energies

Review

Digital Twin Framework for Built Environment: A Review of Key Enablers

Giuseppe Piras *, Sofia Agostinelli and Francesco Muzi

Department of Astronautics, Electrical and Energy Engineering (DIAEE), Sapienza University of Rome, 00184 Rome, Italy; sofia.agostinelli@uniroma1.it (S.A.); francesco.muzi@uniroma1.it (F.M.)
* Correspondence: giuseppe.piras@uniroma1.it

Abstract: The emergence of Digital Twin (DT) technology presents unique opportunities for society by facilitating real-time data transfer from the physical environment to its digital counterpart. Although progress has been made in various industry sectors such as aerospace, the Architecture, Engineering, Construction, and Operation (AECO) sector still requires further advancements, like the adoption of these technologies over traditional approaches. The use of these technologies should become standard practice rather than an advanced operation. This paper aims to address the existing gap by presenting a comprehensive framework that integrates technologies and concepts derived from purpose-driven case studies and research studies across different industries. The framework is designed to provide best practices for the AECO sector. Moreover, it aims to underscores the potential of DT for optimization through overseeing and digital management of the built environment across the entire life cycle of facilities, encompassing design, construction, operation, and maintenance. It is based on an extensive literature review and presents a holistic approach to outlining the roles of Building Information Modelling (BIM), Geographic Information Systems (GIS), Internet of Things (IoT), and other key enablers within the DT environment. These digital tools facilitating the simultaneous evaluation of associated benefits, such as resource savings and future prospects, like monitoring project sustainability objectives.

Keywords: Digital Twin (DT); virtual model; Building Information Modelling (BIM); Geographic Information System (GIS); Internet of Things (IoT); smart cities; artificial intelligence (AI)

check for updates

Citation: Piras, G.; Agostinelli, S.; Muzi, F. Digital Twin Framework for Built Environment: A Review of Key Enablers. *Energies* **2024**, *17*, 436. https://doi.org/10.3390/en17020436

Academic Editor: Álvaro Gutiérrez

Received: 30 November 2023
Revised: 10 January 2024
Accepted: 11 January 2024
Published: 16 January 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The impact of the built environment, which includes infrastructure, buildings, and urban spaces, on our daily lives cannot be overstated. It is responsible for nearly 40% of global energy consumption and carbon dioxide emissions, making it a crucial area for sustainability efforts (UN Environment, 2018) [1]. To make necessary improvements in sustainability, efficiency, and occupant comfort, building owners, facility managers, and city planners require precise and comprehensive information about the performance of the built environment. To obtain this information, Digital Twin technology can be utilized in order to create a virtual replica of a physical system allowing for real-time monitoring, analysis, and optimization.

The continuous evolution of technology has played a vital role in providing quick access to vast amounts of information, bringing about considerable advancements in several fields, particularly digital technology [2]. With the increasing development of virtual modeling and data collection technology, the Digital Twin (DT) concept has become increasingly feasible as it involves the creation of a digital model of the physical environment that adapts to real-time changes and provides optimal outcomes quickly. Digital Twin (DT) platforms have the capability to improve and advance themselves by utilizing data gathered from installed sensors that update and simulate information from the environment [3]. In the first phase, virtual models of the physical environment are used to create DT platforms, and the gathered physical data are integrated to establish a unified connection with the physical environment, enabling real-time monitoring. Therefore, DT platforms manage and supervise the physical conditions of the environment through their corresponding DT.

In addition, DT platforms offer features that can increase efficiency, prolong lifespan, and lower operational expenses of the targeted physical environment through proactive and predictive monitoring and maintenance tools [4]. Furthermore, the latest mapping technologies utilizing data gathered from the physical environment and remote sensing from Earth Observation (EO) satellites are integrated into the built environment tools within DT platforms [5,6]. While still in their early phases, DT platforms have already demonstrated numerous capabilities in various scientific domains.

A review of published articles on DT platforms has revealed a significant gap in the implementation of DT platforms in the construction sector. Although DT platform applications have been explored in multiple sectors, including construction, the industry has not fully adopted the DT paradigm. This can be attributed to the various stakeholders involved. The goal of this article is to conduct a thematic analysis to provide an up-to-date review of DT platform applications. It will examine the extent of DT implementation in the AECO sector, define the principal concepts and significant enablers, and identify recommendations from other industrial sectors.

Recent studies have highlighted the benefits of implementing DT technology, which includes monitoring facility performance and operation, as well as cost analysis and reliable scenarios for maintenance. Although significant investment is required for launching and developing digital platforms, it can provide a long-term return on investment [6].

Digital platforms offer several benefits, such as effective data management, anomaly detection in maintenance and control stages, and management of different departments. Parrott et al. [7] reported that digital platforms increase quality, reduce warranty, service, and operational costs; introduce new digital products; and create opportunities for capital growth.

The practical advantages of digital platforms in the construction and urban development sector include real-time monitoring of construction progress; updated use of maps and models; appropriate planning for resource support; monitoring safety departments and structure quality; equipment optimization monitoring, supervision, management, and operation of facilities; improved decision-making; and sustainable development of buildings and cities [8].

The construction industry has not fully utilized the advantages of digital platforms yet, but there is hope that it will soon take full advantage of the potential of DT by implementing it as much as possible in the construction industry. Additionally, the growing trend of intelligent building construction and big data can significantly impact the mandatory growth of DT platforms in this industry. Digital platforms have made many advances in other industries, which can show significant benefits. However, compared to other industries, the growth of digital platforms in the construction sector has not been very impressive due to different factors [9].

To fully realize the potential of digital platforms, it is essential to aggregate and utilize vast datasets from diverse sources in an objective manner. The slow growth and development of digital platforms in the construction industry can also be attributed to the nature of the industry, where each project differs from another. The use of different standards in the development of digital platforms can effectively help the growth and development of DT technologies. Therefore, increasing the development of standardization in this sector can significantly help produced valuable digital products.

According to a study by Siemens, another limitation of adopting digital platforms in the construction industry is the lack of defined budgets for developing these platforms in "digital" planning and simulation to reduce costs in the long term [10].

According to several studies conducted in the United States, 89% of IoT platforms will contain some form of Digital Twin capacity by 2025 [11]. As a result of the COVID-19 pandemic, 31% of companies are using Digital Twin systems to improve employee safety, such as using remote asset monitoring systems to reduce the need for in-person monitoring [12]. According to a report by Markets and Markets [13], the global value of the Digital Twin market was estimated at $3.1 billion in 2020 and is expected to reach $48 billion by 2026.

From literature analysis, the absence of a holistic and comprehensive perspective on the implementation of Digital Twins within the built environment, as a definitive reference point, emerges. Consequently, this paper endeavors to bridge this gap by presenting a framework that integrates technologies and concepts derived from purpose-driven case histories and extensive research studies. Through this approach, the paper seeks to make a valuable contribution to the field by establishing a structured framework aligning with the multifaceted requirements of Digital Twin implementation in the built environment and beyond.

Based on the findings obtained from the examination of definitions, key enablers, and successful Digital Twin implementations across various domains, along with the exploration of BIM-GIS integration and IoT and smart cities as pivotal catalysts for the Digital Twin foundation within the built environment domain, this paper presents a proposed conceptual framework for DT developments. The framework aims to facilitate comprehension of essential components and potential system architectures pertinent to the deployment of Digital Twins in the built environment.

The implementation of DT-based systems in the building sector can have significant spill-over effects on society. These include improvements in the efficiency of building projects, reductions in operating costs, the promotion of sustainability, stimulation of technological innovation, improvement of quality of life, and development of technical skills. In summary, implementing decision-tree-based systems in the building sector can lead to significant improvements, contributing to the overall progress of society.

1.1. Definitions and Key Enablers

The concept of "twinning" was initially introduced in the aerospace industry during the NASA Apollo project of 1960 [14]. The project required the spacecraft to communicate with its Earth-bound twin, as if it were on a space mission [15]. Later, Dr. Michael Grieves coined the term "Digital Twin" related to Product Lifecycle Management (PLM) [16].

PLM is an all-encompassing strategy for managing every aspect of a product, and it entails the use of several tools, technologies, and procedures to streamline product development and management. In this context, Kritzinger et al. [17] describe DT as a digital information system that can be employed to simulate and optimize various stages of a product's lifecycle. The various definitions and applications of DT have characterized this idea as a digital model connected to a physical entity using smart devices and a stable real-time communication network.

Different authors have provided diverse definitions to explain the meaning and objectives of DT technologies. Grieves defined DT as an information model that reflects the product's lifecycle management [18] Similarly, other authors have also given their own descriptions of DT. For instance, Rosen et al. [19] defined DT as a combination of physical and virtual spaces that can mirror each other to evaluate physical lifecycle operations. Boschert and Rosen [15] asserted that DT includes all valid physical and functional data of a system, with their definition focusing on data exchange and algorithms controlling physical behavior and virtual models. However, this definition only concentrates on DT data and disregards its components and purpose. Grieves [17], on the other hand, presented DT as a set of virtual information structures in product lifecycle management, with the ability to represent data linked to a possible or actual physical product.

Regarding the engineering design of the physical environment, the objective of DT is to achieve the final product quality using digital design while reducing the gaps between design and implementation.

According to Liu et al. [6], a digital twin is a model of a system that dynamically adapts to changes in the physical environment by using collected data and information to predict future changes. Digital Twin (DT) employs a spectrum of technological methodologies, tools, and internet systems to acquire real-time data from the physical environment, subsequently employed for simulation and virtual modeling purposes. As explained by Madni et al. [20] a DT serves as a virtual representation of the performance, maintenance, and health of a physical environment, continuously updated throughout the system's lifecycle. Liu et al. [21] further suggested that a DT can operate over time to enhance its performance by utilizing the information received from the physical environment.

The emergence of DT platforms has opened new avenues for more precise and accessible functions and services in various fields. The domain of DT platforms can be defined by the interaction principles between the physical and virtual worlds that enable data analysis and system monitoring [4]. This interaction between the physical environment and virtual modeling is greatly facilitated by communication platforms that are enhanced using real-time data and dataset updates. In this context, the Internet of Things (IoT) can be mentioned as a highly dependable communication system that operates on sensors, cloud computing, and data analysis. Therefore, the continuous flow of data and information transferred between the physical and virtual environments is a crucial element of DTs, enabling the platform environment's lifecycle [22].

The Digital Twin (DT) platform possesses the capability to forecast the future state of the physical environment by continuously adapting to operational variations through real-time data collection and information assimilation. Therefore, the DT platform consists of integrating systems from data sources and datasets, supported or formed by embedded sensors, wireless sensor networks, and digitized lifecycle systems and integration with cloud services and data providers [23]. Advancements in sensor design and fabrication make it easy to synchronize the DT platform with collected information from the physical environment. These sensors immediately receive information and enable the virtual model's continuous ability. Based on this, the DT paradigm can be divided into three parts: (a) Physical product; (b) Virtual product; (c) Communication infrastructure and data collection systems. As such, one of the critical aspects of the DT is the connection between "Physical Twin" and "Digital Twin" environments, which involves various approaches and sub-components at each stage (Figure 1).

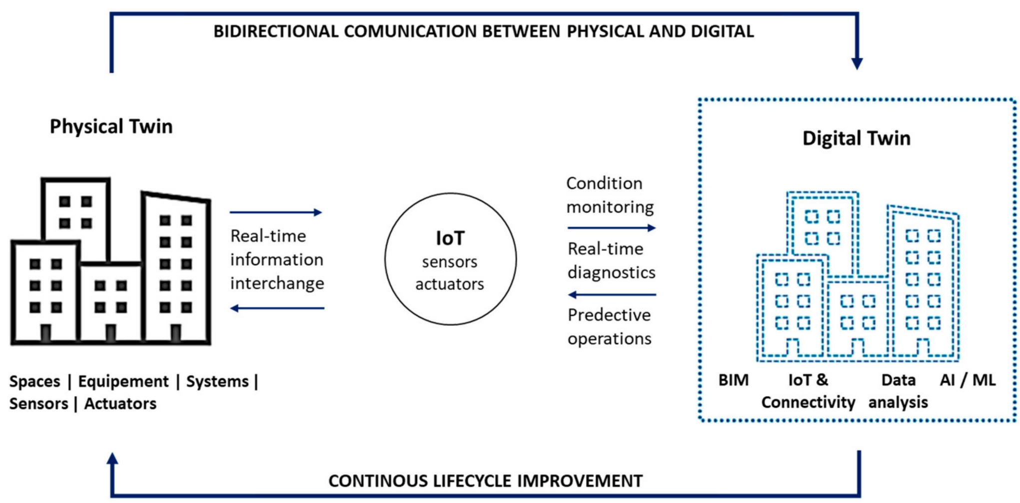


Figure 1. Main Digital Twin components.

1.1.1. Internet of Things (IoT)

The concept of the Internet of Things (IoT) [24] is a key element in the context of DT for the built environment. IoT refers to the interconnected network of physical devices equipped with sensors, actuators, and communication technologies that enable them to collect and exchange data. This interconnection of physical objects provides a fundamental substrate for the creation of dynamic and informed Digital Twins. Objects in the built environment can be enhanced using a variety of advanced devices that enable automation and remote control of a wide range of systems, including temperature, humidity, motion, and more. These sensors provide real-time data that feeds the Digital Twin, enabling an accurate representation of environmental conditions. They can also act autonomously thanks to distributed intelligence [25] provided by embedded algorithms and processing systems. This enables rapid and adaptive response to changing environmental conditions. The IoT provides ubiquitous connectivity, enabling continuous communication between devices. This network of connections helps keep the DT up to date [26], ensuring that information is timely and reliable. L. Sciullo et al. [27] presented research that introduces the Relativistic Digital Twin (RDT) framework. This innovative approach is characterized by the automatic generation of general-purpose DTs for IoT entities, whose adaptability over time is ensured by continuous observation of real-life behavior.

L. Cecere et al. [28] propose an application case where data from IoT sensors fits the big data paradigm [29], which is generally characterized by a significant size that makes it difficult to analyze using traditional methods. In order to extract new information from historical data, deep learning techniques have been employed. These methods demonstrate the ability to intuitively analyze and identify relationships between data that may elude traditional analysis methods.

Data security in the IoT context is a critical issue [30] due to the vast landscape of interconnected devices. Limited device resources present challenges in securing data in transmission, potentially exposing it to threats such as man-in-the-middle attacks or security compromises at the device or network level. Considerations include implementing robust encryption practices, secure identity and access management, and protecting the privacy of sensitive data. Adopting standard protocols, incorporating cybersecurity best practices, and providing ongoing user training are essential approaches to addressing IoT data security challenges. Constant adaptation to evolving threats requires a vigilant and proactive approach to secure IoT operations. A. K. Singh et al. [31] highlight the challenges and issues envisaged in the area of security in the context of the Internet of Things (IoT), with the aim of providing guidance on authentication procedures to ensure the security of IoT services. M. Kiran et al. [32] present the Ownership Transfer Protocol (OTP) to ensure the secure transfer of digital ownership of IoT objects, using Physically Unclonable Function (PUF) and blockchain. This process eliminates the reliance on trusted third parties and supports partial transfer of ownership and is notable for its innovative use of blockchain.

1.1.2. Lighting Systems

Numerous studies have explored methods to reduce energy consumption in lighting technology and its control systems [33]. The incorporation of LED lights has been identified as one such approach, capable of reducing energy consumption by 10–25%. Furthermore, the integration of sensor control technology can reduce lighting energy consumption by over 50%. Juntunen et al. [34] utilized passive infrared (PIR) sensors to intelligently track pedestrian movement and dynamically control lighting devices, resulting in savings of over 60% compared to traditional street lighting systems. Optical sensors may also be implemented to optimize the sensor installation location and adjust brightness, which can potentially reduce energy consumption by 45–61%.

A mathematical model based on a matrix was constructed using a Radial Basis Function (RBF) neural network. The utilization of genetic algorithms facilitated the refinement of sensor allocation by Gao et al. [35]. Van De Meugheuvel et al. [36] proposed a distributed lighting control system that makes use of sensors to adjust lighting levels efficiently in response to ambient lighting. In addition, Wagiman et al. [37] suggested a new technique for optimizing optical sensors by using particle swarm optimization (PSO) algorithms to minimize light and energy consumption. Sun et al. [38] integrated several technologies such as routers, databases, and servers to create a distributed multi-agent framework for multiple sensors. This integration augments the capacity to interact with the environment and bolster intelligent control within lighting systems.

1.1.3. Computer Vision

The technology of computer vision and the tools used for processing and analyzing images can be seen as an emulation of biological vision, and it includes various subsets, such as object detection, scene reconstruction, 3D pose estimation, video tracking, image recovery, and 3D scene modeling. These technologies are extensively employed in everyday life due to significant advancements in computer vision and smart city construction [39]. Various industries have made significant progress in enhancing efficiency, safety, and smartness, particularly within the domain of remote computer vision. This progress is evident in the areas of facial recognition [40], smart locks [41], and entrance and exit control in office buildings [42].

Computer vision has the potential to significantly contribute to energy conservation in buildings, in addition to its various applications. For instance, deep learning techniques have been employed by researchers to detect equipment and heat increase in office buildings [43] and forecast heating energy demand in residential buildings [44]. Moreover, computer vision has a great potential for intelligent lighting systems, as demonstrated in several studies. Zawadzki et al. [44] suggest the use of a microprocessor controller for image analysis and remote control of light beam direction. Carrillo et al. [45] utilized a digital camera to improve the environment's lighting by adapting it to artificial light, providing a better effect on the buyers while also saving energy. Wu et al. [46] presented a method for adaptive adjustment of light brightness using quasi-real calculations of ambient brightness for high dynamic range (HDR) imaging. Motamed et al. [47] conducted research on visual sensors with a high dynamic range to monitor lighting systems, while Liu et al. [6] used infrared image processing for intelligent control of library lighting devices. Finally, Shanmugam et al. [48] employed computer vision and integrated deep learning algorithms for video stream processing to investigate warehouse material transfer in their intelligent lighting control. Computer vision has significantly contributed to many fields, such as calculating ambient light, assessing lighting quality, and controlling intelligent lighting systems, resulting in substantial energy savings.

1.1.4. Building Information Modelling (BIM)

The process of simulating physical models and updating data in multidisciplinary and multiscale domains can be accomplished through digital platforms [48]. To accurately represent real-world information in a virtual environment, these platforms use powerful models. In a study by Yue Pan et al. [49], a digital platform framework for advanced project management was built using BIM and IoT. Similarly, Zhao et al. [50] employed IoT and BIM technology to develop DT platforms for designing intelligent storage systems and managing goods safety. Additionally, Digital Twins have been utilized by researchers to monitor the management of smart urban infrastructures [51]. Digital Twins have also proven useful in the field of damage detection in smart city infrastructures [52]. By identifying damages to the built environment, Digital Twins enable risk-based decisions and reduce environmental stress using smart management approaches [53,54]. BIM and DT technologies have a deep relationship, and BIM adds engineering support to digital platforms. Several researchers have explored the concept of BIM technology in digital platforms and presented case studies [54]. Combining BIM models and IoT has also been beneficial [55], as the models provided by BIM technology utilize different sensors for dynamic collection and integration of data and operations within the BIM environment [56].

BIM models contain real-time building information, enabling the ability to make quick decisions and respond to emergencies. Srinivasan et al. [57] used BIM models to examine the combination of 3D heat transfer analysis results. Additionally, BIM models are utilized for other applications such as monitoring construction facilities [57], emergency evacuation of buildings [58], and developing prefabricated buildings [59].

1.1.5. Systems and Data Integration

Effective collaboration among stakeholders is crucial for the success of construction projects as it enables the use of new and updated data. Outdated or incorrect data can impede both building upkeep and operations, emphasizing the criticality of timely and precise information. Facility management (FM) provides a fitting example of the benefits of using building maintenance systems data, which can save up to 80% of efficient time compared to paper reports or Excel spreadsheets [60]. In contrast, traditional transmission methods can lead to lengthy maintenance services and processes [61]. In facility management, Digital Twin technology has garnered significant attention due to its potential to enhance asset performance, operational efficiency, and reduce maintenance costs. Numerous scientific research studies have supported the benefits of Digital Twin implementation in facility management:

- Predictive maintenance: Digital Twin technology enables facility managers to predict equipment failure, resulting in proactive maintenance scheduling. Digital Twin technology can reduce maintenance costs by up to 40% by predicting maintenance needs and preventing unexpected equipment downtime.
- Improved energy efficiency: Digital Twins can monitor and optimize energy consumption in buildings, which can lead to a 20–30% reduction in energy usage and cost savings, as well as reduced carbon emissions, according to Jamil S. et al. [62].
- Improved occupant comfort: DT technology enables facility managers to enhance occupant comfort by controlling and fine-tuning environmental conditions like temperature, air quality, and lighting. A study by [63] found that the use of Digital Twins in HVAC systems can improve thermal comfort by up to 20%.
- Improved asset management: digital Twin technology can provide facility managers with real-time information on the status and performance of building assets, resulting in increased productivity, reduced costs, and improved asset utilization [64].

In building maintenance operations, BIM models can serve as a source and repository of information alongside other services. Due to their compatibility with various technologies and support for all stakeholders' activities, BIM models can offer robust solutions in a short amount of time during the building's lifespan [65]. Effective integration of these models into digital platforms can help maintain the system's achievements. Therefore, it is crucial to develop techniques that use BIM data combinations according to data specifications (COBie and IFC) to achieve these objectives [66,67].

2. Research Methodology

The research employed a scientometric analysis approach [68], utilizing the Web of Science database, to focus on pertinent keywords: ("digital twin" OR "digital twinning" OR "digital twins") AND ("built environment" OR "AECO"). This methodology aimed to retrieve pertinent sources within the context of the built environment as reported in Table 1. In pursuit of a comprehensive comparison across diverse industries, a similar methodology was adopted for the manufacturing, aerospace, and energy sectors. For each respective sector, the keywords ("digital twin" OR "digital twinning" OR "digital twins") were combined with the appropriate industry-related terms: ("industry" OR "manufacturing"), ("aerospace"), and ("energy").

The developed image (Figure 2) facilitates comprehension of the proposed research methodology. The hierarchical structure visually represents the main concepts related to the research methodology, its application fields, and features, enabling prompt visualization of their interrelationships. The visual representation aids in comprehending the relationship between research methodology and the previously mentioned areas, as well as its relevance in digital contexts. This graphical depiction is especially beneficial as it presents a concise overview of the methodology and its practical usage, clarifying the context in which the research methodology is implemented. Following this comprehensive analysis, a screening phase was conducted. This phase involved a detailed assessment of alignment with the research's objectives and goals, resulting in the identification of 69 studies. As a result, a total of 46 keywords were identified and subsequently categorized into four primary clusters within distinct domains:

1. Modeling and Digitalization.
2. Advanced Technologies.
3. Lifecycle and Sustainability.
4. Information Management.

Table 1. Clusters and keywords from co-occurrence based scientometric analysis.

Cluster	Keywords	Number
1. Modeling and digitalization	3d model; agent; connection; data collection; dataset; digital twin model; digitalization; digitization; machine learning; pointcloud; prediction; scenario; urban environment; virtual environment; virtual representation; visualization;	110
2. Advanced Technologies	Artificial intelligence; augmented reality; blockchain; cloud; communication; digital environment; digital transformation; internet; iot; metaverse; smart city; web;	93
3. Lifecycle and Sustainability	Automation; cyber physical systems; energy; energy consumption; energy efficiency; interoperability; lifecycle; manufacturing; sustainability;	65
4. Information Management	Bim; bim model; building information modeling; digital representation; digital twins; facility management; gis; information modeling; lifecycle;	68

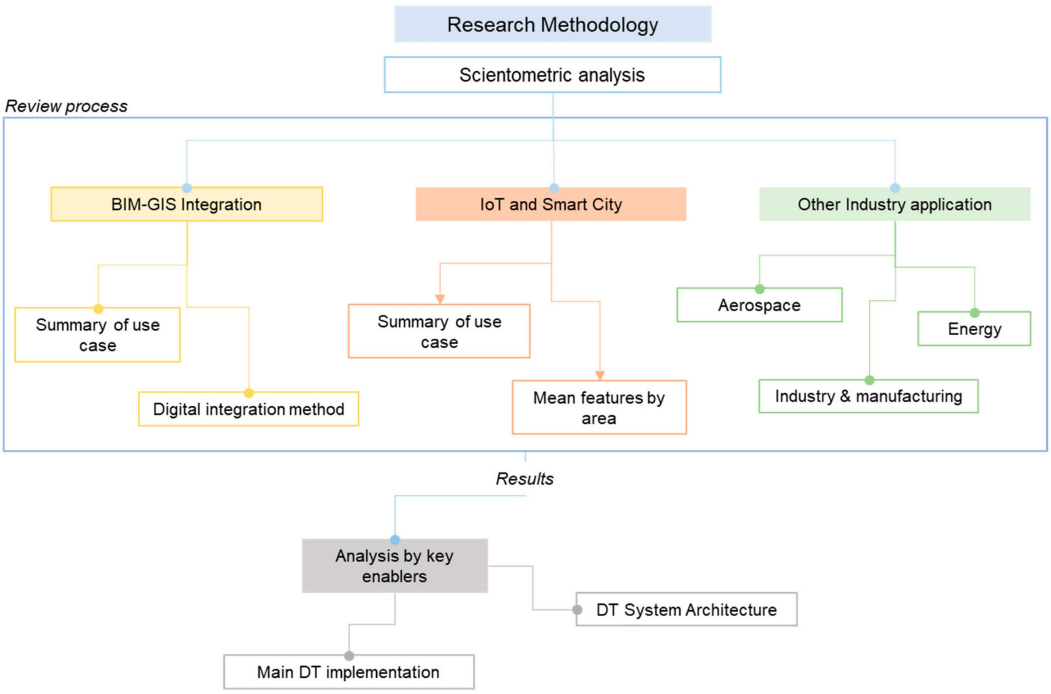
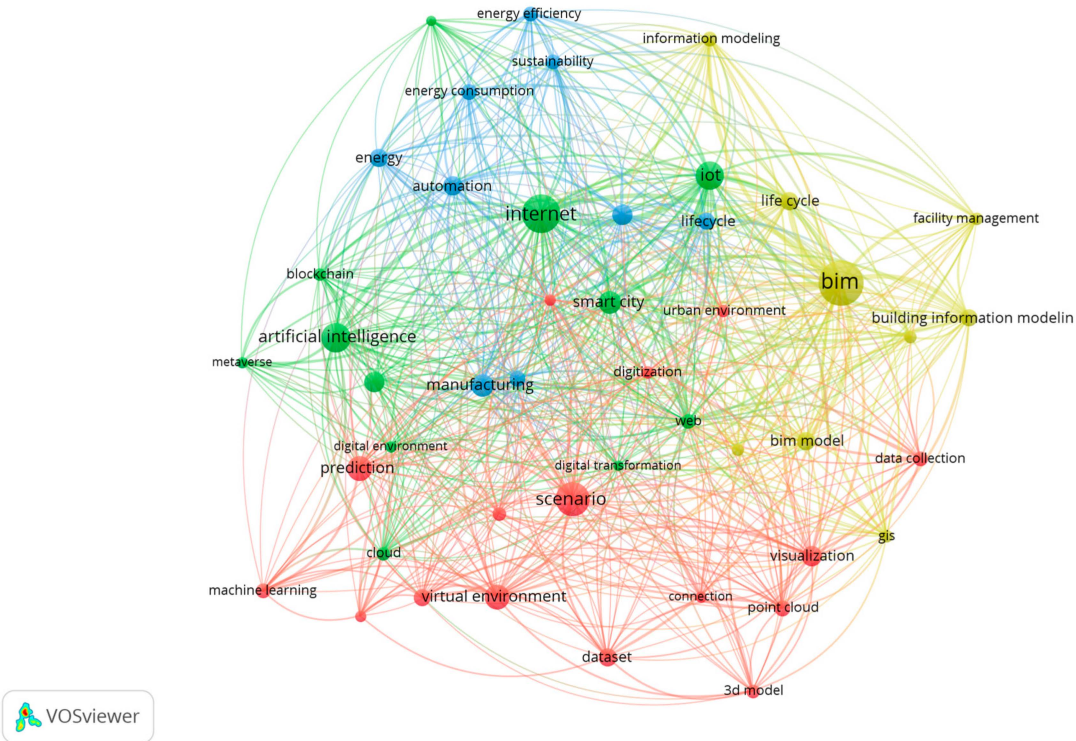


Figure 2. Visual representation of methodology workflow.

The specifics of these clusters are outlined in detail within Table 1, while the graphical representation can be found in Figure 3. This approach allowed for a structured and comprehensive exploration of the interrelated dimensions of the research, enhancing the depth and breadth of insights gained from the study.



1. Modeling and digitalization
2. Enabling technologies
3. Sustainability
4. Information Management

Figure 3. Scientometric analysis conducted using co-occurrence methods. Source: VOSViewer.

Based on the findings of the scientometric analysis (Figure 3) conducted using co-occurrence methods, three sub-areas of investigation have emerged, holding significant relevance and offering essential insights into the potential and challenges of implementing Digital Twins in the built environment:

1. GIS-BIM integration.
2. IoT and Smart cities.
3. Other industries applications.

The details of these subcategories are outlined below, this section offers a more specific understanding of the various sub-areas explored in the study process.

1. GIS-BIM integration

The identified keywords such as "bim", "gis", "3D model," "point cloud," and "urban environment" highlight the spatial dimension of Digital Twins as BIM (Building Information Modeling) and GIS (Geographic Information Systems) integration. According to the definition provided in Figure 1, it is related to the multiscale digital counterpart's domain. While BIM focuses on representing the physical and functional characteristics of a built asset, GIS deals with spatial data analysis and mapping. The integration of BIM and GIS, often referred to as BIM-GIS integration, is a logical step in enhancing the understanding of built assets' spatial relationships and dynamics. Investigating the application of Digital Twins within this integration addresses how real-time data from physical assets can be merged with spatial data, creating a holistic digital representation that facilitates improved decision-making, maintenance, and asset management.

2. IoT and Smart cities

The identified enabling technology keywords like "smart city", "internet of things (IoT)", "augmented reality", "communication", and "data collection" emphasize the role of advanced technology in shaping urban environments. According to the definition provided in Figure 1, IoT and smart cities represent the enablers for communication between physical and digital counterparts. Smart cities represent a burgeoning field wherein urban infrastructure is equipped with advanced technologies to enhance the quality of life for residents and optimize resource utilization. Digital twins have immense potential in this domain, as they allow for a comprehensive simulation of the entire urban environment, incorporating various interconnected systems, such as transportation, energy, water, and waste management. Investigating the application of Digital Twins within smart cities delves into how these virtual representations can aid in urban planning, predictive analysis, resource optimization, and efficient governance.

3. Other industries applications

The identified sustainability-related keywords like "energy consumption", "lifecycle", and "automation" underscore the relevance of other industries applications such as manufacturing and energy in terms of resource efficiency and long-term viability.

As these industries have already embraced Digital Twins for optimizing operations, predictive maintenance, and resource efficiency, the literature review seeks to uncover transferable strategies and lessons that can be adapted to the built environment. As a result, the integration of spatial data with BIM, the evolution of urban spaces into smart cities, and the lessons from successful Digital Twin implementations in diverse industries were identified as primary areas of investigation to achieve a comprehensive understanding.

2.1. GIS-BIM Integration

The management of cities and districts is highly dependent on the use of GIS software layers [69]. BIM models can offer crucial data and layers that are indispensable for infrastructure planning and construction procedures. The integration of GIS software and BIM models is a fundamental requirement for software function integration, including co-ordinate systems, semantic standards, data formats, and other parameters. To enhance the performance of models, several researchers have focused on maximizing their integration. Integrating GIS software and BIM models can save time and allow for more precise monitoring of construction and post-construction processes. Numerous studies have demonstrated the successful utilization of GIS software and BIM model integration for developing and visualizing a range of functions [70,71].

The availability of updated information models is essential to retrieve information and obtain a comprehensive view of different stages of urban construction. Such information can assist urban planners in estimating and analyzing urban sustainability more scientifically and accurately. The support of GIS and BIM technologies is crucial in this regard, and their practical development is necessary to understand, recognize, develop, and improve urban laws on a large scale. The development of these technologies and integration of GIS and BIM have provided a more scientific and practical approach to urban planning [72]. Prior studies have shown how to extract information from BIM and 3D urban models to urban information models [73].

GIS and BIM have been instrumental in effectively overseeing urban data. The creation of the City Information Models (CIM) registry database is crucial for the development and expansion of urban information [73,74]. Integrating GIS and BIM technologies with urban registry management can help increase and expand the standardization of the BIM modeling process and unify the information data formats used to facilitate it [70,75].

A Digital Twin system architecture has been proposed to merge Building Information Modeling (BIM) and Geographic Information System (GIS) data as well as relevant static and operational data associated with assets. The ultimate aim of this proposal is to facilitate building management. The system's layout is displayed in Figure 4. A summary of the literature review based on main objectives is presented in Table 2.

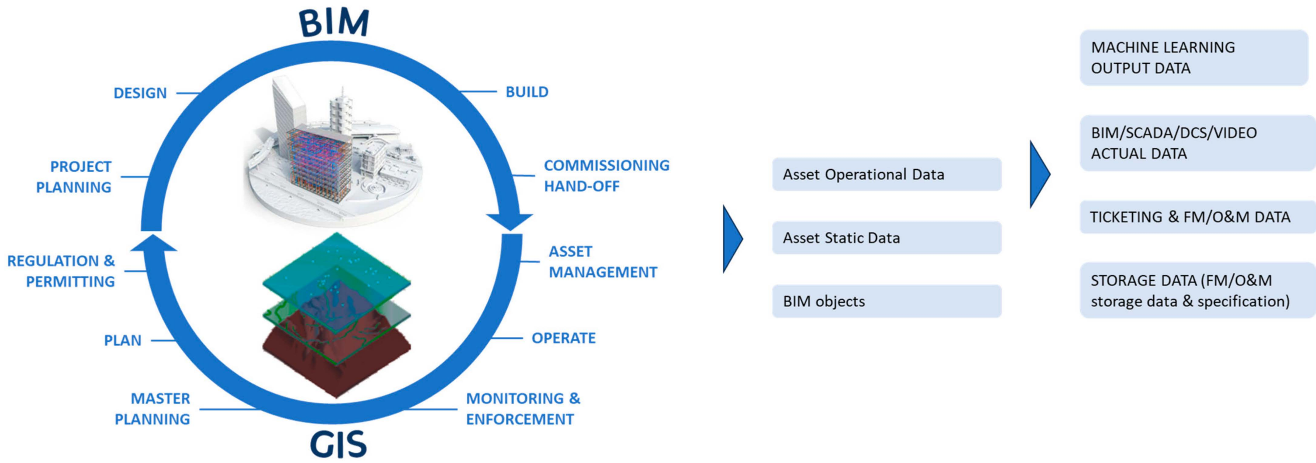


Figure 4. Integrating BIM and GIS for multi-scale Digital Twins.

Table 2. Review summary on BIM-GIS integration use cases.

Objective	Summary	Reference
Infrastructure Design	BIM models provide essential layers and data for infrastructure design and construction, while GIS software is integral for managing cities and districts. The seamless integration of these technologies is fundamental, ensuring coordinated functions, semantic standards, data formats, and other crucial parameters.	[69]
Urban Sustainability Analysis	Updated information models are pivotal for understanding various stages of urban construction. The integration of GIS and BIM is essential for accurately estimating and analyzing urban sustainability. This combination provides a more scientific and practical approach to urban planning, enabling the development and improvement of urban laws on a larger scale.	[72,76]
Urban Registry and City Information Models (CIM)	The synergy between GIS and BIM is instrumental in managing urban information effectively. The creation of the City Information Model (CIM) registry databases is vital for urban information expansion and standardization. Integrating these technologies further facilitates the standardization of the BIM modeling process and unifies information data formats.	[70,73–75]
Building Management	The proposed Digital Twin system architecture involves combining BIM and GIS data with asset static and operational data for building management. This integration has diverse benefits, including energy consumption reduction, optimized construction sites, and improved architectural designs. Ongoing research explores integrating GIS software and BIM model technology across sectors like water projects, tunnels, and bridges, indicating its broad applicability.	[77–79]

2.2. IoT and Smart Cities

Advanced technologies are utilized for efficient and timely analysis and integration of crucial information systems in urban areas [80] to facilitate data-driven decision making in various domains like environmental management, public safety, and city services [81]. Digital platforms have many potential applications in urban planning for immediate, medium-term, and long-term improvement of people's quality of life. One such application is the use of a Digital Twin (DT) platform for water supply management in Carson, Nevada that can increase water efficiency and prevent wastage [82].

Virtual Singapore is another notable project in this field that integrates 3D maps and urban models into one platform, providing detailed information on building materials, texture, and facility components. This platform is instrumental in enhancing decision making in managing resources and responding to emergencies, enabling citizens, businesses, and research communities to test new ideas [82].

The city of Amaravati, located in India, is a noteworthy project in this field. A DT platform is being developed covering various facilities, such as metro networks, main roads, hospitals, schools, universities, and buildings [83,84]. Similarly, the Australian government has launched a project to create a DT platform near Melbourne that visualizes real-time data on public transport, building sectors, and traffic analysis and forecasts electricity and water consumption [85].

Moreover, digital platforms can be utilized for emergency response management during disasters [54,86]. For example, White et al. [87] state that river level data can be used to predict flooding and warning citizens about possible flooding can help minimize the damages. Historical information about flooding in smart cities can be used for long-term prevention of future flooding. The extensive use of DT platforms can change people's perspectives on cities and living spaces, providing ample opportunities for urban designers, architects, engineers, builders, property owners, and citizens to analyze the city in various scenarios [87]. Thus, with the participation of all stakeholders, cities can become more democratic [88]. These outcomes collectively underline the significance of fostering innovation, sustainability, and efficient resource utilization in modern urban environments as shown and summarized in Table 3.

Table 3. Review summary on Smart cities use cases.

Objective	Summary	Reference
Efficient Data-Driven Decision-Making	The integration of advanced technologies within urban areas is facilitating efficient and data-driven decision making across domains such as environmental management, public safety, and city services. This intersection empowers cities to address challenges more effectively and enhance overall operational efficiency.	[80,81]
Innovative Urban Planning	Digital platforms are ushering in a new era of urban planning by offering immediate, medium-term, and long-term improvements in the quality of life for city residents. The utilization of Digital Twin platforms for specific purposes, like water supply management in Carson, Nevada, underscores their potential to optimize resource utilization and minimize waste.	[82]
Enhanced Resource Management	The Virtual Singapore project showcases the potential for Digital Twins to enhance resource management. By integrating 3D maps and urban models into a unified platform, this initiative provides detailed insights into building components, textures, and materials. This approach empowers decision makers to manage resources more effectively and respond swiftly to emergencies, while also providing an environment for innovation and testing.	[89]
Transformative Urban Infrastructure Projects	Major urban infrastructure projects, like the Amaravati development in India, highlight the transformative potential of Digital Twin platforms. Such projects, which encompass diverse facilities like metro networks, roads, hospitals, and educational institutions, showcase the significance of Digital Twins in orchestrating large-scale urban transformations.	[83,84]
Real-Time Data Visualization and Forecasting	The initiatives launched by the Australian government near Melbourne exemplify the practical applications of digital twins in real-time data visualization and forecasting. By providing insights into public transport, building sectors, traffic patterns, and resource consumption, these platforms offer a holistic understanding of urban dynamics.	[85]
Disaster Preparedness and Long-Term Urban Planning	The integration of digital platforms is crucial in emergency response management during disasters. Through predictive analysis and historical data utilization, these platforms assist in flood prediction, minimizing damage and enabling long-term urban planning for disaster prevention.	[90]
Empowering Stakeholders and Fostering Innovation	The extensive use of digital twin platforms empowers various stakeholders, from urban designers and architects to citizens and property owners, to analyze cities in diverse scenarios. This homogenized of insights fosters innovation, collaboration, and a more comprehensive approach to urban development.	[87,88]

Based on the insights arising from the literature review, Table 4 provides a comprehensive overview of the primary attributes and essential components for the successful realization of BIM-GIS integration, as well as for the efficient acquisition and management of data within the context of IoT and smart cities towards intelligent urban environments.

Table 4. Main characteristics of Digital Twins were reported in each area by different studies.

Aim and Characteristics	Year	Reference
BIM-GIS Integration		
Application integrations	2022	[3]
Ontology-based data integration	2022	[91]
BIM, GIS, and IoT collaboration	2022	[92]
Data intersection from systems	2021	[93]
Geos-spatial management through parametric modelling and visual programming	2021	[94]
IFC common geo-referencing approach	2021	[95]
Linking GIS and BIM local coordinates	2020	[96]
Bidirectional transformation methods and data aggregation	2020	[80]
IoT and Smart Cities		
Integrated energy systems	2022	[90]
Integration of AI and IoT	2022	[42]
Big Data Analysis on IoT data	2022	[97]
Urban Facility Management	2021	[98]
Smart cities monitoring	2021	[99]

2.3. Other Industries Applications

The continuous progress of technology has paved the way for the integration of DT platforms in various industrial and commercial sectors. These platforms can offer numerous benefits to society, particularly in industrial settings. For instance, DT platforms can create a virtual replica of the actual industrial environment in real-time, allowing for better and more precise monitoring of the final products [100]. To further understand the viability of DT platforms in different industries and showcase their accomplishments, several industrial sectors with significant growth in DT platform development and design have been analyzed. This comparison can aid in assessing the potential application of DT platforms in different industries.

2.3.1. Aerospace

In the US Air Force Research Laboratory, the aerospace industry is utilizing digital platforms to create a precise flight model. This virtual model's data is combined with the data from the physical models to produce highly accurate predictions [7]. Using digital platforms can be helpful in predicting the structural life re-engineering process of an aircraft [101]. Design systems and components manufacturing for aerospace and defense organizations have been implemented with a dedicated Digital Twin approach for test equipment. Moreover, Digital Twin platforms can be used for damage detection in aircraft structural health management, assessing and updating the latest damage status and flight status in real-time [102]. In the aerospace industry, Digital Twin platforms are currently being used in various stages of product and service delivery and maintenance.

2.3.2. Industry and Manufacturing

The automotive industry, which produces cars in various models and designs, requires advanced capabilities to ensure the quality of final products. In recent years, there has been significant growth in car design technology, with more cars moving towards automatic control systems. Lane monitoring systems, hands-free driving, and alarm sensors that detect objects in proximity are some examples of automatic systems used in designing new cars [103]. In the near future, DT's digital platforms can play an important role in the success of autonomous vehicles. The first step is to design a digital version of the car, which is then analyzed using data obtained from actual test drives in simulation models to determine how the car will perform before designing. The simulation uses data such as aerodynamic data, engine specifications, body design, and materials to be used. The use of digital technology in this process can help the automobile industry grow even further. With the progress of the Internet of Things, cloud computing, and artificial intelligence, more manufacturing industries are expected to benefit from intelligent technologies in their production processes [95]. Roy et al. [104] have reviewed the evolution of the manufacturing industry after the industrial revolution, examining the different stages and discussing their integration. Digital platforms with real-time data management enable intelligent production in industries, leading to more opportunities for automated data collection and optimization. Digital Twin platforms have the potential to enhance supply chain effectiveness, optimize energy usage, and enhance the steps involved in product assembly. They can also be used for monitoring and control in production stages and have other advantages, such as multi-objective optimization and machine simulation and monitoring [105].

2.3.3. Energy

In the present era, there is a noticeable rise in the number of newly constructed energy farms being established and operated to diminish air pollution and combat global warming. The integration of DT technology in the energy sector has multiple advantages, which include enhanced efficiency, decreased expenses, and improved safety measures. One of the significant benefits of DT is its capability to simulate real-life situations, enabling energy firms to optimize their activities and minimize the likelihood of costly downtime. Yu et al. (2020) [106] examined the use of DT technology in the maintenance of power plants. The study found that the deployment of a DT system in a power plant led to a reduction in unexpected downtime, increased safety measures, and improved efficiency. Furthermore, the DT system provided valuable insights into the plant's operation, enabling the maintenance teams to recognize potential issues before they arose.

According to Bortolini research (2021) [107], the use of digital technologies (DTs) can optimize energy systems and improve their efficiency, resulting in reduced energy consumption. DTs can monitor and manage renewable energy sources, such as wind turbines and solar panels, improving their performance and reducing maintenance costs. To meet the growing demand for electricity, clean energy farms, including wind and wave farms, are being installed and operated in offshore areas worldwide. Remote digital platforms that are affected by weather conditions such as wind, waves, water level, or temperature can reduce the operation and maintenance costs of marine turbines and wave converters by up to 25% [108].

In this industry, developing digital platform technology is crucial. These platforms can help facility management and improve the performance of built projects by monitoring and controlling their health status in real-time. In order to make necessary improvements in sustainability, efficiency, and occupant comfort, building owners, facility managers, and city planners require precise and comprehensive information about the performance of the built environment [2]. To obtain this information, Digital Twin technology can be utilized, which creates a virtual replica of a physical system and allows for real-time monitoring, analysis, and optimization. The continuous evolution of technology has played a vital role in providing quick access to vast amounts of information, bringing about considerable advancements in several fields, particularly digital technology [2]. With the increasing development of virtual modeling and data collection technology, the Digital Twin (DT) concept has become increasingly feasible. DT technology involves the creation of a digital model of the physical environment that adapts to real-time changes and provides optimal outcomes quickly.

DT platforms can improve their performance by using data from installed sensors that update and simulate information from the surrounding environment. This enables the platforms to refine their performance over time. The Digital Twin turbine displays all the data needed to determine the physical turbines' performance based on wind power and turbine engine temperature, and sensors connected to the turbines display the data virtually on the platform. A software application for monitoring and predicting turbine and wave converter temperatures could be developed and utilized in the subsequent phase. The outcomes underscore how Digital Twin platforms are transforming various industries by facilitating accurate predictions, optimizing operations, enhancing decision making, and improving overall efficiency. The application of Digital Twins in aerospace, manufacturing, and energy sectors showcases the potential of these platforms to drive innovation and transformative change across different domains (Table 5).

Table 5. Review summary on aerospace, industry, manufacturing, and energy use cases.

Objective	Summary	Reference
Aerospace	Digital Twin platforms are making substantial contributions to the aerospace industry. They enable the creation of precise flight models by combining virtual and physical model data, resulting in highly accurate predictions. These platforms aid in predicting aircraft structural life re-engineering processes and have been successfully used for developing dedicated Digital Twin approaches in test equipment.	[101,102,109,110]
Industry and Manufacturing	In the automotive industry, Digital Twin platforms are playing a pivotal role in the advancement of self-driving cars. These platforms facilitate the design and analysis of cars through simulation models, ensuring performance evaluation before actual manufacturing. Additionally, Digital Twins are contributing to the evolution of Industry 4.0, enabling intelligent production processes, supply chain optimization, energy consumption reduction, and enhanced product assembly.	[103,111]
Energy	The energy sector is witnessing the integration of Digital Twin technology to enhance efficiency, reduce expenses, and improve safety. These platforms simulate real-life scenarios, optimizing energy operations and minimizing downtime. They find application in power plant maintenance, monitoring renewable energy sources, and managing energy systems. Digital twins play a crucial role in enhancing facility management, improving performance, and optimizing energy consumption in built environments.	[107,108,112–116]

Based on the information gained from the literature review, Table 6 presents a thorough analysis of the key features and critical elements required for the effective implementation of digital twins with a cross-domain perspective encompassing aerospace, industry, manufacturing, and energy applications.

Table 6. Various studies in different fields have reported the main characteristics of digital twins.

Aim and Characteristics	Year	Reference
Aerospace		
Quality management in assembly process	2022	[117]
Information management	2022	[118]
Geometrical variation prediction	2022	[119]
Multi-input loads monitoring	2022	[120]
AR-based Learning Speed and Task Performance.	2021	[121]
Multi-dimensional machining process data	2021	[122]
Condition Based Maintenance	2021	[123]
Modelling simulations	2020	[103]
Industry and Manufacturing		
Model-driven engineering	2021	[124]
DTs and CPS	2019	[125]
Production control optimization	2019	[126]
Real-time feedback from virtual to real space	2021	[51]
Planning and commissioning optimization	2021	[127]
Smart Manufacturing System early detection	2021	[108]
Energy		
DT-based energy optimization solutions	2019	[128]
Distributed real-time process data	2017	[129]
Performance predictions	2020	[130]
Continuous tracking and simulation	2020	[131]
Hybrid modelling performance monitoring method	2020	[114]

3. Results: Digital Twin Framework for Built Environment

According to the literature review, Digital Twins for the built environment can be composed of multiscale modelling such as BIM-GIS-integrated information models, real-time data sources, and digital platforms. As such, below are some DT key elements and system architecture proposed with reference to the management of built assets during design, construction, delivery, operation, maintenance, renewal, and end-of-life stages (Table 7).

Table 7. Key outcomes of DT implementation in the built environment lifecycle.

Lifecycle Stage	Objective
Design	Model, simulate, and conduct what-if scenarios. Improve and optimize design. Environmental impacts analysis. Individual asset scale, district, or city level analysis. Design informed by data, information, and connected ecosystems. Improve the built environment's operational efficiency (traffic flow, occupancy, energy, etc.).
Construction	Site-based process enhancement (sensors, drones, and laser scanning). Supply chain allowing real-time inventory tracking. Prefabrication and industrialised construction. Benefits in production management, work performance, health, safety, and wellbeing of workers, materials, and equipment tracking. Streamline the management of data and information during construction.
Operation and maintenance	Predictive maintenance (monitoring of health of building systems and equipment in real-time, enabling predictive maintenance and reducing downtime and repair costs); Improved energy efficiency optimizing building systems and operations. Better asset management (track the location, condition, and performance of building assets); Enhanced safety and security (simulation of emergency scenarios, identification of potential safety and security risks, and proactive measures); Reduced operational costs (identification of inefficiencies and areas of waste). Improved occupant experience (tracking occupant behaviour); Increased sustainability (track and reduce the environmental impact of buildings).
Decommissioning	Planning and executing the decommissioning process safely and efficiently. Simulate and optimize different decommissioning scenarios and identify potential risks. Reducing the potential for unexpected delays or operational complications. Facilitate collaboration and communication between different stakeholders. Progress tracking and monitoring. Improved sustainability and resource efficiency.

3.1. Key Elements

Virtual representation: refers to a digital copy of the construction elements and processes under consideration (ISO 23387 [132]). This digital representation comprises a series of interconnected digital assets, such as computer-aided design (CAD) models, building information models (BIM), geographic information systems (GIS), as well as images, videos, point clouds, documents, and spreadsheets to capture the as-built construction condition. Additionally, virtual representation is supported by data coming from the construction phase including information related to products, systems, materials, elements, entities, processes, work performances, and more. The utilization of digital resources and supportive data is aimed at managing past, present, and future potential statuses of assets from the design stage to the end-of-life or decommissioning stage. Redundant data and information are continuously updated, overwritten, or archived as appropriate. This data can be employed to enhance the entire comprehension of the asset or to plan out particular scenarios.

Entities and processes in the real world: Can be categorized into three levels—(I) Construction elements such as products, systems, spaces, or components; (II) Built assets such as bridges, industrial plants, or buildings; (III) Asset portfolios such as, highway networks, wind farms or architectural structures. The physical environment related to the entire lifecycle of entities is also relevant as DTs are driven by purposes, and driving the development of the DT and helping DT developers define the system architecture and technical specifications according to the scope and the asset's lifecycle phase is essential, (e.g., pre-design, design, or operation).

Synchronization: The connection between virtual and real-world entities which is critical and sets DTs apart from other digital models as it enables a loop between the virtual and physical worlds for management, forecasting, optimization, and simulation processes. Synchronization allows one-way connections with sensors providing data on real-world entity performance as well as bidirectional flows with control systems to actuators with or without human intervention. It also plays a relevant role in the design, development, distribution, and use of DTs, which need to be regularly updated. The synchronization mechanism is also relevant in creating DT connected ecosystems linking other external data sources such as local weather, environmental, and economic data.

Frequency of synchronization: Determines the timing of synchronization between virtual and physical entities as the digital asset needs to represent the actual state of connected assets and processes. Frequency synchronizations is related to the DT use case, available resources, real-world assets type, and real-time data acquisition methods. Regular updates are necessary to prevent the virtual representation from becoming obsolete and limiting the usefulness of the Digital Twin. Without proper monitoring and maintenance of synchronization frequency, confidence in the DT's ability to meet requirements and provide benefits will decrease.

Fidelity: Pertains to the precision and accuracy of the virtual representation and the synchronization mechanisms used. It is also an indicator of the data governance and information management framework that ensures accurate data collection, tracking, and maintenance for the model. The level of fidelity varies based on the intended use of the DT. The degree of fidelity is driven by the granularity of the synchronized information. For instance, some applications may only require time-series data on a building's overall energy consumption, while others may need data on specific equipment, systems, and devices on each floor of the same building. Just like frequency, if the data source is not accurately maintained, it impacts the trustworthiness of the DT. In the context of the built environment industry, frequency and fidelity pertain to the amount of effort needed to keep the virtual representation current and accurate.

The development and administration of a Digital Twin model for Built Environment Management requires the integration of numerous linked elements that form a Digital Twin platform.

3.2. System Architecture

According to the selected DT key elements, the system architecture for a typical Digital Twin system for Built Environment Management is proposed below.

Digital Twin Model: The core component of the system, consisting of mathematical models that simulate the physical behavior of the real-world system. These models can be based on first principles, empirical data, or a combination of both, and can represent various aspects of the built environment, such as energy consumption, indoor air quality, and occupant behavior [133] which can be updated in real-time based on data collected from various sensors and IoT devices.

Data Acquisition and Integration: Another critical component of the Digital Twin system, responsible for collecting data from sensors, IoT devices, and Building Management Systems (BMS). This data is then processed and integrated into the Digital Twin Model to provide a more accurate representation of the real-world system.

Data Analytics and Machine Learning techniques: Used to analyze the data and extract valuable insights, such as energy consumption patterns, equipment performance, and occupant behavior [134]. This component also includes data pre-processing and filtering algorithms to ensure that the data is accurate and reliable. The Data Analytics and Machine Learning component processes the data collected by the Data Acquisition and

Integration component. This element employs various data analytics and machine learning techniques to extract meaningful insights from data. These insights can be used to optimize the performance of the physical system, predict maintenance requirements, and identify anomalies or faults.

Visualization and User Interface: Provide a user-friendly interface for interacting with the Digital Twin system. This component enables users to view and analyze the data collected from the real-world system and make informed decisions regarding optimization and maintenance. The interface can be in the form of a web application, dashboard, or augmented reality (AR) visualization [135].

Communication and Interoperability: Enable the Digital Twin system to communicate with external systems and platforms, such as BIM (Building Information Modeling) software, GIS (Geographic Information System), and energy management systems. This component facilitates data exchange and interoperability, allowing for more comprehensive and accurate analysis and optimization [134]. A conceptual representation of the proposed Digital Twin framework for a building asset portfolio is displayed in Figure 5, which demonstrates main components and data aggregation from multiple sources.

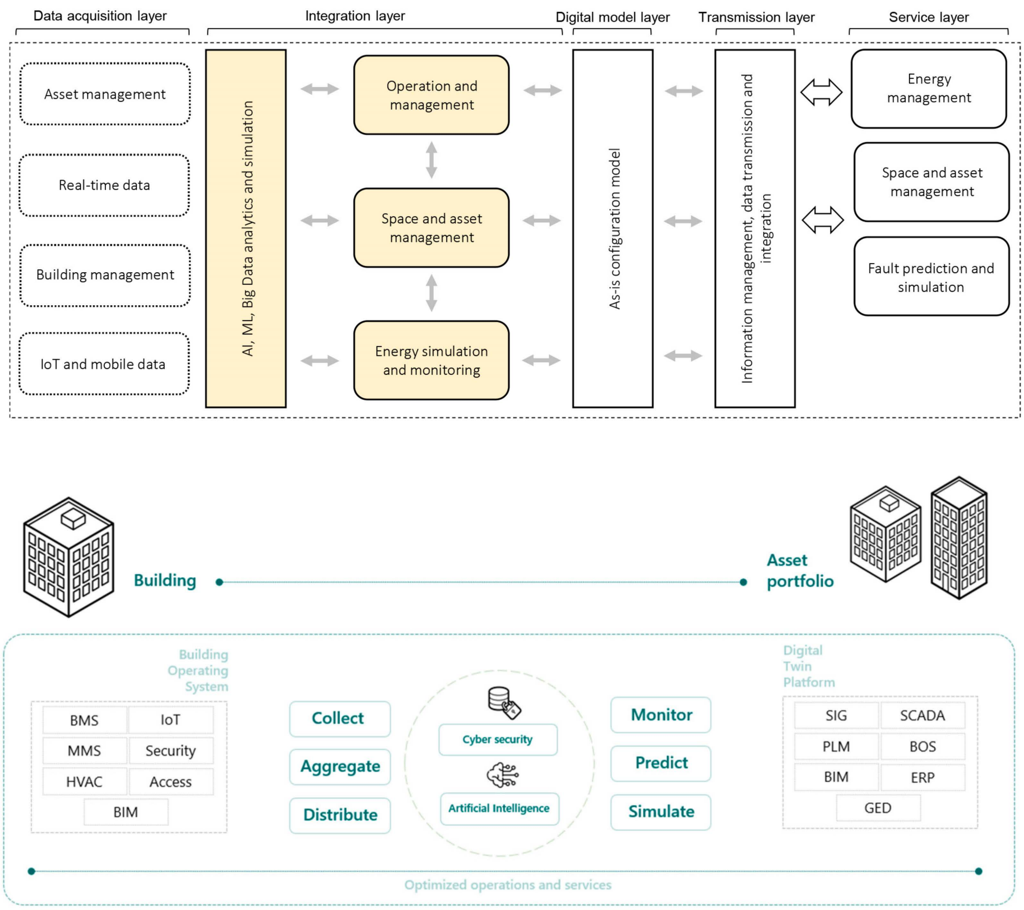


Figure 5. Digital Twin conceptual architecture for multidomain data management.

4. Discussions

With the progress of technology and transformative trends in the ICT sector facilitating investment in emerging areas such as smart buildings and smart cities, a diverse range of possibilities arises to redefine the attributes and qualities of the built environment. A primary objective is meeting the growing need for innovative strategies to counter contemporary issues like urbanization, population expansion, and urban management.

The present study aimed at identifying relationships between the key components of Digital Twins in the context of the built environment and their applicability in various other industries. The study was conducted through an extensive examination of the existing literature, highlighting multiscale modeling and real-time data acquisition and management as essential attributes for the successful deployment of Digital Twins across the entire lifecycle of built assets.

The framework proposed within this study is designed to showcase the need for the integration of diverse components, enabling technologies, and essential capabilities within a holistic system architecture. This comprehensive framework serves to illustrate how these elements converge to form an effective digital twin system. The outcomes presented in this section show the findings derived from the literature analysis concerning the conceptualization and mechanisms underpinning the digital twin paradigm.

Definitions and Scientometric Analysis

By conducting a systematic analysis, the fundamental catalysts behind the digital twin concept emerged. In order to define these core catalysts, a thorough scientometric evaluation of the pertinent literature was conducted. Utilizing the VOSviewer application, the examination sorted through the literature according to a co-occurrence analysis, discerning potential keywords associated either directly or indirectly with a specific theme.

A correlation diagram depicting Interconnected concepts extracted from the literature is generated. Findings of the scientometric assessment of the articles under review are presented in Figure 6.

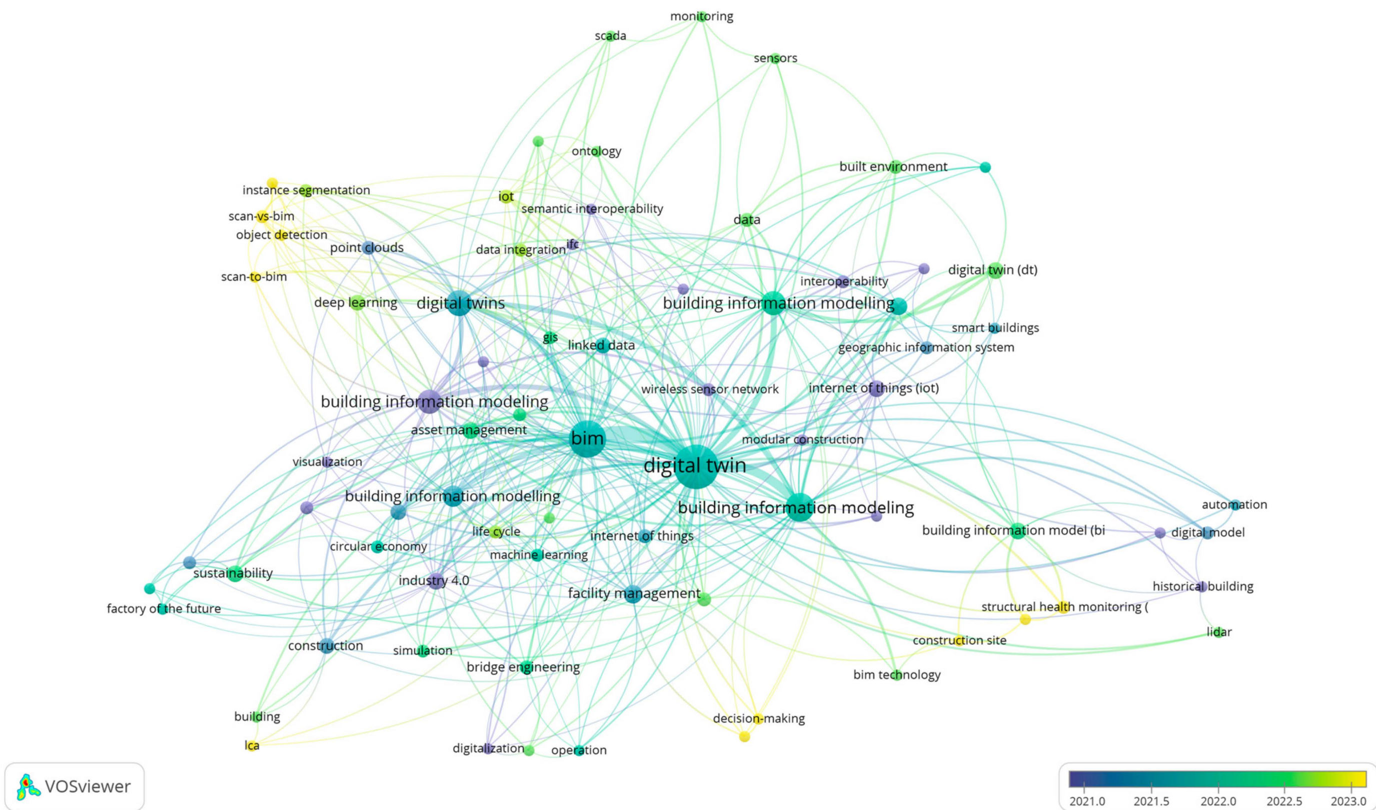


Figure 6. Scientometric analysis. Systematic review timeframe.

As indicated by the outcomes, the ensuing concepts were identified as interrelated factors steering the development of the Digital Twin paradigm: Simulation environment, decision making, digital transformation, artificial intelligence, smart city, BIM model, visualization, and information modeling are some of the main emerging keywords. Within the scope of the literature review, these concepts were articulated to exert a significant impact on shaping the definition, structure, and attributes of the digital twin paradigm.

Although the concept of Digital Twinning emerged within various contexts in the literature during the early 2000s related to engineering domains, particularly in areas like manufacturing and production [136], definitions of the term "Digital Twin" varied in the literature based on their application, usage, and disciplinary context. According to the studies analyzed, DT emerges as a highly promising technology with the potential to facilitate a diverse spectrum of applications aimed at augmenting the overall quality, performance, and living experience within physical built assets. However, it is recognized in the literature that a Digital Twin constitutes a virtual representation of a tangible object [136–138]. For this representation to be dynamically functional, it necessitates innovative applications that establish a real-time connection between the physical and digital realms [136,138] serving as one such application, generating a digital counterpart of the physical world, and facilitating a continuous real-time exchange of information between the physical and digital domains [138,139]. Three primary forms of digitalization within the realm of the built environment emerged from the study. To comprehend the opportunities related to Digital Twinning in this context, it is necessary to differentiate among the three domains of digitalization processes and methods—building information modelling (BIM), geographic information systems (GIS) [140], and smart cities (DT) [136]—as distinct enablers in terms of tools and processes needed depending on the scale and degree of data integration [136,137,140].

At the scale of individual structures, the utilization of BIM applications has gained significant traction in recent years. BIM serves as a process for creating a digital replica of a tangible asset, facilitating an efficient methodology for designing, managing, and sustaining physical structures [137]. BIM encompasses both geometrical and statistical data of a physical asset. However, it lacks a real-time linkage between the tangible asset and its virtual representation, requiring periodic "manual" updates to synchronize any modification made to the digital replica of the physical entity [137].

At the urban scale, GIS introduces an additional layer of information, specifically through the integration of geospatial data [140], where urban components are incorporated into a digital model and enhanced using geospatial information acquired through ICT solutions. These data points are interlinked with the digital portrayal of the city and are harnessed for purposes such as urban planning, urban analysis, and city management applications configuring CIMs [136,140]. As demonstrated in the literature, the integration of GIS software and BIM model technology can benefit buildings in various fields, such as reducing energy consumption, optimizing the construction site, and improving architectural designs [141]. Research on using the integration of GIS software and BIM model technology is ongoing and can be applied in many sectors, such as water and hydropower protection projects [77], tunnels [78], and bridges [79]. Given its extensive range of uses, the incorporation of GIS software technologies and BIM models can serve as a Digital Twin tool to facilitate digital transformation in large-scale projects.

Moreover, the concept of Digital Twinning is connected to the conceptualization of smart cities. In this regard, the urban Digital Twin is viewed as an integral component in the realization of digital smart cities [140,142]. As DT is described in the literature as having the capability to establish a real-time link between the tangible and virtual environments, the digital replica is connected to the physical asset through a dynamic and even bidirectional exchange of information. This connection is made possible through the deployment of sensors as a general approach. These sensors are designed to perceive, engage with, and measure the conditions prevailing in the physical realm. Concurrently, they transmit data to the digital twin, where the digital counterpart has the potential to assimilate and evaluate the incoming information. Subsequently, it can provide potential solutions, responses, or recommendations [137,139].

This relationship underscores how the urban Digital Twin operates as a linchpin, bridging the gap between physical urban realms and their virtual counterparts, while enabling a new realm of possibilities for urban planning, management, and transformation [140,142]. The urban Digital Twin, in its role as an integral component of the digital smart city vision, serves as a catalyst for innovation and efficiency, facilitating real-time insights, predictive modeling, and informed decision making that collectively contribute to the holistic advancement of urban life. The emerging outcomes focusing on the relationship between smart cities and Digital Twins reveal a multifaceted synergy that spans several critical areas of urban development and technology integration. In summary, the emerging outcomes of the smart city and Digital Twin relationship encompass a wide array of areas, demonstrating the transformative potential of integrating advanced technologies into urban planning, management, and development. In such a dynamic scenario, users emerge as co-creators, engaging with the urban digital twin to shape their environment, influence decision making processes, and enhance their daily lives. The urban Digital Twin, as a fundamental component of digital smart cities, empowers users by providing them with unprecedented access to real-time data, insights, and interactive interfaces that foster a deeper understanding of the urban built environment. This user-centric approach not only facilitates informed choices but also encourages a sense of ownership and responsibility, ultimately leading to the co-development of more efficient, sustainable, and responsive urban spaces. By integrating the urban digital twin as an essential link between physical and virtual realms, digital smart cities harness the collective intelligence and creativity of their inhabitants. This active involvement of users generates a harmonious synergy where data-driven innovations and human aspirations converge, shaping urban environments that cater to the evolving needs of citizens. As users become active agents in the transformation of their surroundings, the urban Digital Twin evolves into a platform for meaningful collaboration, driving the holistic realization of smarter, more inclusive, and adaptive cities.

5. Conclusions

The purpose of this article was to conduct a systematic review of recent studies around digital technology applied in various industries, with a focus on the construction sector. The systematic review focused attention to the design and main enabling technologies of Digital Twins for managing the built environment across the entire lifecycle from designing, constructing, operating, and maintaining facilities [143]. As the use of digital technologies and platforms in construction sectors increases, data collected in real-time can provide essential information to various purposes, aiding in monitoring and controlling assets, optimizing processes, and creating economic value. Despite the significant expansion of online platforms in many sectors, including construction, their full potential has not been realized.

The review of the existing literature underscores that the conceptualization of the Digital Twin concept often revolves around isolated technologies like BIM, GIS, and smart cities. This highlights a notable deficiency in adopting a holistic and synergistic purpose-driven approach that integrates these technologies comprehensively. A conceptual framework is proposed to address the gap and identify essential elements and key enablers to ensure successful implementations. Through the analysis of successful studies, the opportunity arises to enhance the utilization of DT platforms across various industries and domains, thereby outlining their intended objectives. The rise of advanced technologies such as BIM, GIS, 3D reality capture, artificial intelligence, machine learning for data analysis, and IoT, combined with the seamless integration of DT platforms within the construction sector, serves as catalysts for the successful implementation and DT deployments.

The application of DT platforms in the realm of construction can prove instrumental in multiple aspects. It can facilitate the analysis of design feasibility, ensuring alignment with set objectives. Moreover, these platforms can aid in monitoring project progress as per established schedules, while also overseeing building performance and effectively managing facilities. The systematic review presented an in-depth analysis conducted based on the literature related to BIM-GIS integration, IoT, smart cities, and insights from other industry applications as the main enablers for DT implementation in built environment. The outcomes suggest future developments analyzing the impact and role of artificial intelligence (AI) in Digital Twins for the AECO industry as it enhances virtual replicas by enabling advanced data analysis, predictive modeling, and real-time decision making. Combining AI into DT is a crucial area for future research, as it can significantly enhance functionality. This involves sophisticated data analysis to gain a deeper comprehension of building performance and operational efficiency.

It is expected that there will be an expansion of bidirectional interaction capabilities. This implies a smoother transmission of information and data between the physical environment and its digital representation, further enhancing real-time decision making capabilities. Another direction of development could be the evolution of industry regulations and standards, which may influence the future developments of Digital Twins. The adoption of common standards could promote greater coherence and interoperability among different projects and systems, promoting a more harmonized and resilient built environment over time. The outcomes also result in practical applications of the proposed framework for the configuration of DT platforms addressing different issues currently faced by the industry, to enhance building performance and integrate artificial intelligence and automation systems supporting and optimizing decision making processes.

Author Contributions: Conceptualization, G.P., S.A. and F.M.; methodology, G.P., S.A. and F.M.; validation, G.P., S.A. and F.M.; formal analysis, G.P., S.A. and F.M.; investigation, G.P., S.A. and F.M.; resources, G.P., S.A. and F.M.; data curation, G.P., S.A. and F.M.; writing—original draft preparation, G.P., S.A. and F.M.; writing—review and editing, G.P., S.A. and F.M.; visualization, G.P., S.A. and F.M.; supervision, G.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. UN Environment. Global Status Report for Buildings and Construction. 2018. Available online: https://www.worldgbc.org/sites/default/files/UNEP%20188_GABC_en%20(web).pdf (accessed on 1 March 2023).
2. Negroponte, P.N. *Being Digital*; Random House Incorporated: New York, NY, USA, 1995.
3. Carrasco, C.A.; Lombillo, I.; Sánchez-Espeso, J.M.; Balbás, F.J. Quantitative and Qualitative Analysis on the Integration of Geographic Information Systems and Building Information Modeling for the Generation and Management of 3D Models. *Buildings* **2022**, *12*, 1672. [CrossRef]
4. Agostinelli, S.; Cumo, F.; Nezhad, M.M.; Orsini, G.; Piras, G. Renewable Energy System Controlled by Open-Source Tools and Digital Twin Model: Zero Energy Port Area in Italy. *Energies* **2022**, *15*, 1817. [CrossRef]
5. Cinquepalmi, F.; Piras, G. Earth Observation Technologies for Mitigating Urban Climate Changes. In *Technological Imagination in the Green and Digital Transition*; Springer: Cham, Switzerland, 2023; pp. 589–600. [CrossRef]
6. Liu, Z.; Meyendorf, N.; Mrad, N. *The Role of Data Fusion in Predictive Maintenance Using Digital Twin*; AIP Publishing: Melville, NY, USA, 2018; p. 020023. [CrossRef]
7. Parrott, A.; Warshaw, L. *Industry 4.0 and the Digital Twin*; Deloitte University Press: New York, NY, USA, 2017.
8. Tao, F.; Sui, F.; Liu, A.; Qi, Q.; Zhang, M.; Song, B.; Guo, Z.; Lu, S.C.-Y.; Nee, A.Y.C. Digital twin-driven product design framework. *Int. J. Prod. Res.* **2019**, *57*, 3935–3953. [CrossRef]
9. Pan, Y.; Borrmann, A.; Mayer, H.-G.; Brilakis, I. Built Environment Digital Twinning. 2019. Available online: https://publications.cms.bgu.tum.de/reports/2020_Brilakis_BuiltEnvDT.pdf (accessed on 11 July 2023).
10. Identity Management Institute. Digital Twin Technology Benefits and Challenges. 2020. Available online: https://www.identitymanagementinstitute.org/digital-twin-technology-benefits-and-challenges (accessed on 24 June 2023).
11. Research and Markets. Digital Twin Market Research Report: By Type, Technology, Enterprise, Application, Industry—Global Industry Analysis and Growth Forecast to 2030. Available online: https://www.researchandmarkets.com/reports/5128896/digital-twin-market-research-report-by-type (accessed on 16 October 2023).
12. Gartner. Market Guide for Digital Twin Portfolios and Enabling Technologies. 2022. Available online: https://www.gartner.com/en/newsroom/press-releases/2019-02-20-gartner-survey-reveals-digital-twins-are-entering-mai (accessed on 12 June 2023).
13. Digital Twin Market. Global Forecast to 2027. Available online: https://www.marketsandmarkets.com/Market-Reports/digital-twin-market-225269522.html (accessed on 21 June 2023).
14. Datta, S.P.A. Emergence of Digital Twins. *arXiv* **2016**, arXiv:1610.06467.
15. Rosen, R.; Boschert, S.; Sohr, A. Next Generation Digital Twin. *Atp Mag.* **2018**, *60*, 86–96. [CrossRef]

16. Zhuang, C.; Liu, J.; Xiong, H. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 1149–1163. [CrossRef]
17. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-Pap.* **2018**, *51*, 1016–1022. [CrossRef]
18. Grieves, M. Digital Twin: Manufacturing Excellence through Virtual Factory Replication. White Paper. 2014. Available online: https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication (accessed on 21 June 2023).
19. Rosen, R.; von Wichert, G.; Lo, G.; Bettenhausen, K.D. About The Importance of Autonomy and Digital Twins for the Future of Manufacturing. *IFAC-Pap.* **2015**, *48*, 567–572. [CrossRef]
20. Madni, A.; Madni, C.; Lucero, S. Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems* **2019**, *7*, 7. [CrossRef]
21. Liu, W.; Zhang, W.; Dutta, B.; Wu, Z.; Goh, M. Digital Twinning for Productivity Improvement Opportunities with Robotic Process Automation: Case of Greenfield Hospital. *Int. J. Mech. Eng. Robot. Res.* **2020**, *9*, 258–263. [CrossRef]
22. Martinez Hernandez, V.; Neely, A.; Ouyang, A.; Burstall, C.; Bisessar, D. Service Business Model Innovation: The Digital Twin Technology. Cambridge Serv. Alliance. 2019. Available online: https://www.repository.cam.ac.uk/items/fcc51ffa-af08-4091-9d9d-cfaa64c023d4 (accessed on 14 July 2023).
23. Abramovici, M.; Göbel, J.C.; Dang, H.B. Semantic data management for the development and continuous reconfiguration of smart products and systems. *CIRP Ann.* **2016**, *65*, 185–188. [CrossRef]
24. Buyya, R.; Dastjerdi, A.V. *Internet of Things, Principles and Paradigms*; Elsevier: Amsterdam, The Netherlands, 2016; ISBN 9780128053959.
25. Alsboui, T.; Qin, Y.; Hill, R.; Al-Aqrabi, H. Distributed Intelligence in the Internet of Things: Challenges and Opportunities. *Sn Comput. Sci.* **2021**, *2*, 277. [CrossRef]
26. Zhang, H.; Luo, T.; Wang, Q. Adaptive Digital Twin Server Deployment for Dynamic Edge Networks in IoT System (2023). In Proceedings of the 2023 IEEE/CIC International Conference on Communications in China (ICCC 2023), Dalian, China, 10–12 August 2023. [CrossRef]
27. Marchi, A.D.; Trotta, A.; Montori, F.; Bononi, L.; Di Felice, M. Relativistic Digital Twin: Bringing the IoT to the future. *Future Gener. Comput. Syst.* **2024**, *153*, 521–536.
28. Cecere, L.; Colace, F.; Lorusso, A.; Marongiu, F.; Pellegrino, M.; Santaniello, D. IoT and Deep Learning for Smart Energy Management. Lecture Notes in Networks and Systems. In Proceedings of the 8th International Congress on Information and Communication Technology (ICICT 2023), London, UK, 20–23 February 2023; pp. 1037–1046.
29. Nuryanto, U.W.; Basrowi; Quraysin, I. Big data and IoT adoption in shaping organizational citizenship behavior: The role of innovation organizational predictor in the chemical manufacturing industry. *Int. J. Data Netw. Sci.* **2024**, *8*, 255–268. [CrossRef]
30. Dhar, S.; Khare, A.; Dwivedi, A.D.; Singh, R. Securing IoT devices: A novel approach using blockchain and quantum cryptography. *Internet Things* **2024**, *25*, 101019. [CrossRef]
31. Singh, A.K.; Saxena, S.; Tripathi, A.; Singh, A.; Tiwari, S. Futuristic Challenges in Blockchain Technologies. *Blockchain Deep. Learn. Smart Healthc.* **2023**, *9*, 100344. [CrossRef]
32. Ray, B.; Hassan, J.; Kashyap, A.; Chandrappa, V.Y. Blockchain based secure Ownership Transfer Protocol for smart objects in the Internet of Things. *Internet Things* **2024**, *25*, 101002.
33. Siemens. Digital Twin–Driving Business Value throughout the Building Life Cycle. Available online: https://assets.new.siemens.com/siemens/assets/api/uuid:610b5974-241d-4321-8ae6-55c6167446bf/bim-digitwin-ru.pdf (accessed on 19 August 2023).
34. Juntunen, E.; Sarjanoja, E.-M.; Eskeli, J.; Pihlajaniemi, H.; Österlund, T. Smart and dynamic route lighting control based on movement tracking. *Build. Environ.* **2018**, *142*, 472–483. [CrossRef]
35. Gao, Y.; Lin, Y.; Sun, Y. A wireless sensor network based on the novel concept of an I-matrix to achieve high-precision lighting control. *Build. Environ.* **2013**, *70*, 223–231. [CrossRef]
36. Van de Meugheuvel, N.; Pandharipande, A.; Caicedo, D.; van den Hof, P.P.J. Distributed lighting control with daylight and occupancy adaptation. *Energy Build* **2014**, *75*, 321–329. [CrossRef]
37. Wagiman, K.R.; Abdullah, M.N.; Hassan, M.Y.; Radzi, N.H.M. A new optimal light sensor placement method of an indoor lighting control system for improving energy performance and visual comfort. *J. Build. Eng.* **2020**, *30*, 101295. [CrossRef]
38. Sun, F.; Yu, J. Indoor intelligent lighting control method based on distributed multi-agent framework. *Optik* **2020**, *213*, 164816. [CrossRef]
39. Wei, W.; Wu, J.; Zhu, C. Special issue on role of computer vision in smart cities. *Image Vis. Comput.* **2021**, *107*, 104113. [CrossRef]
40. Ramanathan, S.S.K.; Basha, R.F.K.; Banu, A. A novel face recognition technology to enhance health and safety measures in hospitals using SBC in pandemic prone areas. *Mater. Today Proc.* **2021**, *45*, 2584–2588. [CrossRef]
41. Zhu, Z.; Cheng, Y. Application of attitude tracking algorithm for face recognition based on OpenCV in the intelligent door lock. *Comput. Commun.* **2020**, *154*, 390–397. [CrossRef]
42. Seelam, V.; Penugonda, A.K.; Kalyan, B.P.; Priya, M.B.; Prakash, M.D. Smart attendance using deep learning and computer vision. *Mater. Today Proc.* **2021**, *46*, 4091–4094. [CrossRef]
43. Wei, S.; Tien, P.W.; Calautit, J.K.; Wu, Y.; Boukhanouf, R. Vision-based detection and prediction of equipment heat gains in commercial office buildings using a deep learning method. *Appl. Energy* **2020**, *277*, 115506. [CrossRef]

44. Zawadzki, A. Lighting Fitting Controller Using Image Processing System. *IFAC Proc. Vol.* **2009**, *42*, 133–136. [CrossRef]
45. Carrillo, C.; Diaz-Dorado, E.; Cidrás, J.; Bouza-Pregal, A.; Falcón, P.; Fernández, A.; Álvarez-Sánchez, A. Lighting control system based on digital camera for energy saving in shop windows. *Energy Build* **2013**, *59*, 143–151. [CrossRef]
46. Wu, Y.; Këmpf, J.H.; Scartezzini, J.-L. Characterization of a quasi-real-time lighting computing system based on HDR imaging. *Energy Procedia* **2017**, *122*, 649–654. [CrossRef]
47. Motamed, A.; Deschamps, L.; Scartezzini, J.-L. On-site monitoring and subjective comfort assessment of a sun shadings and electric lighting controller based on novel High Dynamic Range vision sensors. *Energy Build* **2017**, *149*, 58–72. [CrossRef]
48. Shanmugam, M.; Aravind, S.; Yuvashree, K.; JaiVignesh, M.; Shrinivasan, R.J.; Santhanam, V. Energy efficient intelligent light control with security system for materials handling warehouse. *Mater. Today Proc.* **2021**, *37*, 1884–1886. [CrossRef]
49. Pan, Y.; Zhang, L. A BIM-data mining integrated digital twin framework for advanced project management. *Autom. Constr.* **2021**, *124*, 103564. [CrossRef]
50. Zhao, Z.; Shen, L.; Yang, C.; Wu, W.; Zhang, M.; Huang, G.Q. IoT and digital twin enabled smart tracking for safety management. *Comput. Oper. Res.* **2021**, *128*, 105183. [CrossRef]
51. Huang, J.; Zhao, L.; Wei, F.; Cao, B. The Application of Digital Twin on Power Industry. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *647*, 012015. [CrossRef]
52. Shahzad, M.; Shafiq, M.T.; Douglas, D.; Kassem, M. Digital Twins in Built Environments: An Investigation of the Characteristics, Applications, Challenges. *Buildings* **2022**, *12*, 120. [CrossRef]
53. Fan, C.; Jiang, Y.; Mostafavi, A. Social Sensing in Disaster City Digital Twin: Integrated Textual–Visual–Geo Framework for Situational Awareness during Built Environment Disruptions. *J. Manag. Eng.* **2020**, *36*, 04020002-1. [CrossRef]
54. Ham, Y.; Kim, J. Participatory Sensing and Digital Twin City: Updating Virtual City Models for Enhanced Risk-Informed Decision-Making. *J. Manag. Eng.* **2020**, *36*, 04020005-12. [CrossRef]
55. Dutta, S.; Cai, Y.; Huang, L.; Zheng, J. Automatic re-planning of lifting paths for robotized tower cranes in dynamic BIM environments. *Autom. Constr.* **2020**, *110*, 102998. [CrossRef]
56. Alves, M.; Carreira, P.; Costa, A.A. BIMSL: A generic approach to the integration of building information models with real-time sensor data. *Autom. Constr.* **2017**, *84*, 304–314. [CrossRef]
57. Srinivasan, R.S.; Rinker, M.E.; Thakur, S.; Parmar, M.; Akhmed, I. Towards the implementation of a 3D heat transfer analysis in dynamic-bim (dynamic building information modeling) workbench. In Proceedings of the Winter Simulation Conference 2014, Savannah, Georgia, 7–10 December 2014; pp. 3224–3235. [CrossRef]
58. Edmondson, V.; Cerny, M.; Lim, M.; Gledson, B.; Lockley, S.; Woodward, J. A smart sewer asset information model to enable an 'Internet of Things' for operational wastewater management. *Autom. Constr.* **2018**, *91*, 193–205. [CrossRef]
59. Chen, X.-S.; Liu, C.-C.; Wu, I.-C. A BIM-based visualization and warning system for fire rescue. *Adv. Eng. Inform.* **2018**, *37*, 42–53. [CrossRef]
60. Zhou, J.X.; Shen, G.Q.; Yoon, S.H.; Jin, X. Customization of on-site assembly services by integrating the internet of things and BIM technologies in modular integrated construction. *Autom. Constr.* **2021**, *126*, 103663. [CrossRef]
61. Atkin, A.B.B. *Total Facility Management*; John Wiley & Sons Inc.: New York, NY, USA, 2015.
62. Jamil, S.; Rahman, M.; Fawad. A Comprehensive Survey of Digital Twins and Federated Learning for Industrial Internet of Things (IIoT), Internet of Vehicles (IoV) and Internet of Drones (IoD). *Appl. Syst. Innov.* **2022**, *5*, 56. [CrossRef]
63. Khallaf, R.; Khallaf, L.; Anumba, C.J.; Madubuike, O.C. Review of Digital Twins for Constructed Facilities. *Buildings* **2022**, *12*, 2029. [CrossRef]
64. Nasab, S.N.; Azeri, A.R.K.; Mirbazel, S. Ideal physical features of environmental design in children's hospital. *Facilities* **2020**, *38*, 445–466. [CrossRef]
65. Parsanezhad, P.; Dimyadi, J. Effective Facility Management and Operations via a BIM based integrated information system. In Proceedings of the CIB W070, W111 & W118 Conference, Copenhagen, Denmark, 21–23 August 2014.
66. Volk, R.; Stengel, J.; Schultmann, F. Building Information Modeling (BIM) for existing buildings—Literature review and future needs. *Autom. Constr.* **2014**, *38*, 109–127. [CrossRef]
67. De Silva, R. Related Papers the Need for an Integrated Cost Modelling Framework for Building Information Modelling (BIM). In Proceedings of the Second World Construction Symposium 2013: Socio-Economic Sustainability in Construction, Colombo, Sri Lanka, 14–15 June 2013.
68. Tan, L.; Kong, T.L.; Zhang, Z.; Metwally, A.S.M.; Sharma, S.; Sharma, K.P.; Eldin, S.M.; Zimon, D. Scheduling and Controlling Production in an Internet of Things Environment for Industry 4.0: An Analysis and Systematic Review of Scientific Metrological Data. *Sustainability* **2023**, *15*, 7600. [CrossRef]
69. Deng, Y.; Cheng, J.C.P.; Anumba, C. Mapping between BIM and 3D GIS in different levels of detail using schema mediation and instance comparison. *Autom. Constr.* **2016**, *67*, 1–21. [CrossRef]
70. Giuffrida, D.; Nardo, V.M.; Neri, D.; Cucinotta, G.; Calabrò, I.V.; Pace, L.; Ponterio, R.C. A multi-analytical study for the enhancement and accessibility of archaeological heritage: The churches of san nicola and san basilio in motta sant'agata (RC, Italy). *Remote Sens.* **2021**, *13*, 3738. [CrossRef]
71. Cinquepalmi, F.; Paris, S.; Pennacchia, E.; Tiburcio, V.A. Efficiency and Sustainability: The Role of Digitization in Re-Inhabiting the Existing Building Stock. *Energies* **2023**, *16*, 3613. [CrossRef]

72. Lochhead, I.; Hedley, N. Mixed reality emergency management: Bringing virtual evacuation simulations into real-world built environments. *Int. J. Digit. Earth* **2019**, *12*, 190–208. [CrossRef]
73. Olfat, H.; Atazadeh, B.; Shojaei, D.; Rajabifard, A. The Feasibility of a BIM-Driven Approach to Support Building Subdivision Workflows—Case Study of Victoria, Australia. *ISPRS Int. J. Geoinf.* **2019**, *8*, 499. [CrossRef]
74. Shahi, K.; McCabe, B.Y.; Shahi, A. Framework for Automated Model-Based e-Permitting System for Municipal Jurisdictions. *J. Manag. Eng.* **2019**, *35*, 6. [CrossRef]
75. Sun, J.; Mi, S.; Olsson, P.-O.; Paulsson, J.; Harrie, L. Utilizing BIM and GIS for Representation and Visualization of 3D Cadastre. *ISPRS Int. J. Geoinf.* **2019**, *8*, 503. [CrossRef]
76. Rong, Y.; Zhang, T.; Zheng, Y.; Hu, C.; Peng, L.; Feng, P. Three-dimensional urban flood inundation simulation based on digital aerial photogrammetry. *J. Hydrol.* **2020**, *584*, 124308. [CrossRef]
77. Zhang, S.; Jiang, P. Implementation of BIM + WebGIS Based on Extended IFC and Batched 3D Tiles Data: An Application in RCC Gravity Dam for Republication of Design Change Model. *KSCE J. Civ. Eng.* **2021**, *25*, 4045–4064. [CrossRef]
78. Zhang, S.; Hou, D.; Wang, C.; Pan, F.; Yan, L. Integrating and managing BIM in 3D web-based GIS for hydraulic and hydropower engineering projects. *Autom. Constr.* **2020**, *112*, 103114. [CrossRef]
79. Borrmann, A.; Kolbe, T.H.; Donaubauer, A.; Steuer, H.; Jubierre, J.R.; Flurl, M. Multi-Scale Geometric-Semantic Modeling of Shield Tunnels for GIS and BIM Applications. *Comput. Aided Civ. Infrastruct. Eng.* **2015**, *30*, 263–281. [CrossRef]
80. Pan, Z.; Shi, J.; Jiang, L. A Novel HDF-Based Data Compression and Integration Approach to Support BIM-GIS Practical Applications. *Adv. Civ. Eng.* **2020**, *2020*, 8865107. [CrossRef]
81. Razmjoo, A.; Mirjalili, S.; Aliehyaei, M.; Østergaard, P.A.; Ahmadi, A.; Nezhad, M.M. Development of smart energy systems for communities: Technologies, policies and applications. *Energy* **2022**, *248*, 123540. [CrossRef]
82. Janoskova, P.; Stofkova, K.R.; Kovacikova, M.; Stofkova, J.; Kovacikova, K. The Concept of a Smart City Communication in the Form of an Urban Mobile Application. *Sustainability* **2021**, *13*, 9703. [CrossRef]
83. Foundation, N.R. Virtual Singapore. Available online: https://www.nrf.gov.sg/programmes/virtual-singapore (accessed on 19 April 2023).
84. Amaravati Smart City. Available online: https://cityzenith.com/customers/amaravati-smart-city (accessed on 25 August 2023).
85. SmartCitiesWorld. Digital Twin Created for New Indian Smart City. 2018. Available online: https://www.smartcitiesworld.net/news/news/digitaltwin-created-for-new-indian-smart-city-3674 (accessed on 23 July 2023).
86. Fishermans Bend Digital Twin. 2020. Available online: https://www.delwp.vic.gov.au/maps/digital-twin (accessed on 19 June 2023).
87. White, G.; Zink, A.; Codecá, L.; Clarke, S. A digital twin smart city for citizen feedback. *Cities* **2021**, *110*, 103064. [CrossRef]
88. Hämäläinen, M. Smart city dvelopment with digital twin technology. In *33rd Bled eConference—Enabling Technology for a Sustainable Society: June 28–29, 2020, Online Conference Proceedings*; University of Maribor Press: Maribor, Slovenia, 2020; pp. 291–303. [CrossRef]
89. Persson, A. The Digital Twin—Unsung Hero in F1 and in the Smart City. Available online: https://sensative.com/thedigital-twin-unsung-hero-in-f1-and-in-the-smart-city/ (accessed on 25 August 2023).
90. Ford, D.N.; Wolf, C.M. Smart Cities with Digital Twin Systems for Disaster Management. *J. Manag. Eng.* **2020**, *36*, 04020027. [CrossRef]
91. Xia, H.; Liu, Z.; Efremochkina, M.; Liu, X.; Lin, C. Study on city digital twin technologies for sustainable smart city design: A review and bibliometric analysis of geographic information system and building information modeling integration. *Sustain. Cities Soc.* **2022**, *84*, 104009. [CrossRef]
92. Ali, K.N.; Alhajlah, H.H.; Kassem, M.A. Collaboration and Risk in Building Information Modelling (BIM): A Systematic Literature Review. *Buildings* **2022**, *12*, 571. [CrossRef]
93. Miller, C.; Abdelrahman, M.; Chong, A.; Biljecki, F.; Quintana, M.; Frei, M.; Chew, M.; Wong, D. The Internet-of-Buildings (IoB)—Digital twin convergence of wearable and IoT data with GIS/BIM. *J. Phys. Conf. Ser.* **2021**, *2042*, 012041. [CrossRef]
94. Sammartano, G.; Avena, M.; Cappellazzo, M.; Spanò, A. Hybrid gis-bim approach for the torino digital-twin: The implementation of a floor-level 3d city geodatabase. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2021**, *XLIII-B4-2021*, 423–430. [CrossRef]
95. Zhu, J.; Wu, P. A Common Approach to Geo-Referencing Building Models in Industry Foundation Classes for BIM/GIS Integration. *ISPRS Int. J. Geoinf.* **2021**, *10*, 362. [CrossRef]
96. Diakite, A.A.; Zlatanova, S. Automatic geo-referencing of BIM in GIS environments using building footprints. *Comput. Environ. Urban. Syst.* **2020**, *80*, 101453. [CrossRef]
97. Li, X.; Liu, H.; Wang, W.; Zheng, Y.; Lv, H.; Lv, Z. Big data analysis of the Internet of Things in the digital twins of smart city based on deep learning. *Future Gener. Comput. Syst.* **2022**, *128*, 167–177. [CrossRef]
98. Bujari, A.; Calvio, A.; Foschini, L.; Sabbioni, A.; Corradi, A. A Digital Twin Decision Support System for the Urban Facility Management Process. *Sensors* **2021**, *21*, 8460. [CrossRef]
99. Ana, R.R.S.; Escoto, J.E.; Fargas, D., Jr.; Panlilio, K.; Jerez, M.; Sarmiento, C.J. Development of a digital twin for the monitoring of smart cities using open-source software. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2021**, *XLVI-4/W6-2021*, 281–288. [CrossRef]
100. Mylonas, G.; Kalogeras, A.; Kalogeras, G.; Anagnostopoulos, C.; Alexakos, C.; Munoz, L. Digital Twins From Smart Manufacturing to Smart Cities: A Survey. *IEEE Access* **2021**, *9*, 143222–143249. [CrossRef]

101. Tuegel, E.J.; Ingraffea, A.R.; Eason, T.G.; Spottswood, S.M. Reengineering Aircraft Structural Life Prediction Using a Digital Twin. *Int. J. Aerosp. Eng.* **2011**, *2011*, 154798. [CrossRef]
102. Seshadri, B.R.; Krishnamurthy, T. Structural Health Management of Damaged Aircraft Structures Using Digital Twin Concept. In Proceedings of the 25th AIAA/AHS Adaptive Structures Conference, Grapevine, TX, USA, 9–13 January 2017; American Institute of Aeronautics and Astronautics: Reston, VI, USA, 2017. [CrossRef]
103. Yin, Z.H.; Wang, L. Application and Development Prospect of Digital Twin Technology in Aerospace. *IFAC-Pap.* **2020**, *53*, 732–737. [CrossRef]
104. Roy, R.B.; Mishra, D.; Pal, S.K.; Chakravarty, T.; Panda, S.; Chandra, M.G.; Pal, A.; Misra, P.; Chakravarty, D.; Misra, S. Digital twin: Current scenario and a case study on a manufacturing process. *Int. J. Adv. Manuf. Technol.* **2020**, *107*, 3691–3714. [CrossRef]
105. Lahoti, N. How Is Digital Twin Technology Impacting the Automotive Industry? Available online: http://mobisoftinfotech.com/resources/blog/digital-twin-technology-impacting-automotive-industry/ (accessed on 25 August 2023).
106. Yu, J.; Liu, P.; Li, Z. Hybrid modelling and digital twin development of a steam turbine control stage for online performance monitoring. *Renew. Sustain. Energy Rev.* **2020**, *133*, 110077. [CrossRef]
107. Bortolini, R.; Rodrigues, R.; Alavi, H.; Vecchia, L.F.D.; Forcada, N. Digital Twins' Applications for Building Energy Efficiency: A Review. *Energies* **2022**, *15*, 7002. [CrossRef]
108. Leng, J.; Wang, D.; Shen, W.; Li, X.; Liu, Q.; Chen, X. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *J. Manuf. Syst.* **2021**, *60*, 119–137. [CrossRef]
109. Medina, F.G.; Umpierrez, A.W.; Martinez, V.; Fromm, H. A Maturity Model for Digital Twin Implementations in the Commercial Aerospace OEM Industry. In Proceedings of the 2021 10th International Conference on Industrial Technology and Management (ICITM), Virtual, 26–28 March 2021; pp. 149–156. [CrossRef]
110. West, T.D.; Pyster, A. Untangling the Digital Thread: The Challenge and Promise of Model-Based Engineering in Defense Acquisition. *Insight* **2015**, *18*, 45–55. [CrossRef]
111. Mourtzis, D.; Vlachou, E.; Milas, N. Industrial Big Data as a Result of IoT Adoption in Manufacturing. *Procedia CIRP* **2016**, *55*, 290–295. [CrossRef]
112. Muzi, F.; Marzo, R.; Nardi, F. Digital Information Management in the Built Environment: Data-Driven Approaches for Building Process Optimization. In Proceedings of the International Conference on Technological Imagination in the Green and Digital Transition, Rome, Italy, 30 June–2 July 2022; Springer International Publishing: Cham, Switzerland, 2023; pp. 123–132.
113. Agostinelli, S.; Cumo, F.; Marzo, R.; Muzi, F. Digital construction strategy for project management optimization in a building renovation site: Machine learning and big data analysis. In Proceedings of the International Conference on Trends on Construction in the Post-Digital Era, Guimarães, Portugal, 7–9 September 2022; Springer International Publishing: Cham, Switzerland, 2022. [CrossRef]
114. Yu, J.; Petersen, N.; Liu, P.; Li, Z.; Wirsum, M. Hybrid modelling and simulation of thermal systems of in-service power plants for digital twin development. *Energy* **2022**, *260*, 125088. [CrossRef]
115. Garcia, D.A.; Cumo, F.; Tiberi, M.; Sforzini, V.; Piras, G. Cost-benefit analysis for energy management in public buildings: Four Italian case studies. *Energies* **2016**, *9*, 522. [CrossRef]
116. Basso, G.L.; Rosa, F.; Garcia, D.A.; Cumo, F. Hybrid systems adoption for lowering historic buildings PFEC (primary fossil energy consumption)—A comparative energy analysis. *Renew. Energy* **2018**, *117*, 414–433. [CrossRef]
117. Zhuang, C.; Liu, Z.; Liu, J.; Ma, H.; Zhai, S.; Wu, Y. Digital Twin-based Quality Management Method for the Assembly Process of Aerospace Products with the Grey-Markov Model and Apriori Algorithm. *Chin. J. Mech. Eng.* **2022**, *35*, 105. [CrossRef]
118. Conde, J.; Munoz-Arcentales, A.; Romero, M.; Rojo, J.; Salvachúa, J.; Huecas, G.; Alonso, Á. Applying digital twins for the management of information in turnaround event operations in commercial airports. *Adv. Eng. Inform.* **2022**, *54*, 101723. [CrossRef]
119. Hultman, H.; Cedergren, S.; Wärmefjord, K.; Söderberg, R. Predicting Geometrical Variation in Fabricated Assemblies Using a Digital Twin Approach Including a Novel Non-Nominal Welding Simulation. *Aerospace* **2022**, *9*, 512. [CrossRef]
120. Candon, M.; Esposito, M.; Fayek, H.; Levinski, O.; Koschel, S.; Joseph, N.; Carrese, R.; Marzocca, P. Advanced multi-input system identification for next generation aircraft loads monitoring using linear regression, neural networks and deep learning. *Mech. Syst. Signal Process* **2022**, *171*, 108809. [CrossRef]
121. Borgen, K.B.; Ropp, T.D.; Weldon, W.T. Assessment of Augmented Reality Technology's Impact on Speed of Learning and Task Performance in Aeronautical Engineering Technology Education. *Int. J. Aerosp. Psychol.* **2021**, *31*, 219–229. [CrossRef]
122. Liu, S.; Bao, J.; Lu, Y.; Li, J.; Lu, S.; Sun, X. Digital twin modeling method based on biomimicry for machining aerospace components. *J. Manuf. Syst.* **2021**, *58*, 180–195. [CrossRef]
123. Ezhilarasu, C.M.; Skaf, Z.; Jennions, I.K. A Generalised Methodology for the Diagnosis of Aircraft Systems. *IEEE Access* **2021**, *9*, 11437–11454. [CrossRef]
124. Schroeder, G.N.; Steinmetz, C.; Rodrigues, R.N.; Henriques, R.V.B.; Rettberg, A.; Pereira, C.E. A Methodology for Digital Twin Modeling and Deployment for Industry 4.0. *Proc. IEEE* **2021**, *109*, 556–567. [CrossRef]
125. Tao, F.; Qi, Q.; Wang, L.; Nee, A.Y.C. Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. *Engineering* **2019**, *5*, 653–661. [CrossRef]
126. Min, Q.; Lu, Y.; Liu, Z.; Su, C.; Wang, B. Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. *Int. J. Inf. Manag.* **2019**, *49*, 502–519. [CrossRef]

127. Guerra-Zubiaga, D.; Kuts, V.; Mahmood, K.; Bondar, A.; Nasajpour-Esfahani, N.; Otto, T. An approach to develop a digital twin for industry 4.0 systems: Manufacturing automation case studies. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 933–949. [CrossRef]
128. Xu, B.; Wang, J.; Wang, X.; Liang, Z.; Cui, L.; Liu, X.; Ku, A.Y. A case study of digital-twin-modelling analysis on power-plant-performance optimizations. *Clean. Energy* **2019**, *3*, 227–234. [CrossRef]
129. Zhang, H.; Liu, Q.; Chen, X.; Zhang, D.; Leng, J. A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line. *IEEE Access* **2017**, *5*, 26901–26911. [CrossRef]
130. Blume, C.; Blume, S.; Thiede, S.; Herrmann, C. Data-Driven Digital Twins for Technical Building Services Operation in Factories: A Cooling Tower Case Study. *J. Manuf. Mater. Process.* **2020**, *4*, 97. [CrossRef]
131. Pimenta, F.; Pacheco, J.; Branco, C.M.; Teixeira, C.M.; Magalhães, F. Development of a digital twin of an onshore wind turbine using monitoring data. *J. Phys. Conf. Ser.* **2020**, *1618*, 022065. [CrossRef]
132. *UNI EN ISO 23387:2020*; Building Information Modelling (BIM)—Data Templates for Construction Objects Used in the Life Cycle of Built Assets—Concepts and Principles. ISO: Geneva, Switzerland, 2020.
133. Golparvar-Fard, M.; Ham, Y. Automated diagnostics and visualization of potential energy performance problems in existing buildings using energy performance augmented reality models. *J. Comput. Civ. Eng.* **2014**, *28*, 17–29. [CrossRef]
134. Lamagna, M.; Groppi, D.; Nezhad, M.M.; Piras, G. A comprehensive review on Digital twins for Smart energy management system. *Int. J. Energy Prod. Manag.* **2021**, *6*, 323–334. [CrossRef]
135. Motlagh, N.H.; Zaidan, M.A.; Lovén, L.; Fung, P.L.; Hänninen, T.; Morabito, R.; Nurmi, P.; Tarkoma, S. Digital Twins for Smart Spaces—Beyond IoT Analytics. *IEEE Internet Things J.* **2024**, *11*, 573–583. [CrossRef]
136. Ketzler, B.; Naserentin, V.; Latino, F.; Zangelidis, C.; Thuvander, L.; Logg, A. Digital Twins for Cities: A State of the Art Review. *Built Environ.* **2020**, *46*, 547–573. [CrossRef]
137. Shahat, E.; Hyun, C.T.; Yeom, C. City Digital Twin Potentials: A Review and Research Agenda. *Sustainability* **2021**, *13*, 3386. [CrossRef]
138. Sepasgozar, S.M.E. Differentiating Digital Twin from Digital Shadow: Elucidating a Paradigm Shift to Expedite a Smart, Sustainable Built Environment. *Buildings* **2021**, *11*, 151. [CrossRef]
139. Nguyen, H.X.; Trestian, R.; To, D.; Tatipamula, M. Digital Twin for 5G and Beyond. *IEEE Commun. Mag.* **2021**, *59*, 10–15. [CrossRef]
140. Gil, J. City Information Modelling: A Conceptual Framework for Research and Practice in Digital Urban Planning. *Built Environ.* **2020**, *46*, 501–527. [CrossRef]
141. Gotlib, D.; Wyszomirski, M.; Gnat, M. A Simplified Method of Cartographic Visualisation of Buildings' Interiors (2D+) for Navigation Applications. *ISPRS Int. J. Geoinf.* **2020**, *9*, 407. [CrossRef]
142. Deng, T.; Zhang, K.; Shen, Z.-J.M. A systematic review of a digital twin city: A new pattern of urban governance toward smart cities. *J. Manag. Sci. Eng.* **2021**, *6*, 125–134. [CrossRef]
143. Cinquepalmi, F.; Cumo, F.; Vokshi, A. Applying Digital Twin Models to Built Environment: Methodological Approaches and Comparative Experiences. In *Albania in the Third Millennium*; Intergrafika: Tirana, Albania, 2023.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.