Digital twins in the construction industry: a comprehensive review of current implementations, enabling technologies, and future directions

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Review

Digital Twins in the Construction Industry: A Comprehensive Review of Current Implementations, Enabling Technologies, and Future Directions

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Abstract: This paper presents a comprehensive understanding of current digital twin (DT) implementations in the construction industry, along with providing an overview of technologies enabling the operation of DTs in the industry. To this end, 145 publications were identified using a systematic literature review. The results revealed eight key areas of DT implementation including (i) virtual design, (ii) project planning and management, (iii) asset management and maintenance, (iv) safety management, (v) energy efficiency and sustainability, (vi) quality control and management, (vii) supply chain management and logistics, and (viii) structural health monitoring. The findings demonstrate that DT technology has the capacity to revolutionise the construction industry across these areas, enabling optimised designs, improved collaboration, real-time monitoring, predictive maintenance, enhanced safety practices, energy performance optimisation, quality inspections, efficient supply chain management, and proactive maintenance. This study also identified several challenges that hinder the widespread implementation of DT in construction, including (i) data integration and interoperability, (ii) data accuracy and completeness, (iii) scalability and complexity, (iv) privacy and security, and (v) standards and governance. To address these challenges, this paper recommends prioritising standardised data formats, protocols, and APIs for seamless collaboration, exploring semantic data modelling and ontologies for data integration, implementing validation processes and robust data governance for accuracy and completeness, harnessing high-performance computing and advanced modelling techniques for scalability and complexity, establishing comprehensive data protection and access controls for privacy and security, and developing widely accepted standards and governance frameworks with industry-wide collaboration. By addressing these challenges, the construction industry can unlock the full potential of DT technology, thus enhancing safety, reliability, and efficiency in construction projects.

Keywords: digital twin; digital technology; construction industry; intelligent construction; construction 4.0; collaborative platforms

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1. Introduction

The construction industry has emerged as a major contributor to the global gross domestic product (GDP), accounting for nearly 10% of the total output and generating employment opportunities in various countries [1,2]. As per data recorded in 2017, the output of the construction industry was estimated to be approximately USD 10 trillion worldwide [1,3]. In Australia, the building and construction sector accounted for 8.1% of the national GDP and 9% of the employment rate in 2017, while in the UK and China, it influenced 6.5% and 5.7% of their respective national GDPs [1]. However, the industry has been plagued by the persistent issue of low productivity, which has prompted scholars to emphasise the need for performance improvement in the industry [4–7]. One effective strategy for addressing this challenge is the adoption of digital technologies, which have shown promise in enhancing productivity. An exemplar of such technologies is building information modelling (BIM), which has made a substantial impact on the improvement of practices across the construction industry [8–11]. Nevertheless, the construction industry still faces daunting challenges in embracing new technologies due to resistance to change [12–14]. This inability to keep pace with technological advancements is a significant hurdle to the modernisation of the construction industry, particularly when evaluated against the automotive and manufacturing industries [2–4].

In the current era, the rapid development of new information technologies has brought about an unprecedented industrial transformation. One technology that has garnered significant attention in recent years, owing to its potential to transform the construction industry, is the digital twin (DT). Fundamentally, DT implementation revolves around the generation of a digital representation of a physical entity, leveraging data to simulate the actions and functions of the physical entity within its real environment, as illustrated in Figure 1. This enables the augmentation of the physical entity's capabilities with interactive feedback, data fusion analysis, and iterative decision optimisation [3,4,15]. The term "digital twin" was initially introduced by the National Aeronautics and Space Administration (NASA) to describe the construction of two identical spacecraft that replicated the exact conditions experienced by the vehicle during a mission [16]. However, it was not until 2003 that Michael Grieves at the University of Michigan introduced the concept of a "digital equivalent to a physical product", which is widely recognised as the first use of the term DT [17]. In 2006, Hribernik et al. [18] introduced the idea of the "product avatar" as a means to establish an information management framework that facilitates a bidirectional flow of information centred around the product. Ever since, the concept of DT has undergone significant improvements and is now widely used across various industries, including manufacturing as a means for enhancing the efficiency of their manufacturing processes.

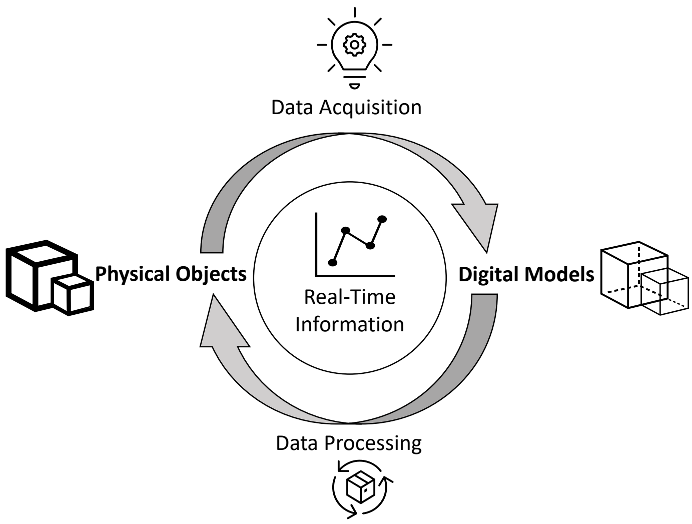

Figure 1. A conceptual model of digital twin technology.

A DT, integrated with a range of devices such as Internet of Things (IoT) devices, data loggers, 3D scanners, thermal imaging cameras, and environmental sensors, has the capability to collect firsthand experiential data pertaining to physical assets [2,15]. The application of a DT enables the prediction of possible failures, feedback to the system, and reaction in accordance with the stimulant information [15]. A DT can also facilitate the continuous monitoring of all processes involved in a given service, enabling the collection of information pertaining to physical assets throughout their life cycles [3,8,15,19]. The immense potential of DTs has sparked interest in their application within the construction industry. An exemplary case of such implementation can be observed in the Ezhou Huahu International Airport project, situated in the eastern region of Ezhou, Hubei Province, China [20]. In this project, Bentley's BIM and iTwin technology were utilised to develop a DT for the airport, enabling seamless integration of extensive engineering and data components. The implementation of the DT was highly effective, resulting in a remarkable reduction of 200 days in the project's delivery time and substantial cost savings of CNY 300 million.

The growing interest in DT applications has also sparked a surge of attention in academia, leading to a plethora of research developed to investigate the potential of this technology across multiple domains in the construction industry. This has subsequently led the current body of literature to become fairly fragmented when it comes to understanding the present-day implementations of DTs in the construction industry. In response, review studies have been developed with the purpose of solidifying the existing knowledge in this area [1–4,8,15,18,21–24]. For instance, Opoku et al. [23] and Opoku et al. [24] investigated barriers and drivers for adopting DT in the construction industry using a systematic literature review approach, respectively. In recent studies, Xie et al. [15] and Almatared et al. [19] analysed the literature connected to DT applications in the construction industry using a scientometric approach. In another review study, Zhang et al. [3] attempted to put forward a unified definition for DTs as it applies to the construction industry. Hou et al. [22] also provided a comprehensive literature review of DT applications in construction workforce safety. In another study, Bortolini et al. [21] reviewed the opportunities for improving energy efficiency in buildings by developing a DT. Salem and Dragomir [25] also carried out a review study on the applications of DTs for construction project management.

Despite the significant contributions made by prior studies, the current state of knowledge regarding DT implementations in the construction industry still remains fragmented. The majority of the reviewed studies have focused on specific aspects of DT application while overlooking potential areas where DTs can be deployed to improve industry practices. This underscores the need for comprehensive research that consolidates the literature and promotes the adoption of DT within the industry. To address this gap, the present paper aims to achieve the following objectives using a systematic review of the literature: (i) to provide a comprehensive understanding of current DT implementations in the construction industry, (ii) to provide a state-of-the-art overview of technologies enabling the utilisation of DTs in the industry, and (iii) to identify and discuss major challenges associated with DT applications in the industry and provide recommendations for future development in the field.

The outcomes of this study can be useful to multiple target groups. Firstly, practitioners in the construction industry can benefit from the insights provided by this research, as the findings identify potential areas where DTs can be applied to improve productivity in the industry. This paper also offers a comprehensive overview of the challenges and opportunities associated with DT implementations in the industry and its fundamental technologies; hence, the outcomes can be used as a point of reference by scholars and researchers for future development in the field.

2. Research Methodology

This paper used a systematic literature review approach to identify publications pertaining to the implementations of DTs in the construction industry. A comprehensive search was conducted across multiple databases, including Web of Science, ProQuest, and Scopus, using a comprehensive set of keywords to capture relevant studies (Table 1). Utilising multiple databases enhanced the robustness and comprehensiveness of the search process, as it allowed for compensating the limitations of one source with the strengths of others. These keywords were searched with respect to their applications in the construction industry. The search scope was limited to scholarly "articles", "review articles", and "book chapters", chosen due to their comprehensive and reputable nature as recognised sources of validated knowledge [9,26]. As a result, the initial search yielded 350 publications that met the established search criteria.

Table 1. A list of keywords used to identify materials related to DT implementation in construction.

Keywords Deployed during the Initial Search
Digital Twin; Digital Technology; Construction Industry; Intelligent Construction; Construction 4.0; Collaborative Platforms; Smart Construction; Industry 4.0; Digitalisation; Digital Transformation; Virtual Construction; Cognitive Technology; Virtual Twin; Digital Replica; Cyber–Physical System; Cyber Twin; Digital Shadow; Digital Clone; Intelligent Twin; Digital Doppelganger.

After collecting the dataset, the first step involved removing duplicate records to ensure data integrity. Duplicate removal was carried out by comparing and eliminating redundant instances of data within the dataset. This led to the elimination of nearly 30 duplicate articles. Afterwards, a preliminary qualitative search was conducted to evaluate the relevance of the selected materials. This assessment was based on an analysis of the "titles", "abstracts", and "conclusions" of the identified sources. To ensure that only resources directly related to the concept of DTs in the construction industry were considered, several exclusion criteria were applied. Firstly, studies published in non-English languages and non-peer-reviewed journals were excluded. Additionally, filtering functions in the selected databases were used to eliminate resources from unrelated fields, such as medical or agricultural sciences. As a result, 125 publications were excluded. Furthermore, only studies directly related to the application of DTs in the construction industry were retained, resulting in a final set of 145 relevant materials for an in-depth examination. Figure 2 shows the methodology steps and research direction.

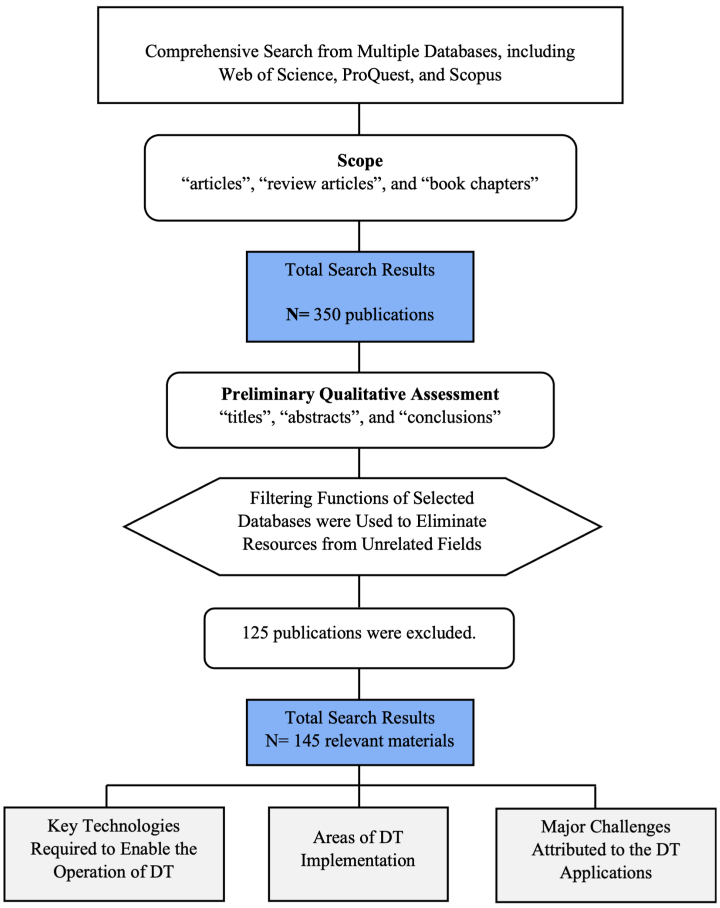

Figure 2. Flowchart showing the Methodology Research.

3. Results and Analysis

The results of analyses carried out on the 145 selected materials are reported in three sub-sections. First, the areas of DT implementation in the construction industry are discussed. This is followed by highlighting the key technologies required to enable the operation of DTs in the construction industry. The third part of the Result and Analysis section discusses the major challenges attributed to DT applications in the industry, along with offering recommendations for future development in the field.

3.1. Current Implementations of Digital Twins in the Construction Industry

The results of analyses addressing the first objective of this study, which aimed to provide a comprehensive understanding of current DT implementations in the construction industry, are presented in this section and demonstrated in Figure 3.

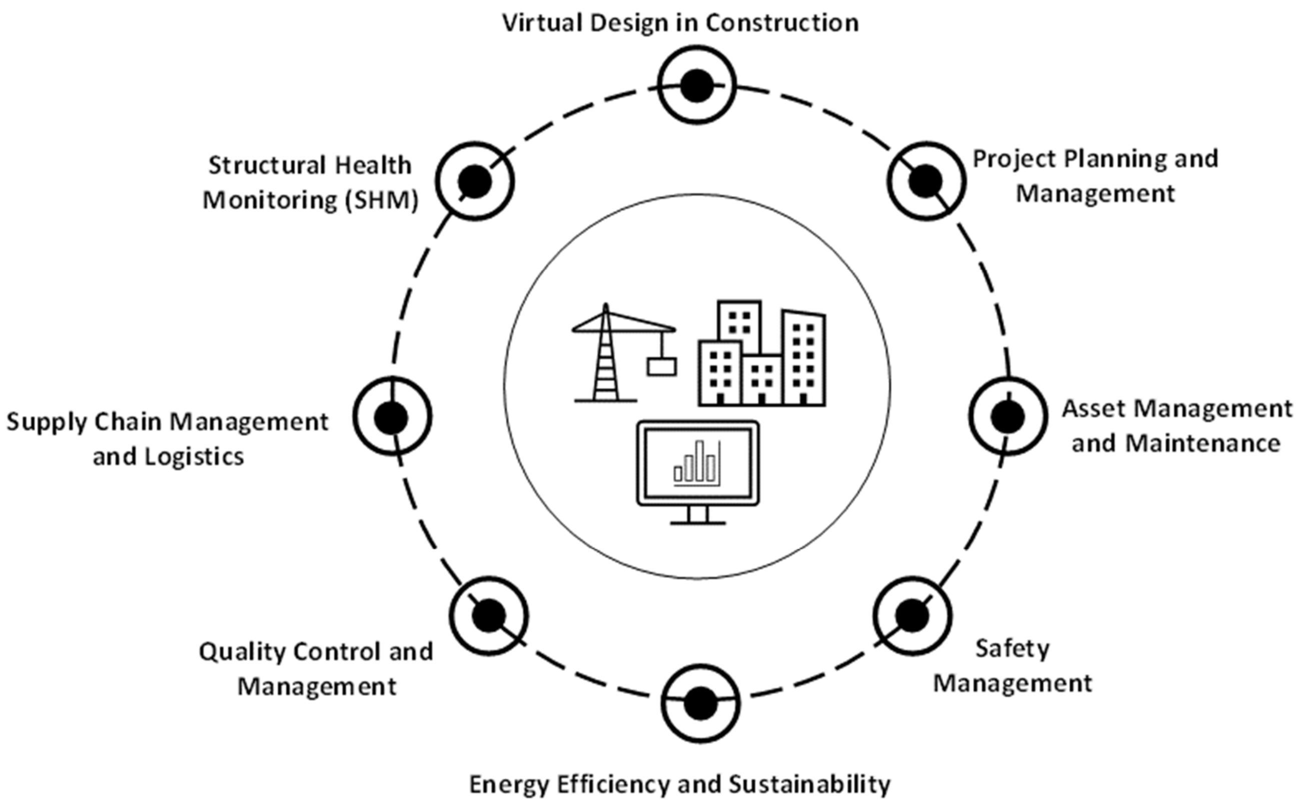

Figure 3. The present directions and areas for implementing digital twins in the construction industry.

3.1.1. Virtual Design in Construction

DT technology is transforming the way that virtual design is performed in the construction industry. The implementation of this technology allows designers to optimise their designs for better performance and increased viability by developing high-fidelity models of physical assets and systems [2,15,27]. In the context of simulation modelling, the term "fidelity" pertains to the level of intricacy and authenticity depicted in the model, which can vary from simple prototypes to highly immersive models [28]. Models with varying levels of fidelity may be suitable for different phases of the design process or for addressing different types of design inquiries [2,4,15,27]. Typically, the levels of fidelity are classified into three categories including low, medium, and high tiers, which denote the level of detail and accuracy present in the model [28].

DT is one of the technologies that enable users to develop models with high fidelity. This technology allows the creation of digital replicas of physical assets, which can be used to analyse and optimise performance, simulate scenarios, and predict outcomes [1,15,19]. The high-fidelity models generated using DT technology can thence provide an unprecedented level of accuracy and detail, which can help designers and engineers to make informed decisions throughout the design and development process. With the aid of DT technology, designers can create virtual prototypes that are almost identical to their physical counterparts, allowing for more precise testing and analysis. In this regard, attempts have been undertaken to develop DT prototypes that can facilitate architectural building design [28,29]. For instance, Kalantari et al. [28] developed a digital twin prototype called "Ph2D" that combines physical and digital technology for architectural designs. The tool uses interconnectable tiles that can be customised with 3D printing or digital design, allowing changes made to a physical floorplan model to be reflected and analysed in a digital platform. Testing the tool with 182 users showed that it was easy to use and increased the value of physical prototyping in design. Non-designers also showed interest in using the tool, suggesting it could be effective in design education and team communication.

Presently, the use of DT technology has begun to gain momentum in the construction industry owing to its potential for optimising the design process. Studies attempted to test the applicability of DT in civil infrastructure systems [30–32] and to optimise buildings' design [33–37]. For instance, Lu and Brilakis [32] developed a slicing-based object fitting method that generated a geometric DT of existing bridges and achieved an average modelling distance of 7.05 cm and a modelling time of 37.8 s, which was a significant improvement over manual methods. Other studies used DT technology for optimising building design performance. For instance, Liu et al. [35] proposed a system for managing green building operation costs based on digital twin technology, which led to improved efficiency and quality in the management process. Studies also applied DT technology for improving occupant comfort in buildings [36,38]. An example is the study carried out by Hosamo et al. [38], who aimed to evaluate the comfort levels of occupants in two non-residential buildings in Norway using a Bayesian network model. The proposed model was developed based on integrating BIM, real-time sensor data, and occupant feedback while using a DT approach to detect and predict issues that could impact comfort. The results showed that the proposed method could increase the lifetime of HVAC by 10% or more, leading to significant cost savings and more sustainable and energy-efficient buildings.

Indeed, DT is a promising technology capable of transforming the way virtual design is performed in the construction industry. The technology enables users to create high-fidelity digital replicas of physical assets, which can be used to simulate scenarios, analyse and optimise performance, and predict outcomes with an unprecedented level of accuracy and detail. DT has already been tested in various construction domains, including infrastructure systems and building design, where it has shown potential for improving design efficiency, reducing costs, and enhancing performance. The studies discussed highlight the advantages of using DT technology in the construction industry, demonstrating its effectiveness in optimising building design performance, managing green building operation costs, and improving occupant comfort in buildings. Thus, the application of DTs in infrastructure projects is becoming increasingly important, as it can lead to more sustainable and energy-efficient buildings and infrastructure systems, ultimately contributing to the development of smart cities and a more sustainable future.

3.1.2. Project Planning and Management

Another application of DTs relates to using this technology for improving the process of planning and management in the construction industry. DT technology is rapidly transforming the construction industry by providing a virtual replica of physical assets, processes, and systems, and it can play a crucial role in optimising the processes of construction planning and management [39,40]. Using a simulation of various design scenarios, construction managers can evaluate the impacts on project timelines and costs and identify potential issues and challenges prior to initiating the actual construction process [39–41]. This subsequently may minimise the possibility of delays in the project. The efficacy of DT technology was demonstrated by Jiang et al. [42], who studied a smart modular system based on the integration of DT technology and robotics, aiming to help with assembling modular components on-site. In another study, Jiang et al. [39] proposed a framework that utilises high-fidelity DT to provide real-time information on resource status and construction progress, with the goal of facilitating planning, scheduling, and execution processes in construction projects.

In addition, DT technology can also enhance collaboration and communication amongst stakeholders involved in construction projects [40,43]. By providing a shared virtual environment, DTs enable architects, engineers, contractors, and clients to visualise the project, discuss design alternatives, and make informed decisions [40,43–45]. For instance, Pan and Zhang [46] developed a DT framework that integrates BIM, IoT, and data mining techniques for smart construction project management. The framework captures real-time data and discovers hidden knowledge to simulate task execution and worker cooperation in a virtual model. By predicting possible bottlenecks and optimising work and staffing under changeable conditions, the framework facilitates more efficient project management. Furthermore, the study demonstrated that the framework has great potential for facilitating data communication and exploration, leading to a better understanding, prediction, and optimisation of physical construction operations. In another study, Jiang et al. [40] proposed a blockchain-enabled DT collaboration platform aimed at facilitating modular construction fit-out operations. The outcomes showed that DT technology can provide a virtual environment for real-time monitoring, decision-making, and communication between various stakeholders involved in the project. The integration of blockchain and DT technology helps in ensuring data integrity, security, and trustworthiness, thereby enabling more effective collaboration among stakeholders.

In summary, the use of DT technology for the purpose of construction management and planning has the potential to revolutionise the industry, providing significant benefits such as improved productivity, enhanced collaboration, and better project outcomes.

3.1.3. Asset Management and Maintenance

DT technology is increasingly being recognised as an important tool for asset management and maintenance in the construction industry. The use of DTs can facilitate real-time monitoring of physical assets, enabling predictive maintenance and reducing the likelihood of unexpected failures [47–49]. DT technology has shown grave potential in improving the accuracy of maintenance planning, allowing for more efficient use of resources and reducing operational costs [49–51]. This can be particularly effective in enhancing maintenance procedures for civil infrastructures since a majority of maintenance in this sector is still carried out manually. For instance, it is estimated that the inspections of more than 720,000 bridges throughout Europe are still being performed using only visual assessments [50].

In the context of civil infrastructures, such as bridges, dams, and buildings, sensors can be deployed to continuously monitor the health and condition of these structures. By collecting data on factors like vibrations, temperature, and structural movements, these sensors provide real-time insights and enable proactive measures to be taken when necessary [49,52]. By analysing the data collected with these sensors, anomalies that indicate potential structural issues can be identified [49–51]. This allows engineers and maintenance teams to take proactive measures, such as conducting inspections, performing repairs, or implementing reinforcement, prior to the issues worsening or leading to failures. Constant monitoring and timely intervention based on sensor data can help ensure the safety and longevity of civil infrastructures. By addressing potential problems early on, catastrophic failures can be prevented while reducing repair costs and extending the lifespan of these vital structures [48–53]. Therefore, various studies have pointed out the immense potential of emerging DT technology in the construction industry, especially in civil infrastructure projects [49,53,54]. For instance, Mohammadi et al. [53] proposed a methodology for an advanced asset management system that used BIM data to enhance a bridge management system. This system involved a precise terrestrial laser scan-derived BIM, which was a digital replica of the bridge composed of geometrical and non-geometrical information related to its elements.

In the context of building maintenance, DTs are virtual models that replicate the physical characteristics of a building. These models can be created using 3D modelling software and can be populated with data collected with sensors that monitor the performance and condition of the building in real-time [52,55]. The data collected with DTs can be then analysed using analytics techniques such as artificial intelligence to identify patterns and anomalies that indicate potential maintenance issues. For instance, Arsiwala et al. [37] presented a solution that facilitates the automated monitoring and control of carbon dioxide emissions linked to current assets by integrating IoT, BIM, and artificial intelligence. Another example is the research carried out by Xie et al. [52], which developed a DT model enabling continuous monitoring and anomaly detection for building facilities. The results showed that the proposed framework allowed for ongoing monitoring of assets, utilising the data management capabilities provided by the DT.

3.1.4. Safety Management

DT technology is being increasingly used in the construction industry, with safety and risk management being one of the key areas where its implementation can bring significant benefits [56,57]. The implementation of this technology enables the creation of a virtual replica of a physical structure, facilitating the identification of potential safety hazards and risks at construction sites using constant monitoring prior to their materialisation [56–60]. This can subsequently result in improvements in safety practices, leading to the prevention and minimisation of incidents on construction sites. Studies have shown promising outcomes when DT technology is applied toward such an end. For instance, some studies developed frameworks based on DT technology for improving hoisting safety risk management in construction sites [60–63]. An example is the research carried out by Jiang et al. [61], which developed a DT framework aiming to model various hoisting behaviours with a high degree of realism and evaluate their dynamic impact on tower cranes.

Similarly, Liu et al. [62] presented a DT-based framework enabling the optimisation of safety risks in hoisting operations at construction sites. The proposed framework was formed based on the integration of IoT, BIM, and a security risk analysis method that used the Apriori algorithm and a complex network. The framework enabled the real-time perception and interaction of various sources of information during hoisting, which can be used to mine association rules and coupling relationships among hoisting safety risk factors and visualise time-varying data. The framework was tested during the construction of a large, prefabricated building and showed effectiveness in improving the efficiency of safety management during construction. In another study, Kamari and Ham [56] introduced a new framework that utilises DT technology and computer vision for disaster preparedness on construction sites. The framework uses deep learning to detect and analyse the potential impact of wind-borne debris on construction sites. The results of the implementation demonstrated the effectiveness of the proposed framework in recognising and assessing potential threats, enabling effective and timely measures for hurricane preparedness.

Another research stream focuses on the utilisation of DT technology to monitor the movements and activities of workers on construction sites, aiming to provide real-time observations of possible safety hazards and to enable prompt interventions when safety hazards are detected [59,64]. In a recent study, Wu et al. [59] developed a real-time visual warning system based on the amalgamation of DT, deep learning, and mixed reality technologies. The proposed system provides construction workers with real-time insights into their safety status to avoid accidents. The study also conducted system tests under three quasi-on-site scenarios and demonstrated the system's feasibility in synchronising construction undertakings over a large area and visually demonstrating hazard evidence. The system's testing scenarios during development served as compelling evidence, showcasing its effectiveness in enhancing workers' accuracy in assessing risks, reinforcing their adherence to safety protocols, and presenting construction safety managers with a fresh outlook on analysing the safety status of construction projects.

In summary, DT technology is an effective tool for improving safety and risk management in construction. Its virtual replicas allow real-time monitoring and identification of potential safety hazards, leading to better safety practices and incident prevention. The incorporation of DT with cutting-edge technologies such as deep learning and mixed reality demonstrates its remarkable effectiveness in enhancing the capabilities of this technology, presenting construction safety managers with innovative perspectives to comprehensively assess safety conditions.

3.1.5. Energy Efficiency and Sustainability

The adoption of DTs within the construction sector offers a robust means to enhance energy efficiency and promote sustainability. A DT enables real-time tracking and analysis of energy consumption patterns with the creation of virtual replicas of buildings [65–68] and infrastructure projects [69,70], allowing for the proactive identification of inefficiencies and optimisation prospects [65,67,71,72]. For instance, Seo et al. [66] and Tan et al. [67] developed DT models to optimise energy consumption associated with lighting in university classrooms and a corridor, respectively. In another study, Clausen et al. [65] devised a framework for DTs in buildings, outlining the process of its design and implementation. The framework represents controlled environments as digital entities, with DTs serving as parametrised models integrated into a generic control algorithm. The algorithm utilises various data, including weather forecasts, occupancy information, and the environment's current state in order to enable the creation of a model predictive control (MPC). To ensure seamless applicability, the framework incorporates a uniform data access layer, allowing easy transitions between simulation and real-life scenarios and promoting adaptability in different control environments. The findings indicate the capacity of DT technology for supporting the creation of MPCs that can be used for the improvement of energy efficiency and occupant comfort.

By utilising advanced simulation and predictive analytics, DTs can also assist with simulating various scenarios, evaluating design choices, and optimising the energy performance of buildings. This implementation is manifested in research carried out by Tang et al. [68], which applied a DT for evaluating the viability of vertical greenery systems as a green alternative for renovating traditional commercial and residential buildings in Guangzhou, China. The use of DT technology significantly supported the design process for renovating the selected buildings. Tagliabue et al. [73] introduced a framework that facilitates a dynamic sustainability assessment by integrating DT technology and IoT. This approach allows for real-time evaluation and control of various sustainability criteria, placing a particular emphasis on user-centric perspectives. The framework was tested using the eLUX lab cognitive building, a pilot facility located at the University of Brescia. This educational building used sensorised assets to continuously monitor indoor comfort, air quality, and energy behaviour. The findings demonstrated that the framework could serve as a crucial component of a methodology that leverages the DT approach to enhance decision-making processes throughout the entire life cycle of the building, particularly in relation to sustainability considerations.

DT technology offers valuable assistance in the design and advancement of net-zero energy buildings (NZEBs). Through the creation of a digital duplicate of the structures, DT assists architects and engineers with simulating and improving energy efficiency during the design phase. These virtual models possess the ability to accurately forecast energy consumption and pinpoint areas where enhancements can be made, facilitating a process of iterative design and informed decision-making [74–76]. DTs are capable of simulating the operations of diverse building systems, such as HVAC, lighting, and the integration of renewable energy sources, with the objective of evaluating their effectiveness in achieving net-zero energy objectives [74–76]. Moreover, DTs have the capacity to examine real-time data gathered using sensors embedded in the physical buildings, enabling continuous monitoring of energy usage, identification of inefficiencies, and refinement of energy management strategies [74–76]. This technological advancement empowers designers to experiment with various energy-saving approaches, optimise building performance, and effectively and efficiently attain net-zero energy targets. For instance, Agostinelli [74] used DT-based models to assess the efficiency of integrated systems for harnessing solar energy, with the aim of surpassing the self-generated energy threshold and meeting the requirements for near-zero energy buildings.

In summary, DT technology has a profound impact on enhancing energy efficiency and fostering sustainability in the construction industry. The widespread adoption of this technology empowers stakeholders to make informed, data-driven decisions, optimise building performance, and actively contribute to a greener and more sustainable future.

3.1.6. Quality Control and Management

The implementation of DT technology within the construction industry offers significant potential for enhancing quality control and management processes. By utilising DT applications, such as those used in the production of precast and prefabricated concrete [77–80] and steel modules [81], as well as in 3D concrete printing [82], construction companies can revolutionise their approach to assuring quality. DTs enable real-time monitoring and analysis of construction processes, providing a comprehensive understanding of the project at each stage. This technology allows for virtual simulations and testing, enabling the identification and resolution of potential issues prior to physical implementation [77,78,80]. Early detection and resolution of quality concerns using DTs minimise the occurrence of defects, rework, and costly delays, ultimately resulting in higher-quality construction outcomes [77,78,83]. For instance, Kosse et al. [77] devised a framework based on DT technology that enables the industrialised production of precast concrete elements in a series production setting, leveraging the asset administration shell technique within the context of Industry 4.0. The findings demonstrated that the developed framework has the potential to make a significant contribution to improving decision-making processes, ultimately enhancing the quality of precast concrete module manufacturing.

In the context of manufacturing precast and prefabricated modules, DT technology allows for accurate virtual representations of these components. This facilitates quality inspections and ensures that the manufactured modules adhere to design specifications [77,78,83]. By integrating sensors and data collection mechanisms into these modules, DTs can continuously monitor performance, structural integrity, and maintenance requirements, ensuring ongoing quality control throughout their lifecycle [78,79,83]. In a recent study, Tran et al. [78] developed an innovative framework aimed at assessing the geometric quality of prefabricated façades during the construction process. The framework utilises a 3D model that represents the intended design, along with a 3D semantic model that accurately captures the as-built condition. Built upon a DT approach, the framework facilitates an automatic and quantitative comparison between the 3D as-built digital replica, reconstructed from lidar point cloud data, and the 3D as-designed model. Experimental tests conducted on both a synthetic façade system and an actual prefabricated façade from a construction project demonstrated the framework's ability to identify inconsistencies, evaluate geometric errors with precision, and localise them efficiently and promptly. The proposed framework was shown to be effective in enabling an efficient visual assessment of quality specifically tailored for prefabricated construction. Furthermore, DT applications in 3D concrete printing empower construction professionals to optimise the quality of printed structures [82]. Real-time feedback and analysis enable adjustments during the printing process to maintain accuracy, structural soundness, and overall quality [82]. This level of control and precision significantly reduces the risk of errors and deficiencies in the final printed structure.

By harnessing DT technology for quality control and management, the construction industry can achieve substantial improvements in construction quality, reliability, and efficiency. Using virtual simulations, continuous monitoring, and real-time analysis, these technologies provide a transformative approach to ensuring the highest standards of quality in construction projects.

3.1.7. Supply Chain Management and Logistics

DT technology possesses tremendous potential for enhancing supply chain management and logistics in the construction industry. By encompassing diverse elements such as excavators, logistics, construction vehicles, site personnel, or tower cranes, a DT facilitates continuous monitoring of project conditions and progress in real-time [44,84,85]. Furthermore, the application of this technology allows for the prediction of risks associated with the supply chain, such as schedule deviations, by performing numerous simulations involving "what-if" scenarios [85–87]. This capability provides valuable insights to project participants. By harnessing real-time sensor data, such as GPS information, DTs facilitate effective coordination by providing optimised delivery routes, precise delivery times, and optimal module order times [85–87].

In particular, these advancements hold the promise of greatly enhancing project performance within the realm of modular construction. In a study, Lee and Lee [86] proposed a novel framework utilising DT technology to enable real-time monitoring and simulation of logistics processes in the context of modular construction. The framework introduced a DT that created a virtual representation of physical assets with BIM and simulated diverse logistics scenarios using a GIS-enabled routing application. In a case project, the framework was rigorously tested, and the findings highlighted the DT's ability to accurately predict various logistics risks and calculate a precise estimated time of arrival (ETA). The accurate ETA predictions resulted in a significant reduction of 157.5 h in idle time loss. By enabling the prediction of potential logistics risks and providing accurate ETA calculations with reliable simulation, the developed DT facilitated precise risk assessment and effective coordination within the supply chain among project participants, thereby enabling "just-in-time" module delivery. Notably, the study's results emphasised that the implementation of "just-in-time" delivery in modular construction could effectively reduce scheduling conflicts and costs, consequently promoting the widespread use of modular construction practices across the industry.

3.1.8. Structural Health Monitoring (SHM)

Constantly monitoring the health and safety of civil infrastructures is crucial due to their significant impact on public safety. Thus, the use of SHM technology becomes essential in the architecture, engineering, and construction (AEC) industry. SHM involves various activities such as capturing real-time data, analysing structural performance, utilising predictive modelling, generating actionable insights, and implementing proactive maintenance strategies [88–90]. Conventional monitoring techniques depend on visual examination and manual measurements, which require significant labour and are susceptible to inaccuracies [89,90]. Moreover, their effectiveness is also highly dependent on the expertise and discipline of personnel [89,90]. Given the presence of numerous aging buildings and infrastructure projects, the AEC industry requires an automated framework to enable proactive and accurate evaluation of structural integrity and continuous monitoring of their soundness.

Initially, SHM studies focused primarily on water conservation projects such as bridges and dams [91]. However, as the construction of larger and more complex buildings increased, SHM technology gradually expanded to include other civil infrastructures [90,91]. Despite significant advancements in SHM, accurately evaluating and predicting a structure's condition using SHM data remains challenging due to the diverse structural forms and complex internal components such as beams, plates, and columns [91]. Additionally, substantial variations exist in the states of these factors [90,91]. Therefore, the implementation of DT technology can provide valuable support for SHM efforts [89–91]. DTs create virtual replicas of physical structures and integrate real-time sensor data, enabling comprehensive and precise monitoring of a building's health and safety [88–91]. Using simulations and data analysis, DTs facilitate the early detection of structural abnormalities or damage, enabling proactive maintenance and timely interventions [89–91]. The integration of SHM with DT technology enhances monitoring systems, enabling more accurate evaluation of a building's condition, prediction of potential risks, and optimisation of maintenance strategies [88–92]. Much research has been conducted endeavouring to implement DT technology for enhancing SHM practices in the AEC industry [88,89,91–96].

For instance, Xu et al. [91] proposed a DT-health monitoring information model. The model was capable of integrating a BIM and a real-scene 3D model that enabled simultaneous sensor localisation and data monitoring. The fusion process involved dividing the BIM into sub-BIMs based on building component types and geometric transformations, registering 3D spatial positions using a rigid-body transformation method, and mapping semantic information. Afterwards, the sensor-collected monitoring data were stored within a database management system and seamlessly integrated with the fused model. To assess the viability and usability of the fusion method, a case study was conducted on the Nanjing Museum Old Hall, constructing a DT model of the building. The findings demonstrated the feasibility and effectiveness of the developed DT model for performing SHM in buildings. In another study, Chiachío et al. [88] introduced a comprehensive DT framework designed specifically for structural engineering. This framework encompassed key attributes essential for a functional DT including simulation, learning, and management capabilities. Notably, the focus was placed on highlighting the autonomous interactions between the physical and digital components, as well as incorporating workflow modelling, which is often overlooked in the existing literature on civil and structural engineering. To validate the effectiveness of the framework, a proof of concept was presented, involving the monitoring of a laboratory-scale test structure using IoT-based sensors and actuators. The experimental results affirmed the real-time responsiveness and self-adaptive nature of the virtual counterpart, demonstrating its ability to provide automated decision-making support for ensuring structural integrity.

In summary, the use of DT technology in SHM holds significant potential for the construction industry. It addresses the challenges associated with evaluating and predicting a structure's condition by providing a comprehensive and dynamic virtual representation. With the utilisation of DTs, the construction industry can enhance safety, optimise maintenance efforts, and ensure the long-term structural integrity of buildings and infrastructure.

3.2. Enabling Technologies for Digital Twin Implementation in Construction

To enable the functioning of DTs, it is essential to use a range of techniques. Previous studies suggested models composed of multiple layers, each incorporating various technologies to support the functionality of DTs [27,97–100]. For example, Hu et al. [98] proposed a six-dimensional model designed for the health-condition monitoring of complex equipment in different engineering domains, namely tunnelling, underground space engineering, and marine and wind engineering. In another study, Fuller et al. [97] introduced a generic model consisting of four technology layers to facilitate the realisation of DTs. This study integrates insights from retrospective research and presents a five-layered model encompassing key technologies that enable the operation of DTs in the construction industry.

1. *Technologies enabling perception and control of the physical environment*. The initial stage of developing DTs involves replicating the physical environment. This entails constructing a virtual environment that accurately represents the entities in the physical world, including their constituents, internal interaction logic, and external relationships [27,97,100]. The complexity of this process can vary depending on the desired level of detail for the DTs. Therefore, establishing and improving DTs is a time-intensive process. On one hand, the virtual models corresponding to physical entities are not flawless, requiring a certain degree of adaptability to improve over time in response to changes in the physical environment and its constituent elements [27,101]. This adaptability necessitates a comprehensive perception of the physical world. On the other hand, the digitalisation of physical entities often uncovers implicit associations that can support the evolution and control of the physical world [27]. One of the important steps in reflecting the physical world involves measuring various

parameters (e.g., size, shape, etc.) [27,97,99]. Measurement technologies such as laser measurement, image recognition measurement, conversion measurement, and micro/nano-level precision measurement can be used for this purpose [27]. IoT can also play a crucial role in enhancing the data collection capabilities of DTs by connecting physical objects and devices to the Internet. It enables real-time data collection from various sources within the physical environment, serving as data sensors that capture and transmit information about asset or system state, behaviour, and performance [102,103]. This continuous data monitoring and integration with DTs enhances the accuracy and fidelity of the virtual representation. IoT facilitates the bidirectional flow of data between the physical world and DTs, enabling updates and calibrations based on real-time insights [102,104]. This integration empowers DTs to provide accurate and up-to-date insights, supporting asset management, optimisation, and decision-making across multiple domains in the construction industry.

2. *Technologies enabling data management*. A high-fidelity DT model necessitates secure storage for complex information, including geometry, physical characteristics, and condition data [27,98,99]. Technologies such as bar codes, quick response codes, and radio frequency identification (RFID) can be utilised for the safe storage of data generated using DT systems [98]. Big data storage frameworks like MySQL, HBase, and NoSQL databases are used to effectively manage and utilise large volumes of data. In MySQL, data are organised in tables, with rows representing records and columns containing specific data values [98]. HBase relies on the Hadoop Distributed File System (HDFS) for storage and harnesses Hadoop MapReduce for high-performance computing, whereas NoSQL databases excel in handling extensive data volumes, offering exceptional read-write performance [98].

Another aspect of data management relates to data processing, a procedure through which valuable and meaningful insights from extensive and complex datasets are generated [98]. Big data analytics encompass analytic visualisations, data mining algorithms, and predictive analytics [98,105]. Visualisations use graphical methods to facilitate clear and effective communication, while data mining algorithms enable the discovery of hidden information within large datasets [98]. Predictive analytics also utilise historical data to discover real-time awareness and forecast future events using advanced systems [98]. To manage diverse data sources, data fusion is essential for collecting, transmitting, synthesising, filtering, correlating, and extracting useful information [98,105]. Data fusion methods are categorised into three levels: signal-level fusion, feature-level fusion, and decision-level fusion [98], with several techniques that can be used for effective implementation of data fusion such as Kalman filtering, image regression, principal component transform, K-T transform, and wavelet transform [98]. Additionally, artificial intelligence and machine learning technologies play a vital role in the data processing and analytics of DTs in the construction industry. They are instrumental in handling and analysing the vast amount of data generated with DTs. AI and ML algorithms provide powerful tools for extracting valuable insights and patterns from the data. These technologies enable advanced data processing capabilities, facilitating the identification of correlations, trends, and anomalies within a dataset [106,107]. By leveraging AI and ML, DTs can perform predictive modelling, optimisation, and real-time monitoring, providing construction professionals with actionable information for informed decision-making and improved performance [74,106,107]. The integration of AI and ML algorithms allows for efficient data fusion and integration from multiple sources, creating a comprehensive view of construction projects.

In this layer, the edge computing technique can also be used for the purpose of data processing. Edge computing in the context of DTs refers to the decentralised processing and analysis of data at the network edge, closer to the data source or device generating it [108,109]. Rather than sending all the data to a centralised cloud or server, edge computing enables local data processing, storage, and analytics. This approach brings benefits such as reduced latency, improved real-time responsiveness, enhanced data privacy and security, optimised bandwidth usage, improved reliability, and localised decision-making capabilities [109,110]. By processing data locally, delays caused by transmitting data to a remote server are minimised, ensuring timely decision-making for time-sensitive applications. Additionally, edge computing reduces the risk of security breaches and unauthorised access during data transmission. It also optimises network resources and reduces costs by filtering and aggregating data locally before transmission. The distribution of computing tasks across multiple edge devices enhances system reliability and resiliency. Finally, edge computing allows for localised decision-making and autonomy, enabling the DT to perform analytics and make critical decisions without relying solely on cloud connectivity, which is beneficial in scenarios with limited or disrupted cloud connectivity in addition to edge computing.

3. *Technologies enabling virtual modelling*. Previous research indicated that a rigorous robust model should incorporate key components such as geometry, physical attributes, behavioural characteristics, and rule-based associations [27,98,101]. The geometry aspect involves visualising shape and position utilising well-established computer-aided design (CAD) software [27,98]. Physical information encompasses crucial details like tolerances and material properties that contribute to an accurate representation of the virtual model [27,98,101]. Behavioural models play a significant role in capturing how the virtual model interacts and responds to external stimuli and environmental changes [27]. Rule models are essential for defining associations and constraints that enable performance analysis and optimisation [27,98,101]. Extracting rule information relies on a variety of techniques, including data mining and semantic data analytics, which facilitate the identification and extraction of relevant rules. To ensure the fidelity and reliability of a virtual model, verification, validation, and accreditation technology should be used, which helps evaluate and validate the accuracy of the virtual model against real-world scenarios and data [27,98,101].
4. *Technologies enabling services*. DT technology combines multiple disciplines to achieve advanced monitoring, simulation, diagnosis, and prognosis [27,97,98]. Monitoring involves technologies such as computer graphics, image processing, virtual reality synchronisation, and 3D rendering [27,98]. Simulation encompasses various areas such as structural, mechanical, electronic, control, and process simulation. Diagnosis and prognosis rely on data analysis methods such as statistical theory, machine learning, neural networks, and fault tree analysis. Hardware, software, and knowledge can be encapsulated into services, which go through stages like service generation, management, and on-demand utilisation [27,97,98,100]. Resource and knowledge services, along with application services, are managed with an industrial IoT platform that provides functions like service publishing, searching, communication, and evaluation. Sharing and using models and data is crucial, and services can play a vital role in encapsulating and managing DT components, enabling convenient sharing and reuse. The use of a service platform allows for uniform management of DTs, and service-oriented architecture stands out as a key enabling technology for DT services. In addition, this study recommends integrating blockchain technology into this layer to provide secure and transparent transactions, data sharing, and traceability within the DT environment. Through its decentralised and immutable nature, blockchain ensures the integrity and authenticity of data by securely recording and verifying transactions and data exchanges among stakeholders [111,112]. The use of this technology also enables secure data sharing and collaboration, eliminates the need for intermediaries, and facilitates data tracking and provenance [111,112]. Leveraging blockchain technology allows DTs to enhance data integrity, foster trust, and enable efficient and secure collaboration in construction.
5. *Technologies enabling connectivity and data transmission*. To achieve real-time control and accurate mapping between the virtual and physical states in DTs, establishing a reliable connection is of utmost importance. Various connection protocols exist for data exchange, both between the physical space and the DT, as well as among different software within cyberspace. Data transmission methods include wired options such

as twisted pair, coaxial cable, and optical fibre, and wireless technologies such as Zig-Bee, Bluetooth, Wi-Fi, ultra-wide band (UWB), and near-field communication (NFC) [98,113]. Long-distance wireless transmission can utilise technologies such as GPRS/CDMA, digital ratio, spread spectrum microwave communication, wireless bridge, and satellite communication [97,99,101,105]. In this regard, a wide array of application program interfaces (APIs) is commonly being utilised to facilitate data exchange between different software applications, ensuring seamless data transmission at the software level [98]. The emerging 5G and 6G technologies show promise in meeting the requirements for high data rates, reliability, coverage, and low latency in DT applications [114,115].

The connection technological aspect of DTs is vital for enabling real-time interaction between their various components. However, the lack of uniformity in interfaces, protocols, and standards presents a daunting challenge [27,97–100,116]. Hence, it becomes necessary to investigate interconnection theories, standards, and devices that can support heterogeneous multi-source elements [27,97,116]. To handle the growing data traffic, Qi et al. [27] recommended that multi-dimensional multiplexing and coherent technologies should be further developed, leading to possible enhancement in bandwidth and reduction in latency. Additionally, the development of ultra-large-capacity routers and innovative network architectures is crucial for managing large volumes of data and achieving efficient network control. Considering the rising bandwidth and energy consumption, new strategies and approaches are needed to promote green communication [117].

From the discussion above, this study found that a five-layered model demonstrates key technologies that are framed under three areas to enhance awareness, response, and prediction. Figure 4 shows the three areas including collect, compute, and visualise and how they encompass the five-layered model and enable these technologies for the construction industry.

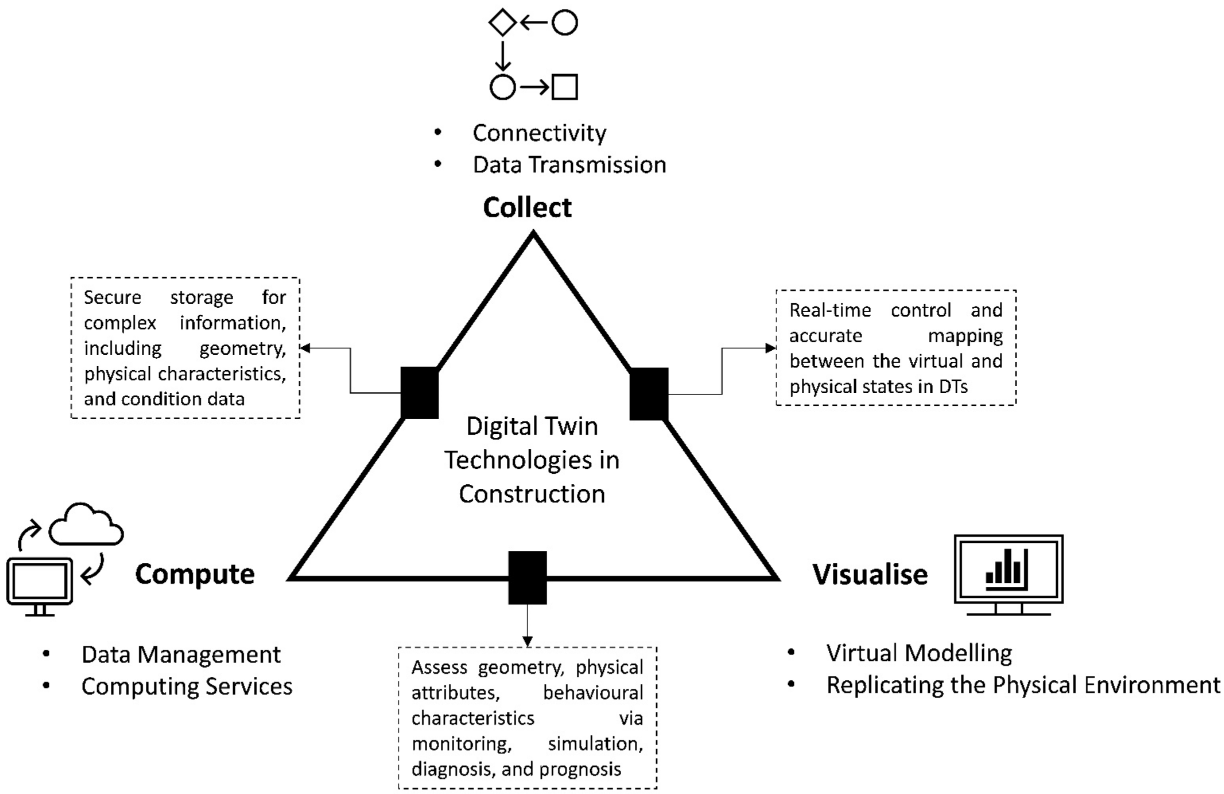

Figure 4. A model for enabling software and hardware technologies within a digital twin for the construction industry.

3.3. Current Challenges and Future Directions

Despite the immense potential of DT technology, its broad adoption in the construction industry faces various obstacles. These impediments must be addressed to unlock the full benefits of DTs and drive the industry towards enhanced efficiency and productivity. This section aims to shed light on the primary challenges that hinder the effective implementation and utilisation of DT technology in construction, along with recommending solutions to overcome the highlighted challenges. A summary of these challenges is discussed and illustrated in Figure 5.

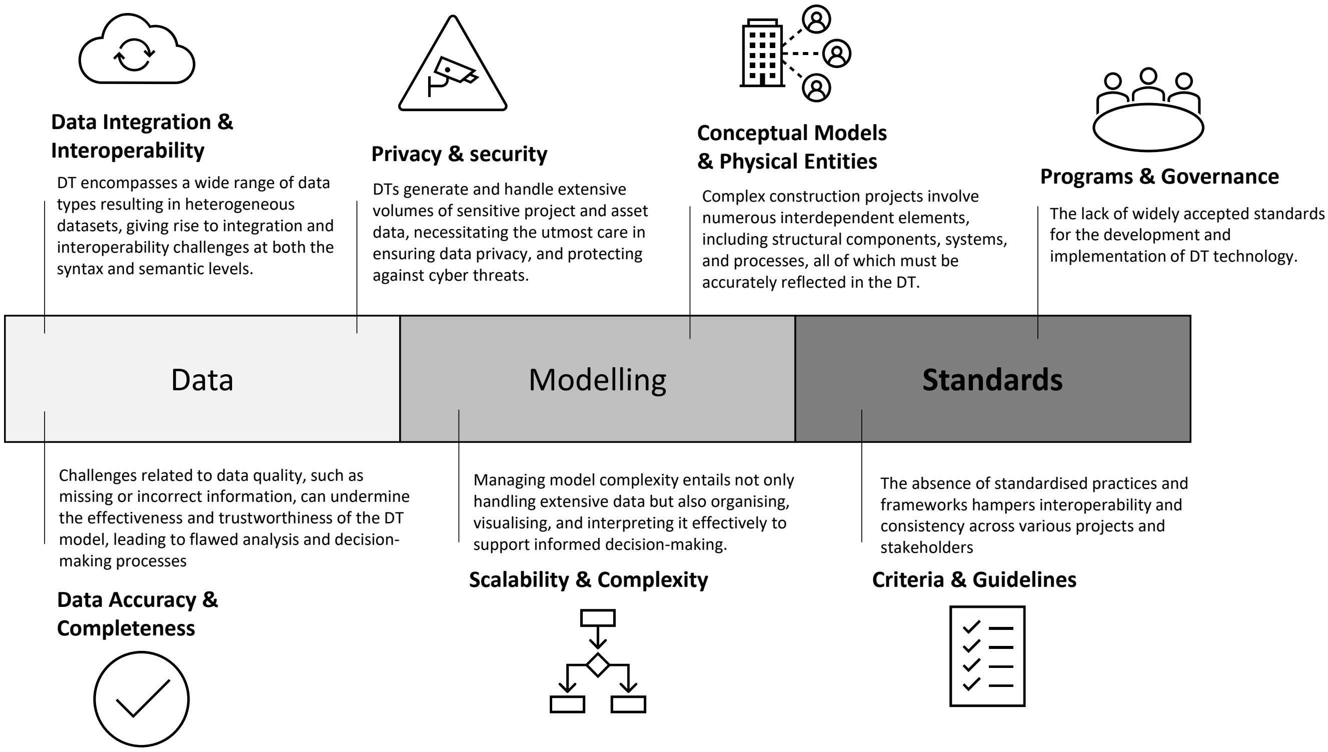

Figure 5. A summary of various obstacles to and future directions for using DT technology in construction.

- Data integration and interoperability: The seamless consolidation and merging of a virtual model and IoT sensor data outline the fundamental basis for the functionality of a DT. As evident from various research studies, the data generated with DTs encompasses a wide range of types, collected using diverse sensors, evolving into heterogeneous datasets that encompass image data, video data, positioning data, environmental data, mechanical data, and more [27,118,119]. These datasets need to be effectively incorporated within BIM models. However, acquiring these data involves sourcing from distinct and diverse arrangements such as building management systems, each operating on different software platforms and having separate syntax and representations [27,118,119]. Consequently, the complexity of DT models increases, giving rise to incorporation and interoperability challenges at both the syntax and semantic stages.

To address this challenge, it is imperative to prioritise the development of standardised data formats, protocols, and application programming interfaces (APIs) that facilitate seamless collaboration and data exchange among diverse software systems and stakeholders. By establishing universally recognised file formats and data interchange rules, effective communication and cooperation can be achieved across different platforms. This collaborative approach enables smooth information sharing throughout the project lifecycle, thereby maximising the benefits and effectiveness of DT implementation in the construction industry.

Studies also suggested that semantic models and ontologies offer viable approaches to address the challenges related to data integration and interoperability in DT models [120,121]. Semantic modelling involves utilising semantic web-based techniques to align data streams, active sensing data, and proprietary relational datasets and combine them with user preferences to establish a dynamic structure of elements [27]. Contrarily, ontologies provide a formal and explicit representation of concepts within a specific domain that can be shared among stakeholders [122]. Therefore, it is essential to explore semantic data modelling for sensor data, BIM model data, and data from other systems to facilitate the standardisation of DT data by promoting data integration and interoperability. In this regard, Tuhaise et al. [118] recommended the use of semantic web-based technologies as an effective solution to overcome the limitations of IFC standard models. These technologies offer flexible methods for integrating data across diverse domains and scales, thereby enabling interoperability among different data sources and systems.

- Data accuracy and completeness: The accuracy of data utilised in a DT is of utmost importance, as it forms the foundation for accurate analysis, simulations, and decision-making processes [4,123,124]. Challenges related to data quality, such as missing or incorrect information, can undermine the effectiveness and trustworthiness of a DT model, leading to flawed analysis and decision-making processes. Inaccurate and incomplete data can stem from various factors, including human errors during data acquisition or entry, difficulties in integrating data from diverse sources with inconsistencies in formats and structures, limitations or malfunctions of sensors used for real-time data capture, and gaps in information that may be unavailable or inadequately recorded [1,15,123]. Therefore, measures should be taken to ensure that data integrated into a DT is precise, up-to-date, and complete.

To achieve data accuracy, thorough validation processes should be implemented to identify and rectify any errors or inconsistencies. Data quality control mechanisms, such as data cleansing and verification, can be used to enhance the accuracy and reliability of information captured within a DT. Additionally, establishing robust data governance practices and protocols can help ensure that data are continuously monitored, updated, and maintained throughout the lifecycle of a DT. Data completeness is equally crucial to avoid gaps or missing information that could compromise the integrity of a DT. It is essential to capture and integrate all relevant data from various sources, including BIM models, sensor data, historical records, and operational data. This comprehensive approach allows for a holistic representation of the physical asset or system being modelled, enabling more accurate simulations and analysis.

- Scalability and complexity: The successful realisation of DT technology in the construction industry encounters challenges associated with scalability and effectively managing the growing complexity of models. Scalability refers to a DT's capacity to accommodate large-scale construction projects and intricate infrastructure while maintaining optimal performance [103,125]. As projects increase in size and complexity, accurately capturing and representing all relevant aspects within a DT becomes progressively more arduous.

Addressing scalability challenges necessitates the development of robust systems and infrastructure capable of efficiently handling the expanding volume of data generated with DTs. This entails harnessing high-performance computing capabilities such as cloud computing, fog computing and edge computing technologies [126,127], using efficient mechanisms for data storage and processing, and utilising scalable network architectures. These measures facilitate seamless integration and analysis of substantial data quantities, enabling DTs to meet the demands of expanding projects. Moreover, effectively managing model complexity is a critical factor. Complex construction projects involve numerous interdependent elements, including structural components, systems, and processes, all of which must be accurately reflected in a DT. This calls for the utilisation of advanced modelling techniques and methodologies capable of capturing the intricate relationships and interactions among various project components. Managing model complexity entails not only handling extensive data but also organising, visualising, and interpreting it effectively to support informed decision-making.

- Privacy and security: The widespread use of DT technology in the construction industry faces a significant challenge related to privacy and security [97,128]. DTs generate and handle extensive volumes of sensitive project and asset data, necessitating the utmost care in ensuring data privacy, protecting against cyber threats, and complying with data governance regulations [27,97]. Hence, robust security measures should be implemented in order to safeguard DT data and prevent unauthorised access [129].

To address the challenge of privacy and security, it is crucial to establish comprehensive data protection protocols and encryption mechanisms. This involves using state-of-the-art cybersecurity technologies and practices to mitigate potential risks [129]. Additionally, implementing access controls, authentication procedures, and user permissions helps restrict data access to authorised individuals or entities, enhancing the overall security posture of the DT ecosystem. Moreover, data governance plays a critical role in ensuring compliance with relevant regulations and standards. This entails establishing clear policies and procedures for data collection, storage, sharing, and retention. By adhering to established data governance frameworks, organisations can demonstrate accountability and transparency in handling sensitive data, building trust among stakeholders.

Collaboration between industry stakeholders, technology providers, and cybersecurity experts is also essential in developing comprehensive privacy and security frameworks for DTs. Regular audits and vulnerability assessments can identify potential weaknesses and allow for prompt remediation. Additionally, fostering a culture of cybersecurity awareness and training among employees helps establish a strong defence against cyber threats. By prioritising privacy and security in the functioning of this technology, the building and construction industry can instil confidence in stakeholders, protect sensitive data, and ensure the responsible and ethical use of DT capabilities.

- Standards and governance: The lack of widely accepted standards for the development and implementation of DT technology poses a significant challenge to its widespread use in the construction industry [27,124,130]. This absence of standardised practices and frameworks hampers interoperability and consistency across various projects and stakeholders. To address this challenge, it is imperative to establish industry-wide standards and governance frameworks that promote harmonisation and enable seamless data exchange.

Developing robust standards for DT implementation necessitates collaboration among industry experts, researchers, and technology providers. These standards should encompass different aspects of DT development, including data formats, models, communication protocols, and interoperability guidelines. By defining and using these standards, the construction industry can ensure consistency and compatibility among different DT solutions, facilitating effective data integration and exchange.

In addition to standards, the establishment of governance frameworks is crucial to provide guidelines and best practices for the utilisation of DT technology. These frameworks can address concerns related to data ownership, access, sharing, and usage rights. They can also outline guidelines for data security, privacy, and ethical considerations, promoting the responsible and transparent use of DTs. Implementing industry-wide standards and governance frameworks will foster collaboration and cooperation among stakeholders involved in DT projects, facilitating the exchange of information, knowledge, and experiences, ultimately leading to improved project outcomes and enhanced efficiency. Furthermore, standardised practices and governance frameworks contribute to the long-term sustainability of DT initiatives, ensuring their continued relevance and adaptability in a rapidly evolving industry.

To achieve widespread adoption of DT technology in the construction industry, active participation from stakeholders is essential in the development and implementation of standards and governance frameworks. Collaborative efforts, industry-wide initiatives, and engagement with regulatory bodies can drive the establishment of these frameworks, promoting interoperability, consistency, and long-term success in the adoption and utilisation of DTs.

Adding to these, the challenges associated with the costs of DT applications can also be highlighted as a hindrance to the widespread adoption of this technology in the construction industry. The implementation of DTs may face challenges related to initial investment costs, data collection and integration, scalability, maintenance, and updates [131], as well as the need for trained personnel, which must be addressed to ensure that the benefits of this technology outweigh the associated costs.

The prioritisation for addressing the identified challenges depends on the nature of the construction industry in different countries, taking into account the varying levels of technological advancement. Each country's unique context, including its digital maturity, regulatory frameworks, and industry practices, will influence the prioritisation strategy. Factors such as the availability of digital infrastructure, workforce capabilities, and technological adoption rates should be considered when prioritising the challenges hindering the implementation of DT technology in the construction industry.

To effectively prioritise the challenges, this paper recommends using a systematic approach. Firstly, it is imperative to evaluate the impact of each challenge on the successful implementation of DT technology in a specific country or region. This includes considering the extent of hindrance caused, potential benefits gained from addressing the challenge, and the urgency of resolution within the given context. By carefully assessing these factors, the challenges can be ranked based on their significance and priority. Secondly, it is important to assess the feasibility of addressing each challenge within the specific country or region. This includes evaluating the available resources, expertise, and technology required to overcome the challenges. Furthermore, any prioritisation for addressing challenges should account for stakeholder perspectives and industry needs within the respected context. It is also important to engage key stakeholders, including construction industry professionals, researchers, and technology providers, to gather their insights on the challenges that have the most significant impact on the industry within that particular context. Their inputs can help prioritise challenges based on their relevance and potential industry-wide benefits within the specific country or region. Moreover, it is crucial to analyse the interdependencies among the identified challenges and their relevance to the country's construction industry. Some challenges may have a direct impact on others, and addressing them in a specific order can lead to synergistic effects. By understanding these interdependencies within the local context, a prioritisation strategy can be developed to ensure that challenges are addressed in a logical and effective manner.

By considering the impact, feasibility, stakeholder perspectives, interdependencies, and unique characteristics of the construction industry in different countries, a comprehensive framework for prioritising the challenges hindering DT implementation can be established. This approach will help allocate resources and efforts effectively, taking into account the country-specific factors and ensuring that the most critical challenges are addressed first, leading to successful DT implementation within the construction industry.

4. Conclusions

The existing state of knowledge regarding DT implementations in the construction and building industry remains fragmented, with a limited focus on specific aspects and limited exploration of its potential. To address this gap, this paper approached the literature aiming to realise three objectives: (i) provide a comprehensive understanding of current DT implementations, (ii) offer a state-of-the-art overview of facilitating expertise, and (iii) identify challenges and provide recommendations for future development. To this end, the current paper used a systematic literature review technique to analyse 145 materials retrieved from multiple sources. The findings identified eight areas in which DT technology has been implemented in the construction industry. These include (i) virtual design,

(ii) project planning and management, (iii) asset management and maintenance, (iv) safety management, (v) energy efficiency and sustainability, (vi) quality control and management, (vii) supply chain management and logistics, and (viii) structural health monitoring.

The findings of this study indicate that DT technology has the capacity to revolutionise the construction industry across the identified areas of implementation. In virtual design, DT technology allows for the creation of high-fidelity models that optimise designs, simulate scenarios, and predict outcomes with increased accuracy and detail. This technology has been applied to improve architectural designs and enhance occupant comfort in buildings. DT technology also improves project planning and management by enabling the simulation of design scenarios, evaluating impacts on timelines and costs, and facilitating collaboration among stakeholders. Additionally, DT technology enhances asset management and maintenance by providing real-time monitoring of physical assets, enabling predictive maintenance, and reducing operational costs. It has been particularly effective in monitoring civil infrastructure, such as bridges and dams, and analysing data from sensors to identify potential issues. Furthermore, DT technology contributes to safety management by allowing the identification of safety hazards and risks at construction sites using constant monitoring, leading to improved safety practices and incident prevention. It can also monitor worker activities and provide real-time observations of safety hazards. DT technology supports energy efficiency and sustainability by tracking and analysing energy consumption patterns, optimising energy performance, and simulating scenarios for design choices. The results of this review pointed out that DT technology can be used to evaluate the viability of green alternatives and enable dynamic sustainability assessment.

DT technology also offers significant potential for improving current practices in quality control and management in the construction industry. DTs enable real-time monitoring and virtual simulations, allowing for the early detection and resolution of potential issues, which can subsequently result in higher-quality construction outcomes. DTs also facilitate accurate virtual representations of components, enabling quality inspections and continuous monitoring of performance and maintenance requirements. The implementation of DTs for purposes of supply chain management and logistics also holds great potential by providing real-time monitoring of project conditions and progress, enabling the prediction of risks, and optimising coordination using data integration and simulations. Notably, the application of DTs in modular construction improves project performance by accurately predicting logistics risks and facilitating “just-in-time” module delivery. In SHM, DTs create virtual replicas of structures, integrate real-time sensor data, and enable comprehensive monitoring, early detection of abnormalities, and proactive maintenance. The application of DTs improves monitoring systems, enabling precise evaluation of a building’s conditions, prediction of risks, and optimisation of maintenance strategies. With the use of DT technology, the construction industry can achieve substantial improvements in construction quality, supply chain management, and SHM, ultimately enhancing safety, reliability, and efficiency in construction projects.

This study also underlined a number of challenges hindering the widespread use of digital twin technology in the building and construction industry. These take into account (i) data integration and interoperability, (ii) data accuracy and completeness, (iii) scalability and complexity, (iv) privacy and security, and (v) standards and governance.

Addressing the identified challenges can help with the further development of the field. To this end, the current study recommends the prioritisation of standardised data formats, protocols, and APIs as a crucial measure to facilitate seamless collaboration and data exchange among different software systems and stakeholders. Additionally, future research should focus on the exploration of semantic data modelling and ontologies in order to facilitate data integration and interoperability, with a potential lead-up to the enhancement of DT data standardisation. The current study also suggests that further attempts should be undertaken to ensure data accuracy and completeness in DTs, even though this requires the implementation of thorough validation processes, data quality control mechanisms, and robust data governance practices. Scalability and complexity were other important challenges associated with using DTs in construction. Addressing this challenge involves harnessing high-performance computing capabilities, utilising efficient data storage and processing mechanisms, and using advanced modelling techniques. This study also suggests that privacy and security concerns can be tackled by necessitating the establishment of comprehensive data protection protocols, encryption mechanisms, access controls, authentication procedures, and user permissions. Finally, the development of widely accepted standards and governance frameworks with industry-wide collaboration will promote interoperability, consistency, and long-term success in the adoption and utilisation of DTs in the construction industry.

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References

1. Opoku, D.G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M. Digital twin application in the construction industry: A literature review. *J. Build. Eng.* **2021**, *40*, 102726. [CrossRef]
2. Ozturk, G.B. Digital Twin Research in the AECO-FM Industry. *J. Build. Eng.* **2021**, *40*, 102730. [CrossRef]
3. Zhang, J.; Cheng, J.C.P.; Chen, W.; Chen, K. Digital Twins for Construction Sites: Concepts, LoD Definition, and Applications. *J. Manag. Eng.* **2022**, *38*, 04021094. [CrossRef]
4. Hosamo, H.H.; Imran, A.; Cardenas-Cartagena, J.; Svennevig, P.R.; Svidt, K.; Nielsen, H.K. A Review of the Digital Twin Technology in the AEC-FM Industry. *Adv. Civ. Eng.* **2022**, *2022*, 2185170. [CrossRef]
5. Omrany, H.; Soebarto, V.; Ghaffarianhoseini, A. Rethinking the concept of building energy rating system in Australia: A pathway to life-cycle net-zero energy building design. *Arch. Sci. Rev.* **2021**, *65*, 42–56. [CrossRef]
6. Ghaffarianhoseini, A.; AlWaer, H.; Ghaffarianhoseini, A.; Clements-Croome, D.; Berardi, U.; Raahemifar, K.; Tookey, J. Intelligent or smart cities and buildings: A critical exposition and a way forward. *Intell. Build. Int.* **2017**, *10*, 122–129. [CrossRef]
7. Ghaffarianhoseini, A.; Berardi, U.; AlWaer, H.; Chang, S.; Halawa, E.; Ghaffarianhoseini, A.; Clements-Croome, D. What is an intelligent building? Analysis of recent interpretations from an international perspective. *Arch. Sci. Rev.* **2015**, *59*, 338–357. [CrossRef]
8. Deng, M.; Menassa, C.C.; Kamat, V.R. From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *J. Inf. Technol. Constr.* **2021**, *26*, 58–83. [CrossRef]
9. Omrany, H.; Ghaffarianhoseini, A.; Ghaffarianhoseini, A.; Clements-Croome, D.J. The uptake of City Information Modelling (CIM): A comprehensive review of current implementations, challenges and future outlook. *Smart Sustain. Built Environ.* **2022**. *ahead-of-print*. [CrossRef]
10. Omrany, H.; Ghaffarianhoseini, A.; Chang, R.; Ghaffarianhoseini, A.; Pour Rahimian, F. Applications of Building information modelling in the early design stage of high-rise buildings. *Autom. Constr.* **2023**, *152*, 104934. [CrossRef]
11. Bakhshi, S.; Chenaghlou, M.R.; Pour Rahimian, F.; Edwards, D.J.; Dawood, N. Integrated BIM and DfMA parametric and algorithmic design based collaboration for supporting client engagement within offsite construction. *Autom. Constr.* **2021**, *133*, 104015. [CrossRef]
12. Chang, R.; Song, X.; Omrany, H. What hinders the transition towards sustainable construction in china? Critical challenges and future directions. *J. Green Build.* **2022**, *17*, 99–127. [CrossRef]
13. Omrany, H.; Soebarto, V.; Zuo, J.; Chang, R. A Comprehensive Framework for Standardising System Boundary Definition in Life Cycle Energy Assessments. *Buildings* **2021**, *11*, 230. [CrossRef]
14. Goulding, J.S.; Rahimian, F.P. *Offsite Production and Manufacturing for Innovative Construction: People, Process and Technology*; Routledge: London, UK, 2019.
15. Xie, H.; Xin, M.; Lu, C.; Xu, J. Knowledge map and forecast of digital twin in the construction industry: State-of-the-art review using scientometric analysis. *J. Clean. Prod.* **2023**, *383*, 135231. [CrossRef]
16. Shafto, M.; Conroy, M.; Doyle, R.; Glaessgen, E.; Kemp, C.; LeMoigne, J.; Wang, L. *NASA Technology Roadmap: Modeling, Simulation. Information Technology & Processing Roadmap*; National Aeronautics and Space Administration: Washington, DC, USA, 2012; pp. 1–38.

17. Ghosh, A.K.; Ullah, A.S.; Kubo, A. Hidden Markov model-based digital twin construction for futuristic manufacturing systems. *Artif. Intell. Eng. Des. Anal. Manuf.* **2019**, *33*, 317–331. [CrossRef]
18. Hribernik, K.A.; Rabe, L.; Thoben, K.-D.; Schumacher, J. The product avatar as a product-instance-centric information management concept. *Int. J. Prod. Lifecycle Manag.* **2006**, *1*, 367. [CrossRef]
19. Almatared, M.; Liu, H.; Tang, S.; Sulaiman, M.; Lei, Z.; Li, H.X. Digital Twin in the Architecture. Engineering, and Construction Industry: A Bibliometric Review. *Constr. Res. Congr.* **2022**, *2022*, 670–678. [CrossRef]
20. Airports International. Case Study: Digital Twinning in Construction 2022. Available online: https://www.airportsinternational.com/article/case-study-digital-twinning-construction (accessed on 21 June 2023).
21. 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]
22. Hou, L.; Wu, S.; Zhang, G.K.; Tan, Y.; Wang, X. Literature Review of Digital Twins Applications in Construction Workforce Safety. *Appl. Sci.* **2020**, *11*, 339. [CrossRef]
23. Opoku, D.-G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M.; Bamdad, K.; Famakinwa, T. Barriers to the Adoption of Digital Twin in the Construction Industry: A Literature Review. *Informatics* **2023**, *10*, 14. [CrossRef]
24. Opoku, D.-G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M.; Famakinwa, T.; Bamdad, K. Drivers for Digital Twin Adoption in the Construction Industry: A Systematic Literature Review. *Buildings* **2022**, *12*, 113. [CrossRef]
25. Salem, T.; Dragomir, M. Options for and Challenges of Employing Digital Twins in Construction Management. *Appl. Sci.* **2022**, *12*, 2928. [CrossRef]
26. Omrany, H.; Chang, R.; Soebarto, V.; Zhang, Y.; Ghaffarianhoseini, A.; Zuo, J. A bibliometric review of net zero energy building research 1995–2022. *Energy Build.* **2022**, *262*, 111996. [CrossRef]
27. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A.Y.C. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. [CrossRef]
28. Kalantari, S.; Pourjabar, S.; Xu, T.B.; Kan, J. Developing and user-testing a "Digital Twins" prototyping tool for architectural design. *Autom. Constr.* **2022**, *135*, 104140. [CrossRef]
29. Rafsanjani, H.N.; Nabizadeh, A.H. Towards digital architecture, engineering, and construction (AEC) industry through virtual design and construction (VDC) and digital twin. *Energy Built Environ.* **2023**, *4*, 169–178. [CrossRef]
30. Callcut, M.; Agliozzo, J.-P.C.; Varga, L.; McMillan, L. Digital Twins in Civil Infrastructure Systems. *Sustainability* **2021**, *13*, 11549. [CrossRef]
31. Broo, D.G.; Schooling, J. Digital twins in infrastructure: Definitions, current practices, challenges and strategies. *Int. J. Constr. Manag.* **2021**, *23*, 1254–1263. [CrossRef]
32. Lu, R.; Brilakis, I. Digital twinning of existing reinforced concrete bridges from labelled point clusters. *Autom. Constr.* **2019**, *105*, 102837. [CrossRef]
33. Lu, V.Q.; Parlikad, A.K.; Woodall, P.; Ranasinghe, G.D.; Heaton, J. Developing a dynamic digital twin at a building level: Using Cambridge campus as case study. In Proceedings of the International Conference on Smart Infrastructure and Construction 2019 (ICSIC) Driving Data-Informed Decision-Making, Churchill College, Cambridge, UK, 8–10 July 2019; ICE Publishing: New York, NY, USA, 2019.
34. Lu, Q.; Parlikad, A.K.; Woodall, P.; Ranasinghe, G.D.; Xie, X.; Liang, Z.; Konstantinou, E.; Heaton, J.; Schooling, J. Developing a digital twin at building and city levels: Case study of West Cambridge campus. *J. Manag. Eng.* **2020**, *36*, 05020004. [CrossRef]
35. Liu, Y.; Sun, Y.; Yang, A.; Gao, J. Digital Twin-Based Ecogreen Building Design. *Complexity* **2021**, *2021*, 1391184. [CrossRef]
36. Hosamo, H.H.; Nielsen, H.K.; Kraniotis, D.; Svennevig, P.R.; Svidt, K. Digital Twin framework for automated fault source detection and prediction for comfort performance evaluation of existing non-residential Norwegian buildings. *Energy Build.* **2023**, *281*, 112732. [CrossRef]
37. Arsiwala, A.; Elghaish, F.; Zoher, M. Digital twin with Machine learning for predictive monitoring of CO_2 equivalent from existing buildings. *Energy Build.* **2023**, *284*, 112851. [CrossRef]
38. Hosamo, H.H.; Nielsen, H.K.; Kraniotis, D.; Svennevig, P.R.; Svidt, K. Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method. *Energy Build.* **2023**, *288*, 112992. [CrossRef]
39. Jiang, Y.; Li, M.; Li, M.; Liu, X.; Zhong, R.Y.; Pan, W.; Huang, G.Q. Digital twin-enabled real-time synchronization for planning, scheduling, and execution in precast on-site assembly. *Autom. Constr.* **2022**, *141*, 104397. [CrossRef]
40. Jiang, Y.; Liu, X.; Wang, Z.; Li, M.; Zhong, R.Y.; Huang, G.Q. Blockchain-enabled digital twin collaboration platform for fit-out operations in modular integrated construction. *Autom. Constr.* **2023**, *148*, 104747. [CrossRef]
41. Petri, I.; Rezgui, Y.; Ghoroghi, A.; Alzahrani, A. Digital twins for performance management in the built environment. *J. Ind. Inf. Integr.* **2023**, *33*, 100445. [CrossRef]
42. Jiang, Y.; Li, M.; Guo, D.; Wu, W.; Zhong, R.Y.; Huang, G.Q. Digital twin-enabled smart modular integrated construction system for on-site assembly. *Comput. Ind.* **2021**, *136*, 103594. [CrossRef]
43. Lin, J.-R.; Wu, D.-P. An approach to twinning and mining collaborative network of construction projects. *Autom. Constr.* **2021**, *125*, 103643. [CrossRef]
44. Lee, D.; Lee, S.H.; Masoud, N.; Krishnan, M.S.; Li, V.C. Integrated digital twin and blockchain framework to support accountable information sharing in construction projects. *Autom. Constr.* **2021**, *127*, 103688. [CrossRef]

45. Zhao, R.; Chen, Z.; Xue, F. A blockchain 3.0 paradigm for digital twins in construction project management. *Autom. Constr.* **2023**, *145*, 104645. [CrossRef]
46. Pan, Y.; Zhang, L. A BIM-data mining integrated digital twin framework for advanced project management. *Autom. Constr.* **2021**, *124*, 103564. [CrossRef]
47. Arisekola, K.; Madson, K. Digital twins for asset management: Social network analysis-based review. *Autom. Constr.* **2023**, *150*, 104833. [CrossRef]
48. Love, P.E.; Matthews, J. The 'how'of benefits management for digital technology: From engineering to asset management. *Autom. Constr.* **2019**, *107*, 102930. [CrossRef]
49. Pregnolato, M.; Gunner, S.; Voyagaki, E.; De Risi, R.; Carhart, N.; Gavriel, G.; Tully, P.; Tryfonas, T.; Macdonald, J.; Taylor, C. Towards Civil Engineering 4.0: Concept, workflow and application of Digital Twins for existing infrastructure. *Autom. Constr.* **2022**, *141*, 104421. [CrossRef]
50. Hüthwohl, P.; Lu, R.; Brilakis, I. Multi-classifier for reinforced concrete bridge defects. *Autom. Constr.* **2019**, *105*, 102824. [CrossRef]
51. Lu, Q.; Xie, X.; Parlikad, A.K.; Schooling, J.M. Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Autom. Constr.* **2020**, *118*, 103277. [CrossRef]
52. Xie, X.; Lu, Q.; Parlikad, A.K.; Schooling, J.M. Digital Twin Enabled Asset Anomaly Detection for Building Facility Management. *IFAC-PapersOnLine* **2020**, *53*, 380–385. [CrossRef]
53. Mohammadi, M.; Rashidi, M.; Yu, Y.; Samali, B. Integration of TLS-derived Bridge Information Modeling (BrIM) with a Decision Support System (DSS) for digital twinning and asset management of bridge infrastructures. *Comput. Ind.* **2023**, *147*, 103881. [CrossRef]
54. Consilvio, A.; Hernández, J.S.; Chen, W.; Brilakis, I.; Bartoccini, L.; Di Gennaro, F.; van Welie, M. Towards a digital twin-based intelligent decision support for road maintenance. *Transp. Res. Procedia* **2023**, *69*, 791–798. [CrossRef]
55. Zhao, J.; Feng, H.; Chen, Q.; de Soto, B.G. Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes. *J. Build. Eng.* **2022**, *49*, 104028. [CrossRef]
56. Kamari, M.; Ham, Y. AI-based risk assessment for construction site disaster preparedness through deep learning-based digital twinning. *Autom. Constr.* **2022**, *134*, 104091. [CrossRef]
57. Teizer, J.; Johansen, K.W.; Schultz, C. The Concept of Digital Twin for Construction Safety. *Constr. Res. Congr.* **2022**, *2022*, 1156–1165. [CrossRef]
58. Liu, Z.; Bai, W.; Du, X.; Zhang, A.; Xing, Z.; Jiang, A. Digital Twin-based Safety Evaluation of Prestressed Steel Structure. *Adv. Civ. Eng.* **2020**, *2020*, 104421. [CrossRef]
59. Wu, S.; Hou, L.; Zhang, G.K.; Chen, H. Real-time mixed reality-based visual warning for construction workforce safety. *Autom. Constr.* **2022**, *139*, 104252. [CrossRef]
60. Zhao, Y.; Cao, C.; Liu, Z. A Framework for Prefabricated Component Hoisting Management Systems Based on Digital Twin Technology. *Buildings* **2022**, *12*, 276. [CrossRef]
61. Jiang, W.; Ding, L.; Zhou, C. Digital twin: Stability analysis for tower crane hoisting safety with a scale model. *Autom. Constr.* **2022**, *138*, 104257. [CrossRef]
62. Liu, Z.; Meng, X.; Xing, Z.; Jiang, A. Digital Twin-Based Safety Risk Coupling of Prefabricated Building Hoisting. *Sensors* **2021**, *21*, 3583. [CrossRef]
63. Liu, Z.-S.; Meng, X.-T.; Xing, Z.-Z.; Cao, C.-F.; Jiao, Y.-Y.; Li, A.-X. Digital Twin-Based Intelligent Safety Risks Prediction of Prefabricated Construction Hoisting. *Sustainability* **2022**, *14*, 5179. [CrossRef]
64. Ye, Z.; Ye, Y.; Zhang, C.; Zhang, Z.; Li, W.; Wang, X.; Wang, L.; Wang, L. A digital twin approach for tunnel construction safety early warning and management. *Comput. Ind.* **2023**, *144*, 103783. [CrossRef]
65. Clausen, A.; Arendt, K.; Johansen, A.; Sangogboye, F.C.; Kjærgaard, M.B.; Veje, C.T.; Jørgensen, B.N. A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings. *Energy Inform.* **2021**, *4*, 40. [CrossRef]
66. Seo, H.; Yun, W.-S. Digital Twin-Based Assessment Framework for Energy Savings in University Classroom Lighting. *Buildings* **2022**, *12*, 544. [CrossRef]
67. Tan, Y.; Chen, P.; Shou, W.; Sadick, A.-M. Digital Twin-driven approach to improving energy efficiency of indoor lighting based on computer vision and dynamic BIM. *Energy Build.* **2022**, *270*, 112271. [CrossRef]
68. Tang, Y.; Gao, F.; Wang, C.; Huang, M.M.; Wu, M.; Li, H.; Li, Z. Vertical Greenery System (VGS) Renovation for Sustainable Arcade-Housing: Building Energy Efficiency Analysis Based on Digital Twin. *Sustainability* **2023**, *15*, 2310. [CrossRef]
69. Kaewunruen, S.; Xu, N. Digital Twin for Sustainability Evaluation of Railway Station Buildings. *Front. Built Environ.* **2018**, *4*, 77. [CrossRef]
70. Alibrandi, U. Risk-Informed Digital Twin of Buildings and Infrastructures for Sustainable and Resilient Urban Communities. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.* **2022**, *8*, 04022032. [CrossRef]
71. Francisco, A.; Asce, S.M.; Mohammadi, N.; Asce, A.M.; Taylor, J.E.; Asce, M. Smart City Digital Twin–Enabled Energy Management: Toward Real-Time Urban Building Energy Benchmarking. *J. Manag. Eng.* **2020**, *36*, 04019045. [CrossRef]
72. Khajavi, S.H.; Motlagh, N.H.; Jaribion, A.; Werner, L.C.; Holmstrom, J. Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings. *IEEE Access* **2019**, *7*, 147406–147419. [CrossRef]

73. Tagliabue, L.C.; Cecconi, F.R.; Maltese, S.; Rinaldi, S.; Ciribini, A.L.C.; Flammini, A. Leveraging Digital Twin for Sustainability Assessment of an Educational Building. *Sustainability* **2021**, *13*, 480. [CrossRef]
74. Agostinelli, S.; Cumo, F.; Guidi, G.; Tomazzoli, C. Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence. *Energies* **2021**, *14*, 2338. [CrossRef]
75. Kaewunruen, S.; Rungskunroch, P.; Welsh, J. A Digital-Twin Evaluation of Net Zero Energy Building for Existing Buildings. *Sustainability* **2018**, *11*, 159. [CrossRef]
76. Zhao, L.; Zhang, H.; Wang, Q.; Wang, H. Digital-Twin-Based Evaluation of Nearly Zero-Energy Building for Existing Buildings Based on Scan-to-BIM. *Adv. Civ. Eng.* **2021**, *2021*, 6638897. [CrossRef]
77. Kosse, S.; Vogt, O.; Wolf, M.; König, M.; Gerhard, D. Digital Twin Framework for Enabling Serial Construction. *Front. Built Environ.* **2022**, *8*, 864722. [CrossRef]
78. Tran, H.; Nguyen, T.N.; Christopher, P.; Bui, D.-K.; Khoshelham, K.; Ngo, T.D. A digital twin approach for geometric quality assessment of as-built prefabricated façades. *J. Build. Eng.* **2021**, *41*, 102377. [CrossRef]
79. Wolf, M.; Vogt, O.; Huxoll, J.; Gerhard, D.; Kosse, S.; König, M. Lifecycle oriented digital twin approach for prefabricated concrete modules. In *ECPPM 2021–eWork and eBusiness in Architecture, Engineering and Construction*; CRC Press: Boca Raton, FL, USA, 2021; pp. 305–312.
80. Xie, M.; Pan, W. Opportunities and challenges of digital twin applications in modular integrated construction. In Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC 2020), Kitakyushu, Japan, 26–30 October 2020; IAARC Publications: Chennai, India, 2020.
81. Liu, Z.; Wu, L.; Liu, Z.; Mo, Y. Quality control method of steel structure construction based on digital twin technology. *Digit. Twin* **2023**, *3*, 5. [CrossRef]
82. Wang, Y.; Aslani, F.; Dyskin, A.; Pasternak, E. Digital Twin Applications in 3D Concrete Printing. *Sustainability* **2023**, *15*, 2124. [CrossRef]
83. Rausch, C.; Lu, R.; Talebi, S.; Haas, C. Deploying 3D scanning based geometric digital twins during fabrication and assembly in offsite manufacturing. *Int. J. Constr. Manag.* **2021**, *23*, 565–578. [CrossRef]
84. Greif, T.; Stein, N.; Flath, C.M. Peeking into the void: Digital twins for construction site logistics. *Comput. Ind.* **2020**, *121*, 103264. [CrossRef]
85. Ivanov, D.; Dolgui, A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Prod. Plan. Control.* **2021**, *32*, 775–788. [CrossRef]
86. Lee, D.; Lee, S. Digital Twin for Supply Chain Coordination in Modular Construction. *Appl. Sci.* **2021**, *11*, 5909. [CrossRef]
87. Park, K.T.; Son, Y.H.; Noh, S.D. The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *Int. J. Prod. Res.* **2020**, *59*, 5721–5742. [CrossRef]
88. Chiachío, M.; Megía, M.; Chiachío, J.; Fernandez, J.; Jalón, M.L. Structural digital twin framework: Formulation and technology integration. *Autom. Constr.* **2022**, *140*, 104333. [CrossRef]
89. Mirzaei, K.; Arashpour, M.; Asadi, E.; Masoumi, H.; Li, H. Automatic generation of structural geometric digital twins from point clouds. *Sci. Rep.* **2022**, *12*, 22321. [CrossRef]
90. Rios, A.J.; Plevris, V.; Nogal, M. Bridge management through digital twin-based anomaly detection systems: A systematic review. *Front. Built Environ.* **2023**, *9*, 61. [CrossRef]
91. Xu, J.; Shu, X.; Qiao, P.; Li, S.; Xu, J. Developing a digital twin model for monitoring building structural health by combining a building information model and a real-scene 3D model. *Measurement* **2023**, *217*, 112955. [CrossRef]
92. Lu, R.; Rausch, C.; Bolpagni, M.; Brilakis, I.; Haas, C.T. *Geometric Accuracy of Digital Twins for Structural Health Monitoring, in Structural Integrity and Failure*; IntechOpen: Rijeka, Croatia, 2020.
93. Futai, M.M.; Bittencourt, T.N.; Santos, R.R.; Araújo, C.R.R.; Ribeiro, D.M.; Rocha, A.R.; Ellis, R. Utilization of Digital Twins for Bridge Inspection, Monitoring and Maintenance. In Proceedings of the 1st Conference of the European Association on Quality Control of Bridges and Structures: EUROSTRUCT, Padua, Italy, 29 August–1 September 2021; Springer International Publishing: Cham, Switzerland, 2022; pp. 166–173.
94. Rojas-Mercedes, N.; Erazo, K.; Di Sarno, L. Seismic fragility curves for a concrete bridge using structural health monitoring and digital twins. *Earthq. Struct.* **2022**, *22*, 503–515.
95. Smarsly, K.; Dragos, K.; Kolzer, T. Sensor-integrated digital twins for wireless structural health monitoring of civil infrastructure. *Bautechnik* **2022**, *99*, 471–476. [CrossRef]
96. Ye, C.; Butler, L.; Calka, B.; Iangurazov, M.; Lu, Q.; Gregory, A.; Girolami, M.; Middleton, C. A digital twin of bridges for structural health monitoring. In Proceedings of the 12th International Workshop on Structural Health Monitoring, Stanford, CA, USA, 10–12 September 2019; DEStech Publications, Inc.: Lancaster, PA, USA, 2019.
97. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
98. Hu, W.; Zhang, T.; Deng, X.; Liu, Z.; Tan, J. Digital twin: A state-of-the-art review of its enabling technologies, applications and challenges. *J. Intell. Manuf. Spéc. Equip.* **2021**, *2*, 1–34. [CrossRef]
99. Thelen, A.; Zhang, X.; Fink, O.; Lu, Y.; Ghosh, S.; Youn, B.; Todd, M.D.; Mahadevan, S.; Hu, C.; Hu, Z. A comprehensive review of digital twin—Part 1: Modeling and twinning enabling technologies. *Struct. Multidiscip. Optim.* **2022**, *65*, 354. [CrossRef]

100. Botín-Sanabria, D.M.; Mihaita, A.-S.; Peimbert-García, R.E.; Ramírez-Moreno, M.A.; Ramírez-Mendoza, R.A.; Lozoya-Santos, J.D.J. Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote. Sens.* **2022**, *14*, 1335. [CrossRef]
101. Tao, F.; Zhang, M. Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access* **2017**, *5*, 20418–20427. [CrossRef]
102. Saad, A.; Faddel, S.; Mohammed, O. IoT-based digital twin for energy cyber-physical systems: Design and implementation. *Energies* **2020**, *13*, 4762. [CrossRef]
103. Al-Obaidi, K.M.; Hossain, M.; Alduais, N.A.M.; Al-Duais, H.S.; Omrany, H.; Ghaffarianhoseini, A. A Review of Using IoT for Energy Efficient Buildings and Cities: A Built Environment Perspective. *Energies* **2022**, *15*, 5991. [CrossRef]
104. Jacoby, M.; Usländer, T. Digital Twin and Internet of Things—Current Standards Landscape. *Appl. Sci.* **2020**, *10*, 6519. [CrossRef]
105. Bilal, M.; Oyedele, L.; Qadir, J.; Munir, K.; Ajayi, S.; Akinade, O.O.; Owolabi, H.A.; Alaka, H.A.; Pasha, M. Big Data in the construction industry: A review of present status, opportunities, and future trends. *Adv. Eng. Inform.* **2016**, *30*, 500–521. [CrossRef]
106. Kaur, M.J.; Mishra, V.P.; Maheshwari, P. The convergence of digital twin, IoT, and machine learning: Transforming data into action. *Digit. Twin Technol. Smart Cities* **2020**, 3–17. [CrossRef]
107. Rathore, M.M.; Shah, S.A.; Shukla, D.; Bentafat, E.; Bakiras, S. The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities. *IEEE Access* **2021**, *9*, 32030–32052. [CrossRef]
108. Cao, K.; Liu, Y.; Meng, G.; Sun, Q. An Overview on Edge Computing Research. *IEEE Access* **2020**, *8*, 85714–85728. [CrossRef]
109. Varghese, B.; Wang, N.; Barbhuiya, S.; Kilpatrick, P.; Nikolopoulos, D.S. Challenges and opportunities in edge computing. In Proceedings of the 2016 IEEE International Conference on Smart Cloud (SmartCloud), New York, NY, USA, 18–20 November 2016; IEEE: New York, NY, USA, 2016; pp. 20–26.
110. Shi, W.; Cao, J.; Zhang, Q.; Li, Y.; Xu, L. Edge Computing: Vision and Challenges. *IEEE Internet Things J.* **2016**, *3*, 637–646. [CrossRef]
111. Yaqoob, I.; Salah, K.; Uddin, M.; Jayaraman, R.; Omar, M.; Imran, M. Blockchain for Digital Twins: Recent Advances and Future Research Challenges. *IEEE Netw.* **2020**, *34*, 290–298. [CrossRef]
112. Hasan, H.R.; Salah, K.; Jayaraman, R.; Omar, M.; Yaqoob, I.; Pesic, S.; Taylor, T.; Boscovic, D. A blockchain-based approach for the creation of digital twins. *IEEE Access* **2020**, *8*, 34113–34126. [CrossRef]
113. Cheng, J.; Chen, W.; Tao, F.; Lin, C.L. Industrial IoT in 5G environment towards smart manufacturing. *J. Ind. Inf. Integr.* **2018**, *10*, 10–19. [CrossRef]
114. Kim, J.H. 6G and Internet of Things: A survey. *J. Manag. Anal.* **2021**, *8*, 316–332. [CrossRef]
115. Wang, D.; Chen, D.; Song, B.; Guizani, N.; Yu, X.; Du, X. From IoT to 5G I-IoT: The Next Generation IoT-Based Intelligent Algorithms and 5G Technologies. *IEEE Commun. Mag.* **2018**, *56*, 114–120. [CrossRef]
116. Mashaly, M. Connecting the Twins: A Review on Digital Twin Technology & its Networking Requirements. *Procedia Comput. Sci.* **2021**, *184*, 299–305. [CrossRef]
117. Mahapatra, R.; Nijsure, Y.; Kaddoum, G.; Hassan, N.U.; Yuen, C. Energy Efficiency Tradeoff Mechanism Towards Wireless Green Communication: A Survey. *IEEE Commun. Surv. Tutor.* **2015**, *18*, 686–705. [CrossRef]
118. Tuhaise, V.V.; Tah, J.H.M.; Abanda, F.H. Technologies for digital twin applications in construction. *Autom. Constr.* **2023**, *152*, 104931. [CrossRef]
119. Daniotti, B.; Masera, G.; Bolognesi, C.; Spagnolo, S.L.; Pavan, A.; Iannaccone, G.; Signorini, M.; Ciuffreda, S.; Mirarchi, C.; Lucky, M.; et al. The Development of a BIM-Based Interoperable Toolkit for Efficient Renovation in Buildings: From BIM to Digital Twin. *Buildings* **2022**, *12*, 231. [CrossRef]
120. Garetti, M.; Fumagalli, L.; Negri, E. Role of Ontologies for CPS Implementation in Manufacturing. *Manag. Prod. Eng. Rev.* **2015**, *6*, 26–32. [CrossRef]
121. Negri, E.; Fumagalli, L.; Garetti, M.; Tanca, L. Requirements and languages for the semantic representation of manufacturing systems. *Comput. Ind.* **2016**, *81*, 55–66. [CrossRef]
122. Gruber, T.R. A translation approach to portable ontology specifications. *Knowl. Acquis.* **1993**, *5*, 199–220. [CrossRef]
123. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2020**, *58*, 346–361. [CrossRef]
124. Boje, C.; Guerriero, A.; Kubicki, S.; Rezgui, Y. Towards a semantic Construction Digital Twin: Directions for future research. *Autom. Constr.* **2020**, *114*, 103179. [CrossRef]
125. Jia, W.; Wang, W.; Zhang, Z. From simple digital twin to complex digital twin Part I: A novel modeling method for multi-scale and multi-scenario digital twin. *Adv. Eng. Inform.* **2022**, *53*, 101706. [CrossRef]
126. Qi, Q.; Zhao, D.; Liao, T.W.; Tao, F. Modeling of cyber-physical systems and digital twin based on edge computing, fog computing and cloud computing towards smart manufacturing. In Proceedings of the International Manufacturing Science and Engineering Conference, College Station, TX, USA, 18–22 June 2018; American Society of Mechanical Engineers: New York, NY, USA, 2018; p. V001T05A018.
127. Pushpa, J.; Kalyani, S. Using fog computing/edge computing to leverage Digital Twin. *Adv. Comput.* **2020**, *117*, 51–77. [CrossRef]
128. Shahat, E.; Hyun, C.T.; Yeom, C. City Digital Twin Potentials: A Review and Research Agenda. *Sustainability* **2021**, *13*, 3386. [CrossRef]

129. Alshammari, K.; Beach, T.; Rezgui, Y. Cybersecurity for digital twins in the built environment: Current research and future directions. *J. Inf. Technol. Constr.* **2021**, *26*, 159–173. [CrossRef]
130. Harper, K.E.; Malakuti, S.; Ganz, C. Digital Twin Architecture and Standards. *J. Innov.* **2019**, 1–12.
131. Bitton, R.; Gluck, T.; Stan, O.; Inokuchi, M.; Ohta, Y.; Yamada, Y.; Yagyu, T.; Elovici, Y.; Shabtai, A. Deriving a cost-effective digital twin of an ICS to facilitate security evaluation. In Proceedings of the Computer Security: 23rd European Symposium on Research in Computer Security, ESORICS 2018, Barcelona, Spain, 3–7 September 2018; Springer International Publishing: Cham, Switzerland, 2018. Part I 23. pp. 533–554.