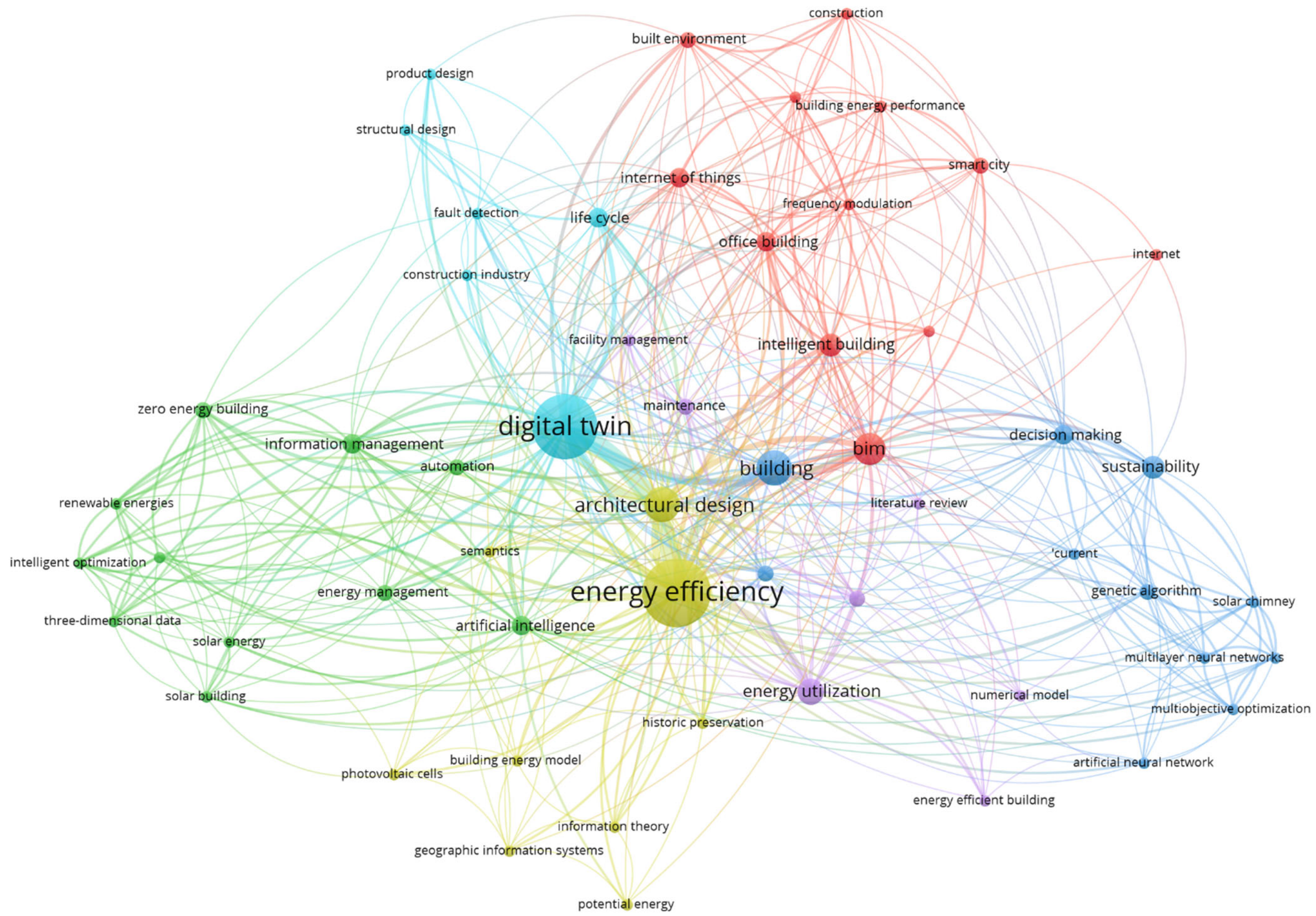

Figure 4. Keyword co-occurrence network.

As expected, the keywords "energy efficiency" and "digital twin" have the highest frequency. The network presented in Figure 4 shows six clusters of keywords. The keywords such as "internet of things" and "intelligent buildings" show strong links with "digital twin", which may indicate that energy efficiency could be improved by the effect that these technologies can have regarding the subjects that these keywords represent. This cluster also shows connection with the keyword "BIM" because BIM is considered the most used technology as a digital representation in a digital twin.

The keyword "energy efficiency" displays strong links with other keywords forming another cluster: "artificial intelligence", "automation", "zero energy buildings" and "information management". As a result, these terms could refer to processes that improve a building's energy efficiency.

Another cluster is formed by the keywords "facility management", "maintenance" and "energy utilization", which reveals studies on DT focused on existing buildings that are working with the energy management of the building stock.

There is also a cluster formed by the keywords "architectural design", "building energy model" and "energy efficiency", which indicates studies on design optimization linked with energy simulation models.

Another cluster includes the links between "genetic algorithms", "artificial neural network" and "decision making". These secondary keywords represent relevant fields of study.

3.3. Publications on Digital Twins for Energy Efficiency

Key topics were found when analyzing the publications. Table 2 lists the publications related to each topic. Although DT for energy efficiency is mainly used during the use and maintenance of a building, some researchers investigated how to optimize the building design through the implementation of DT (Topic 1. Design optimization). During the use and maintenance of a building, two relevant approaches were considered: one is based on a user-centric approach and is focused on the comfort of occupants (Topic 2. Occupants' comfort); and the other is focused on the building performance and its maintenance (Topic 3. Building operation and maintenance). Finally, many researchers focused their studies on analyzing real building energy data collected through DT to simulate and forecast future situations (Topic 4. Energy consumption simulation).

Table 2. Topics identified.

Topic	Publications
Topic 1. Design optimization	[45–52]
Topic 2. Occupants' comfort	[53–59]
Topic 3. Building operation and maintenance	[44,60–63]
Topic 4. Energy consumption simulation	[64–71]

3.3.1. Topic 1—Design Optimization

This topic brings together publications associated with the analysis of optimization of the architectural design to save energy with different approaches. Tariq et al. [45] developed a digital twin model of a solar chimney to maximize the number of air changes per hour. Artificial intelligence methods based on artificial neural network were used in the study to maximize energy efficiency by the calculation of the number of air changes, which also minimized environmental emissions. In another publication, Tariq et al. [46] also presented the study of a digital twin for a solar chimney, having adopted a multi-variable integrated approach to the development of prediction of optimal and sub-optimal outcomes in a variety of external and internal influencing parameters on energy efficiency as well as environmental footprints in various climatic zones. The study correlated the results with various social, economic, energetic, political and environmental problems of the countries. The case study of the solar chimney provided a viable solution to the rising energy consumption in the case studies.

Zhao et al. [48] created a building energy model (BEM) for an existing building using laser scanning to identify and evaluate the feasibility of retrofitting schemes, based on the concept of nearly zero-energy buildings (nZEBs). The aim of the study was to use a scan-to-BIM-based digital twin to improve energy efficiency in buildings using clean energy strategies. DesignBuilder was used to simulate the power generation of solar photovoltaic cells, testing different installation angles. Different renovation typologies were simulated, and the results demonstrated that the building could save 14.1% of energy consumption.

Massafra et al. [47] also worked with the BEM model, but they focused on the proposition of a workflow that integrates Heritage Building Information Modeling (HBIM) and Building Performance Simulation (BPS) tools for the energy improvement in an Italian case study. The study proposed energy intervention measures, computed construction costs and predicted benefits during the intervention in terms of thermal demand. At the end, different intervention combinations were compared indicating the optimal solution for the energy improvement of the building concerning energy, economic and financial issues.

In their study, Lydon et al. [50] focused on the energy domain's modeling technique for supporting the construction of a DT for a multifunctional building element. The thermal design of a heating and cooling system combined with a lightweight roof structure was explored in this research. The design of the concrete roof structure was optimized to produce a low embodied energy construction element that was thermally activated to provide space conditioning from a renewable geothermal source. Also analyzing an HAVC system, Trancossi et al. [49] proposed the design of a revolutionary thermoelectric heating and cooling system for an energy-efficient container house. The goal of this study was to create a thermoelectric heat pump that used the junction box of solar modules and Peltier cells as heat sources, as well as the design and thermodynamic evaluation of such a heat pump. A revolutionary thermoelectric air conditioning system and its integration in a container house were demonstrated in this research.

The goal of the study of Kaewunruen et al. [51] was to define and visualize what an NZEB was, as well as to assess the costs and technical issues of solutions that meet the NZEB criteria and can be implemented in existing buildings. Using a case study, adjustments to the thermal characteristics increased the building's efficiency and resulted in a 6.76% reduction in energy demand. Further analysis simulated the potential energy production that might be derived from the use of solar photovoltaic technology that covered 60% of the roof space, as well as the associated expenses.

Focused on existing buildings, the study of Kaewunruen et al. [52] proposed to focus on elements that can help existing buildings function better and be more sustainable, aiming for achieving NZEB goals. The research focus was an existing townhouse in Washington, DC, to see how the NZEB concept may be used to retrofit or reconstruct the architecture of a structure. The study modeled an existing townhouse to assess the current condition and produce optional models for enhancing energy efficiency. This study presented three models, two solutions, and one alternate option for improving energy efficiency and lowering the carbon footprint.

3.3.2. Topic 2—Occupants' Comfort

This topic embraces publications that are focused on implementing digital twins for energy saving and comfort satisfaction.

Wang et al. [53] used a digital twin in intelligent buildings, using a deep learning approach, with the aim to evaluate residents' environmental satisfaction. The study emphasized the use of Data Fusion Algorithm in Wireless Sensor Networks (WSNs). Although the study focused on satisfaction, the researchers discussed the strategies of energy efficient building digital twins, where BIM is central. The authors mentioned that digital twins in buildings can be regarded as an expression of "BIM+", born to digital descriptions. The study of Zaballos et al. [56] also focused on environmental comfort and the use of wireless sensor networks. Their work proposed a smart campuses concept to investigate the integration of BIM tools with Internet of Things (IoT) for environmental monitoring and emotion detection systems in order to provide insights into the occupants' level of comfort. To improve energy efficiency, the comfort-monitoring system might also be employed to monitor physical characteristics of educational facilities.

Martínez et al. [54] proposed the use of a Smart Readiness Indicator for university buildings as a reference environment for energy efficiency and COVID-19 prevention models. This metric measured a building's (or a building unit's) ability to adapt its overall performance to the needs of its occupants (while simultaneously improving energy efficiency) and to allow energy flexibility in the performance based on various parameters (such as CO_2, temperature, humidity). This article proposes a "measure–analyze–decide and act" methodology to quantify the indicator from a holistic perspective. The DT would act as a virtual support to show available services in a unified and harmonized way to the university community.

Bayer et al. [57] described an approach for validating and calibrating a digital twin of a prefabricated multifunctional radiant heating façade element. Thermal simulation was used to assess two distinct control strategies for minimally invasive radiant heating systems in terms of energy efficiency and variation of the room temperature from a given fixed point. The room temperature was considered a relevant parameter for the characterization of the thermal comfort and therefore for the satisfaction of the tenants. By implementing measured boundary conditions, the validation was carried out by aligning simulation results with measured data. The minimum input flow temperature, the control method, and the thermal behavior can all be multiplied and used in the refurbishment process. Also focused on a room, [55] presented a hybrid methodology that incorporates physics-based and machine learning methodologies to create a digital twin. A case study for a digital twin of a single room is presented, and the preliminary cooling energy comparison between the physical test and the digital twin model was presented. The aim of the study was to create a hybrid digital twin model that uses the best features of physics and machine learning approaches to capture the dynamic behavior of the building's HVAC system for energy efficiency and occupant satisfaction.

Clausen et al. [58] presented a design and implementation of a framework for digital twins for buildings in which the controlled environments are represented as digital entities. In this study, digital twins are parametrized models that are integrated into a generic control algorithm that performs predictive control using data on weather forecasts, current and planned occupancy, as well as the current state of the controlled environment. The technique was shown in a case study of a university building, where a digital twin was utilized to manage heating and ventilation. Their experiments have shown that the suggested system may maintain comfort levels that are comparable to those maintained by existing control strategies performed by a commercial building management system while also allowing for the application of energy-saving strategies.

Zakharov et al. [59] provided a method for automating the management of a heat supply in a smart building with the aim to lower financial costs while maintaining a high level of thermal comfort. The authors analyzed the Internet of Things-based methods for heat supply process automation and proposed a method to get comprehensive data from temperature sensors. The analysis data allowed real-time monitoring of heat changes and the production of appropriate heat management solutions. The authors also created algorithms for classifying rooms based on the temperature mode characteristic. The proposed approach serves as the foundation for an intelligent data analysis system capable of temperature mode modeling and control of the building's heat supply process. The method also provided in-depth analysis and created a digital twin of the case study.

3.3.3. Topic 3—Building Operation and Maintenance

Regarding this topic, the publications are focused on maintenance and using DT to improve energy efficiency in buildings.

Vering et al. [60] used Product Lifecycle Management and Digital Twin Design for HVAC systems, firstly utilizing an energy recovery ventilation (ERV) simulation model in order to achieve high efficiency for the equipment. To forecast physical system behavior, they created a DT prototype of the ERV unit to test functionality and applicability by calibrating the model against physical twin measurement data. The method allows DT to generate predictions for several situations with a view to increasing the system efficiency. The potential of predictive maintenance with various routines regarding air filter replacement for the ventilation system was successfully demonstrated. The use of a DF for HVAC systems analysis increased the lifecycle efficiency in terms of both energy and total costs.

The study of Hosamo et al. [44] also focused on the use of DT for maintenance. They specifically used predictive maintenance strategies to predict the faults in the AHU units. Three aspects were required to implement a practical predictive maintenance program: (i) the collecting of large amounts of data from sensors such as temperature, pressure and air volume, which is critical to understanding how the equipment operates; (ii) a platform for implementing automated fault detection and diagnostics (AFDD) algorithms and determining how to optimize the maintenance system and forecast failures; and (iii) a BIM to avoid the use of traditional data transfer methods (2D models) and depict the findings in a 3D model.

Tan et al. [61] proposed a visualized operation and maintenance platform for a DT lighting system through the combination of computer vision and BIM. The research contributes to the intelligent decision-making on lighting control, which can result in reducing energy consumption and electricity costs.

Torres et al. [63] implemented an artificial neural network as a DT for several existing hotels in Mexico. The DT was then used to model different scenarios for partially replacing energy consuming devices in the hotels. The goal of this research was to obtain the scenario that best combined three indicators: energy use index, equivalent-CO_2-emission index and the energy-cost index. The results aimed to better inform managers in their decision-making processes on the replacement of energy consuming devices in the existing hotels.

Blume et al. [62] outlined a method for developing a data-driven DT for technical building services (TBS) such as cooling towers (CT). In order to enhance operational strategies, this research analyzed the relationships between operational business and technological system. The comparison of various DM algorithms showed that they were all capable of accurately and quickly predicting key operational KPIs like cooling capacity and electricity demand. Accurate cooling capacity predictions offer important insights into the overall system performance and operating dependability, two factors that are essential for the entire production system.

3.3.4. Topic 4—Energy Consumption Simulation

The articles related to this topic are focused on the extensive use of data analysis for energy efficiency.

In the study of Ni et al. [64], a digitization framework for historic buildings is proposed. Advanced techniques such as the Internet of Things (IoT), cloud computing and AI were used to construct DTs for historic buildings. Through analytics of real-time and historical data for specified features, this study employed DT to protect, forecast and optimize building energy efficiency. The DT can accurately portray real-time functioning circumstances and predict future states of historic buildings based on continuously acquired sensing data. With trained AI models, the framework also supports maintenance in order to achieve energy efficiency optimization and long-term preservation.

Also using IoT, AI and machine learning, Agostinelli et al., in the studies [65] and [66], focused on the potential of digital-twin-based methods and approaches for achieving an intelligent optimization and automation system for residential district energy management. The use of integrated dynamic analytic algorithms enabled the evaluation of several energy efficiency intervention scenarios aimed at attaining virtuous energy management of a complex (16 eight-floor buildings) while maintaining current internal comfort and climatic conditions. Using BIM as-built models, IoT and AI, a smart-energy-grid management system was created, resulting in a large as-performed and up-to-date city digital twin. Furthermore, the paper explored the idea that the notion of DT is exceptionally transversal and applicable both to macroscopic and microscopic sizes (from district to apartment). The results of DT-based real-time monitoring can help bridge the gap between building energy performance (as simulated by energy diagnosis) and actual building performance. This was made feasible through data analysis, which enabled more sophisticated energy management techniques to be developed, as well as revealing ineffective user behaviors and rules.

HosseiniHaghighi et al. [68] also focused on an urban scale, developing a city digital twin in CityGML format. The study estimated the district's thermal demand in an urban building energy model (UBEM). Moreover, they evaluated an alternative scenario with the configuration of heat pumps and photovoltaic systems on individual buildings, demonstrating the potential of UBEM for retrofit decision-making, as well as the district's ability to plan net-zero actions. Similarly, Agostinelli et al. [70] adopted an urban scale approach to create a DT of the port area. They used the DT to develop energy efficient procedures for the port's operations. Furthermore, they ran simulations with data from open-source platforms about renewable energy systems (RESs). The aim of this research was to inform the decision-making process to integrate RESs in the port. The port was meant as a starting point to facilitate further investigation and implementation of the DT and the strategies adopted in the surrounding city area. This approach also used building energy models of the buildings integrated in a BIM model for the DT. Also on a city scale, Bass et al. [69] outlined a method for developing urban-scale building energy models, and illustrated the distribution of potential savings from energy efficient building systems. Several corporations, universities and national laboratories are working on urban-scale energy modeling, which will allow for the production of a digital twin of buildings for simulation and optimization of real-world, city-sized areas. A utility's top five use cases and nine monetization scenarios for a digital twin of buildings were reported in this study.

Francisco et al. [67] presented how the results of DT-based real-time monitoring can help bridge the gap between building energy performance (as simulated by energy diagnosis) and actual building performance. This was possible through data analysis, which enables more sophisticated energy management techniques to be developed, as well as revealing ineffective user behaviors and rules. While a building may be efficient overall, it may not be efficient during specific periods, and a building that is inefficient overall may be efficient at specific periods. Fluctuations in energy efficiency over time revealed whether a facility was regularly performing well, consistently underperforming, or whether there was a significant change in performance. This is an important distinction that can help decision makers decide whether to look into operational procedure changes or potential for more capital-intensive improvements. Daily efficiency indicators that were temporally divided and integrated into digital-twin-enabled energy management platforms could transform energy management across a portfolio of buildings.

Pignatta and Alibrandi [71] presented ongoing research to develop a risk-informed Digital Twin (RDT) for the decarbonization of the built environment. A smart building located in Australia was used to demonstrate the framework. The uncertainty quantification module of the DT assesses the probability distribution of the daily energy consumption, while the risk analysis module forecasts the annual lifecycle energy consumption.

4. Discussion

It is relevant to note that most of the studies that focused on design optimization had a retrofit approach considering the entire building or a specific building element to be adapted (e.g., solar chimney, HVAC system). That is, they implemented DT to simulate and inform retrofit scenarios that would be more energy efficient. Only a few studies focused on the initial design. However, even in these cases they were focused on the initial design of certain elements meant to be placed in existing buildings. This approach is consistent with the definitions of DT, which is meat to mimic an existing entity. However, a possible direction which is still to be explored refers to the integration of the original building design as a DT throughout the life cycle of the building. Conceptualizing the design to work as a DT for energy efficiency purposes from the beginning may not only affect the design process but also the final design itself. How it may be affected and potential benefits in terms of energy efficiency are still to be evaluated.

The papers analyzed under topic 2 show that the use of a DT was useful in maintaining or improving appropriate levels of comfort for the occupants while also increasing the energy efficiency of the building or cluster of buildings. In this sense, the automation of some systems through the DT was a key enabler for increasing energy efficiency across the studies in this category. Similarly, IoT and wireless sensor networks seem to play a key role in continually updating the DT, allowing the optimization in energy efficiency while maintaining adequate comfort levels. As shown, most of these publications that consider occupants' comfort focus their studies on university environments. This is probably a reflection of both the convenience of investigating where the research is being conducted and the need of university campuses for more energy efficient solutions. However, equally extensive studies on other types of environments are needed. Such studies may provide insight into the specificities and difficulties faced in in other types of buildings (such as industrial, commercial centers, among others) regarding the interface between occupant comfort and energy efficiency. Challenges faced in other environments may also push the resolution of problems and the optimization of DT processes which could benefit its implementation focused on occupant comfort for any scenario.

The operation and maintenance (O&M) of buildings and infrastructure represents a strategic activity to ensure that they work as intended over time and to lower energy consumption and maintenance costs at building level. The studies presented in topic 3 show the potential of use of DT and predictive maintenance to forecast faults in building equipment and systems (HVAC and MEP systems). This requires a huge collection of data from sensors and methods using AI to automatically detect faults in order to then optimize the building maintenance. The integration of IoT, BIM and AI is becoming more widely used, and DT technology is what O&M will look like in the future. A possible direction in this research line are the challenges posed by the amount of data collection, that is, the creation of intelligent models with this data to provide facility managers the ability to decide and act to improve the operation and maintenance of buildings.

Notably, most of the publications on topic 4 present studies at a macro scale, that is, the development of a DT for an urban or city level. Rather than just allowing them to develop virtual models, DTs enable cities to perform simulations of new policies or infrastructure projects and preview their possible impacts before making decisions in the real world. Future smart cities will be shaped by urban digital twins, but they still have a long way to go. Large data sets that can be analyzed and processed by a variety of sophisticated algorithms and computer models would provide the foundation for these DTs. However, it would call for the use of the cloud as well as the IoT and sensors that gather data on the ground. Another future direction is challenging researchers to create algorithms to evaluate the environmental impact of a city and suggest green components for decarbonization of the built environment. Regarding the methodologies used for creating the DT, the analyzed papers provided different methodologies. Many studies used machine learning (ML) models. Several ML algorithms are available for the modeling step of a DT: supervised, predictive, unsupervised, or descriptive. Within the publications revised, supervised ML algorithms were frequently used. Supervised ML algorithms include regression approaches (e.g., linear, polynomial regression), classification approaches (e.g., support vector machines, decision trees,) or probabilistic algorithms (e.g., ANN, Naive Bayes) [62]. Artificial neural networks (ANN) was identified as the one most frequently applied in the revised literature [44–46,53,62], followed by support vector machines, decision trees [44,59] and Bayesian networks [65,71]. Other researchers utilized a hybrid approach (grey-box models), combining knowledge about the system (white-box models) and statistical information from the data (black-box models) [55].

The majority of the studies reviewed here also adopted BIM as the foundation for the DT, that is, the digital replica of the built asset [44,47–49,53,56]. Within the publications that mentioned the specific software used, Autodesk Revit is the most frequent BIM platform for modeling the DT. Furthermore, it is often integrated with other applications from the same provider such as Green Building Studio, Insight and Dynamo, usually for individual building models [51,52,56]. For those cases which assessed more than one building simultaneously, building performance simulation using BEM models at building level [47,48] and UBEM models at urban level (city) combined with GIS dataset [65,68] were frequent strategies.

The majority of the papers also used IoT devices (e.g., sensors), using smart buildings that track data in real-time, as case studies [54–56,65]. Data were obtained from different kinds of sensors that measure various parameters of interest, such as CO_2, lighting levels, temperature and humidity. Most of the case studies are residential buildings [48,49,52,65], followed by university buildings [56,59,67].

It is important to note that in most of the publications the DT was created for a specific goal. Therefore, the choice of method for its creation is directly linked to the kind of output expected from the DT. Furthermore, the availability of data, tools for data collection and modeling tools also seemed to influence the choice of method.

5. Conclusions and Future Trends

This paper presented an in-depth review of current digital twins' applications in the field of energy efficiency for buildings and, thus, contributes to its body of knowledge. A total of 32 articles published between 2019 and 2022 were identified and reviewed. This review analysis classified the literature into four different topics related to applications of digital twins for building energy efficiency: topic 1. Design optimization; topic 2. Occupants' comfort; topic 3. Building operation and maintenance; and topic 4. Energy consumption simulation. The relatively small number of publications found across the three databases, combined with how recently they were published, demonstrates that the use of digital twins in the field of buildings energy efficiency is still novel. Furthermore, as shown in Section 3, the increase of publications in the last two years demonstrates a recognition of its potential for building energy efficiency. Therefore, it is expected that further topics of application will emerge in the near future as well as further specialization and sub-division of the four topics already identified.

Many different AI methods based on artificial neural networks, algorithms and data analytics were investigated for optimizing building design, improving predictive maintenance and forecasting energy consumption. Through analytics of real-time and historical data, existing studies employ digital twins to protect, forecast and optimize building energy efficiency. The content analysis of this study, specific to DT applications in building energy efficiency, shows that BIM is the starting point of DT platforms which also integrate cloud computing and IoT technologies. This is in line with previous studies that also found most DT applications for the construction industry to be centered around BIM [36]. For the specific application reviewed in this study, we did not find DT to be synonymous to a BIM model as [36] had indicated. Only a few of the studies reviewed here used DT as synonymous to a BIM model.

The research trends demonstrate that there is an increasing interest in implementing DT in the use and maintenance of buildings, and one of the main research interest areas is maintenance management and simulation to improve energy efficiency. Considering that DTs are based on sensors to capture real-time data, developing classification and integration systems and data analysis were found to be the most challenging needs for the future. Future directions of all identified DTs for energy efficiency applications should focus on current gaps such as lack of data integration systems and complex decision-making processes.

The selection of the most suitable sensors to capture data for each application and the development of automatic means to transfer and process data from different databases are needed. Cloud computing and IoT are the basis of this change. Furthermore, data analysis, such as machine learning, allows the creation of algorithms to produce energy prediction models. Future research should also focus on improving these algorithms to make the decision-making processes more efficient, accurate and flexible. Another important research direction refers to improving data visualization for non-experts to facilitate understanding and interpretation of the data analysis, forecasts, etc.

The analyzed publications showed an array of different methods for implementing the DT both for building and city scales. DTs often have a specific purpose and heavily depend on the data and means available for collecting such data. Therefore, it would be relevant for future research to focus on the results yielded by DTs produced through different methods, comparing them. Establishing the potentials and shortcomings of each method specifically for this purpose would help inform future research and DT implementations. Furthermore, there is still a lack of consensus on what can and what cannot be considered a DT [27]. Researchers consider DTs differently. Some researchers do not include exchanging data in real-time between the twins in their studies. In some papers there is no differentiation between DT and BIM. Although not being the goal of this review paper, further analysis is needed to clearly outline what can be considered a DT in the construction industry, and for energy efficiency more specifically.

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