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Review of Digital Twins for Constructed Facilities

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Abstract: Technological advances have enabled the monitoring and control of construction operations and assets remotely. Digital twins, based on computational modeling, have enabled the creation of a digital map for physical structures. Research on digital twins (DTs) for constructed facilities projects has gained widespread traction in the industry. While these applications have increased over the years, there has been sparse review of them. This paper systematically reviews the applications of digital twins in construction using content analysis. We identified and analyzed 53 academic journal and conference papers, which revealed several DT applications that could be categorized into nine areas: lifecycle analysis, facility management, energy, education, disaster, structural health monitoring, DT for cities, infrastructure management, and miscellaneous. This enables the visualization of the current state of DT, comparison with the desired state, and possible integrations with other technologies. Among the observed benefits of DTs are the ability to increase engagement and collaboration, reduce construction and operating costs, reduce human error, automate energy demand, manage assets throughout their lifecycle, and apply structural health monitoring. It also enables the collection of real-time data on an asset's status, history, maintenance needs, and provides an interactive platform for managing an asset. Future directions include addressing how to standardize data acquisition as well as the semantic interoperability and heterogeneity of data. Additionally, modeling human cognitive processes as well as spatiotemporal information would be beneficial to a smart city and other infrastructure systems, especially in disaster situations.

Keywords: digital twins; infrastructure; literature review

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1. Background

The construction industry suffers from several shortcomings including low productivity, lack of investment in innovation, and fragmentation of operations [1,2]. This may be due to the lack of digitalization in comparison to other industries, such as the manufacturing and automotive industries. Additionally, several drivers for change have been observed, including a need for innovation and market opportunities for differentiation [3]. An effective solution to the issue would be the use of digital twins (DT) to digitize, optimize, and streamline operations. This would enable the industry's transformation into the fourth industrial revolution. A digital twin is a cyber-physical integration that leads to a large volume of data, which can then be processed using data analytics [4]. It was first introduced by Grieves in 2003 in his course "product lifecycle management" [5]. DT enables simulation, quick data acquisition, enhances communication, and allows for the real-time monitoring of physical assets, predictive analytics, and production control. It can also enable condition monitoring and the detection of anomalies [6]. DT facilitates the information exchange between physical and virtual components that is enabled using internet-of-things, high speed-networking (5G), and machine learning [7].

With the advent of advanced technologies, it has become imperative to apply these technologies to improve the construction industry's productivity and efficiency. Although

DT was introduced in 2003, the recent technological advancements related to digitalization and the Internet of Things have spurred more research on it. It has been proposed to manage production in construction and leverage data streams from multiple sources in a construction project [7]. The concept of digital twins has been observed to have significant benefits to other industries, such as manufacturing, healthcare, and aviation. Hence, it is expected to have immense benefits for the construction industry as well when it is fully utilized.

2. The Digital Twin Paradigm

Over the years, DT has evolved from an information monitoring tool to digital simulation, IoT implementation and connection, and finally a decision-making tool [6]. Several enabling technologies have been observed for use with DTs, including Internet-of-Things (IoT), Industrial Internet-of-Things (IIoT), cloud computing, virtual/augmented/mixed realities, data analytics, and artificial intelligence [6]. Additionally, DT has the potential to tackle challenges facing the construction industry and improve productivity [2]. Digital twins aim to enhance the current construction processes through their dynamic cyber-physical integration. In addition to portraying an asset's geometry, a DT is also able to show its behavior and spatiotemporal status [8].

A DT can also be labeled as a system-of-systems since it is a platform that integrates multiple systems [3]. This is a hierarchical view of a DT and its components, which can be classified into unit level, system level, and system-of-systems (SoS) level [8]. Ref. [8] applied this hierarchy to manufacturing and proposed that the unit level comprises a single manufacturing activity or component such as equipment or material. The system level comprises an integration of multiple units, such as a production line. Finally, a system-of-systems level comprises an integration of multiple complex systems, such as the various stages of a product lifecycle [8].

According to [9], there are several items that a DT should be able to create, including real-time monitoring, higher efficiency, predictive maintenance, scenario assessment, higher collaboration, better decision support, product personalization, and improved documentation. It can also have different benefits in the separate phases of a project or asset. During the design phase, it is used to evaluate alternatives, redesign existing structures, or make decisions at multiple stages. During the manufacturing phase, it is used for real-time monitoring, performance prediction, asset management, process optimization, and production control [10]. Finally, in the service phase, it is used for predictive maintenance and fault detection and diagnosis [10]. Several DT models/architectures have been proposed in the literature. Refs. [11,12] proposed a five-dimension model consisting of the physical entity, virtual entity, services, data, and connection. Ref. [13] proposed an eight-dimension model comprising four dimensions representing the DT behavior (e.g., simulation capabilities and DT intelligence) and the other four representing context and environment (e.g., connectivity modes and integration breadth). Although the classifications are different, they focus on the same inputs of a DT, which are the physical and virtual entities and the connection between them.

A similar concept to DTs is discussed in the literature and is known as a digital shadow, but it is important to distinguish between them. Whereas a DT would include a bidirectional transfer of data/information between the physical object and the digital model, a digital shadow consists of only a one-way transfer of data from the physical object to the model [14]. A digital model, on the other hand, shows no link between physical and virtual objects [15]. This classification is similar to [15]'s proposal for a digital twin maturity index that consists of six level:

- Static twin (Level 100): a BIM model with no integration between the physical and virtual assets.
- Detailed twin (Level 200): a detailed as-built BIM model with semi-unidirectional integration between the physical and virtual assets.

- As-built twin (Level 300): more detailed than the previous type and enables unidirectional integration between the physical and virtual assets)
- Responsive twin (Level 350): a higher level than the previous one and provides limited bi-directional integration between the physical and virtual assets
- Adaptive twin (Level 400): a higher level that provides semi-bi-directional integration between both assets and a higher degree of data flow.
- Intelligent twin: or digital twin with full bi-directional integration between both assets and a fully autonomous data flow.

To study and report on certain topics, a systematic literature review has been proposed as a methodology for its ability to capture and analyze various data. It is used to systematically identify research areas, hot topics, critical points, past trends, as well as future trends. Previous literature focused on specific applications of DT in construction such as infrastructure management, energy management, and disaster management. Some papers have addressed incorporating other technologies with digital twins such as 3R (AR, VR, and MR) for manufacturing [16]. Ref. [17] proposed a digital twin construction (DTC) model that uses DT, BIM, lean construction principles, and artificial intelligence for data-centric management of construction workflows. Ref. [9] proposed Cog-DT, a DT model using virtual reality to model workers' cognitive reactions and create personalized profiles for each worker. Some researchers have conducted literature reviews on DT for certain aspects of construction, such as safety [18], as a comparison between the construction sector to others [19], or as a gap analysis and recommendations for future research [20]. Ref. [21] conducted a review on the construction sector and classified it into three clusters: design, construction, and operation and maintenance. However, several limitations arise from previous literature. For example, Ref. [22] reviewed only 21 academic publications, Ref. [2] reviewed 22 academic publications, while other literature focused on one specific project or area [2,18,19,23]. Hence, this paper provides a detailed review of DT applications in the construction industry at large and provides recommendations for future applications. The following section discusses the materials and methods applied in this research to report on digital twin applications in construction.

3. Materials and Methods

A systematic review and content analysis-based review method was used for the literature review since it enables objective review and reporting in research. It also creates a systematic procedure to identify, classify, and report on the collected literature, as shown in Figure 1. Content analysis was conducted in this research as detailed by [24,25]. It consists of four phases as shown in Table 1 and detailed below.

(1) Identify the research questions In this step, the research questions to be carried out are identified as follows: RQ1. What are the applications of digital twins in construction? RQ2. How can we classify digital twin applications? To address these questions, all literature on digital twins in construction was collected. RQ1 required the collection and tabulation of all previous research to visualize it. RQ2 involved content analysis on the previously collected literature to identify methods of classification.

(2) Identify the search process and inclusion/exclusion criteria To obtain as many articles as possible, several iterations of searches were conducted. The Scopus database was first used followed by a secondary search on Google Scholar. Additional searches were made in relevant journals, such as the Journal of Computing in Civil Engineering, Automation in Construction, and ASCE Journals (Journal of Construction Engineering and Management, Journal of Management in Engineering, etc.), to ensure the inclusion of all high-quality relevant research. Several search engines and databases were searched to provide a more accurate and comprehensive picture. A keyword search was used due to its popularity in systematic research. The search string consisted of primary and secondary keywords which were combined to collect all literature on DT applications in construction. The primary keyword was 'digital twin' while the secondary keywords were one of the following: 'construction', 'engineering',

OR 'infrastructure'. Additional papers from conference proceedings with the same keywords were also included. The publication year was limited between 2017 and 2021. As a result, a total of 145 papers were identified. A secondary screening was conducted for the abstracts and conclusion to eliminate unrelated articles. Eliminated articles fell under one or more of the following areas: manufacturing sector, discussion of the software/hardware aspects of DT rather than an application/framework, and literature review articles that did not provide an application/framework. Other eliminated articles were those in a language other than English. This resulted in 53 articles that were incorporated into the analysis. Figure 2 shows the distribution of articles over the years, from 2017 to 2021. The two most common journals were 'Automation in Construction' with six articles followed by the 'Journal of Management in Engineering' with five articles.

(3) Conduct data collection Data collected from the studies include authors, year of publication, the objective of the research, type of application of digital twin, research findings, limitations, and recommendations for future work. This data was used to tabulate the results for better visualization. Two authors reviewed the literature and performed the tabulation of the results, which were then reviewed by the remaining two authors to ensure the high quality of the results.

(4) Perform descriptive analysis An assessment of the collected literature was conducted to understand the current state of research on DTs (RQ1). Additionally, it involved examining the studies to identify classifications of DT applications and delineate the categories (RQ2). These categories were chosen based on a content analysis of the identified studies and grouped into nine areas as discussed in the upcoming section. Finally, the selected papers were examined and a discussion on the identified areas was reported. This inductive approach enables objective assessment and reporting on a chosen topic.

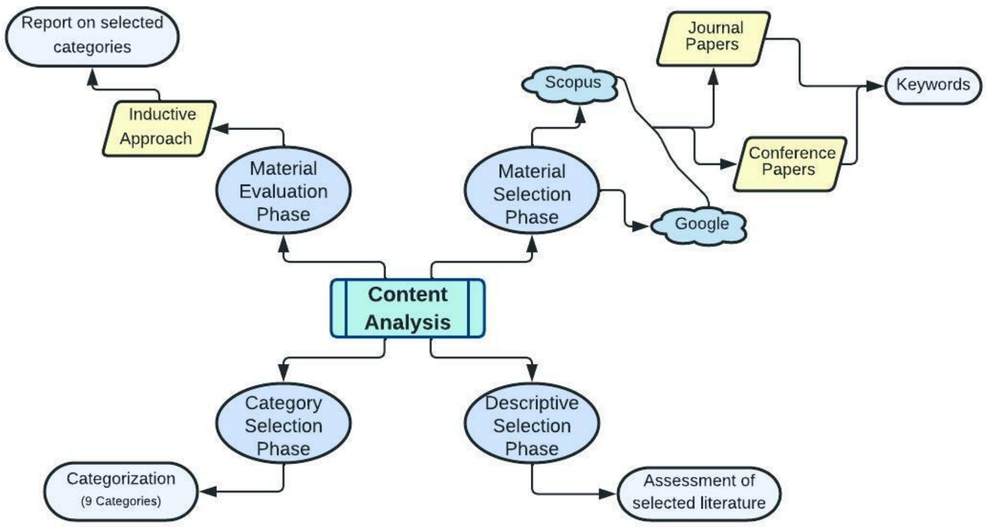

Figure 1. Content Analysis Process.

Table 1. Content Analysis Process.

Criteria	Content
Search engine	Scopus and Google Scholar
Article Type	Peer-reviewed journal and conference articles
Search string	"Digital twin" AND "construction", or "engineering" or "infrastructure"
Screening process	Initial screening of abstract followed by reading the paper

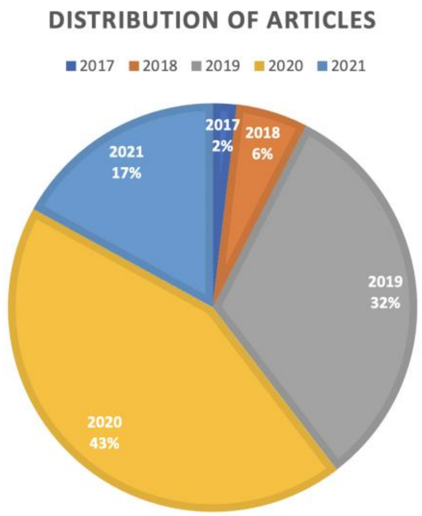

Figure 2. Distribution of Articles over the years.

4. Analysis

Based on the review and content analysis conducted on the 53 papers on digital twins in construction, a taxonomy of their applications was derived, and nine areas were identified as shown in Figure 3. This addresses RQ2 (How can we classify digital twin applications?). These areas include energy, life cycle analysis, disaster management, education, structural health monitoring, facility management, DTs for cities, infrastructure management, and miscellaneous applications. The search resulted in 53 articles, which are discussed in the upcoming sections.

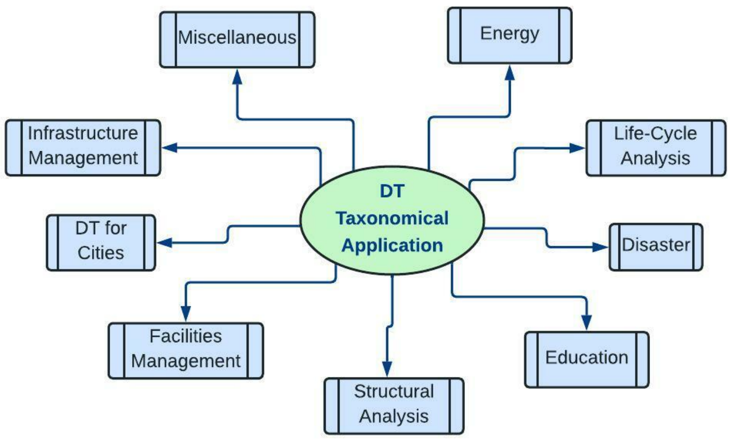

Figure 3. Taxonomy of DT Applications.

4.1. Energy

4.1.1. Growing Interest in Energy

One of the Sustainable Development Goals proposed by the United Nations is clean energy. To reach this goal, several countries have proposed roadmaps consisting of 20–30-year plans. For example, the Egyptian government has proposed an Integrated Sustainable Energy Strategy (ISES 2035) with a target of 42% of the electricity using renewable energy by 2035 [26]. Europe has also enacted a Clean Energy for all Europeans package, which includes updates to the energy policies such as a target of 32% of renewable energy and 32.5% of energy efficiency by 2030 [27]. To achieve these goals, a bottom-up approach is needed to understand building energy use from the consumer level up to the country level. This can be accomplished by tracking the energy consumption across buildings to propose efficient use and optimization methods. Current top-down approaches lack the actionable methods needed to reach energy reduction [28]. Real-time energy management, usage visualization, and monitoring can be enabled through the creation of digital twins for assets. Smart metering can be used to extract energy usage in many locales and study the changes across various times and conditions. Benchmarks can then be created to monitor and compare the usage.

4.1.2. DT Energy Applications

Several researchers have proposed the use of digital twins for energy assessment, modeling, and monitoring. Five papers were found in this area as shown in Table 2. Ref. [29] developed a framework combining DT with energy models to manage and automate building energy demand. Similarly, Ref. [30] proposed the use of DT to optimize and automate building energy systems. Ref. [28] calculated energy use taking into consideration multiple occupancy periods for a more accurate prediction of energy efficiency. Ref. [31] combined hierarchy flowchart with DT to evaluate net zero energy building with a focus on existing buildings. Ref. [32] applied system-of-systems and integrated design and delivery solutions with DT for lifecycle energy modeling of buildings. A municipality in Amsterdam created a digital twin of an area for energy transition [33].

Table 2. Digital Twin for Energy Management.

Author	Methodology/Aim	Findings
[28]	Developed a DT energy management platform using various benchmarks for occupied and unoccupied periods throughout the year for near real-time management.	The proposed method is more accurate in efficiency measurement than a building's overall benchmark. It can aid in the creation of platforms for energy management using digital twin.
[29]	Develops a framework that combines a DT with energy models to manage and automate buildings.	The framework can control and automate building energy demand.
[30]	Proposes the use of DT to automate building energy management systems.	The proposed method can automate and optimize building energy systems.
[31]	Proposes a hierarchy-flow chart and DT-based model to evaluate net zero energy building for existing buildings.	A 23-year payback period was reached using solar (PV) and wind turbines for renewable energy.
[32]	Proposes an energy-focused model for buildings' lifecycle based on: (1) DT; (2) Integrated Design and Delivery Solutions (IDDS) framework; and (3) System of Systems infrastructure.	The proposed model can reduce construction time as well as energy demand and emissions during operation.

However, several limitations have been reported. In some instances, temporal data relating to building occupancies was not available [28] and may have affected the accuracy of energy predictions. Another limitation is that efficiency differs based on the chosen intervals during which the building is observed. A building that is overall performing efficiently might have fluctuations within or between the periods in which it is examined, which would make it difficult to evaluate its overall efficiency and generalize the recommendations for other buildings. It would be important to vary the intervals and perform a statistical analysis of the outcome to reach more reliable conclusions.

Future work in this area should include exploring more renewable energy technologies and modeling case studies for diverse building types such as high-rise buildings [31]. Additionally, energy modeling can be conducted and optimized for new buildings as well as existing ones. Building information modeling has been proposed for use in the built environment [31]. Additionally, geographic information systems (GIS) can be connected to BIM to obtain a 3D district-level model [30]. This can be the first step in mapping out an entire city with the aid of geographic information systems (GIS). It will enable a city-wide real-time monitoring and assessment of energy levels aimed at promoting and adhering to sustainable development goals. Additionally, energy management systems must take into consideration user needs depending on the different seasons, weather conditions, time of day, and other location-specific factors [28]. An optimized system can then be chosen for nationwide application to determine best practices, which can then be used to deliver personalized plans of action to reduce individual energy consumption (for people or even at the building level). Multiple stakeholders can be involved in this endeavor, including urban developers, governmental agencies, builders, operators, and end-users. This can facilitate decision-making and risk management in disaster situations [33]. The data captured can then be processed using machine learning algorithms and analyzed using big data analytics and stored on the cloud to enable constant updates and comparison between previous and current states as well as the prediction of future states [33]. This will enable combining both top-down and bottom-up approaches if the DTs created can be generalized for all assets.

4.2. Life Cycle Analysis (LCA)

4.2.1. Importance of LCA

Life cycle analysis of physically constructed assets is an integral part of managing and operating them effectively. With the advent of Industry 4.0, data-driven management of structures has emerged. The goals of life cycle analysis include optimizing running costs, ensuring more predictable operations, and enforcing structural safety [20]. According to [34], two considerations have to be looked at before making decisions related to an asset: the asset's life cycle and the 'asset hierarchical control level' (i.e., aligning the strategic, tactical, and operation levels). A decision support system that can achieve these goals should be based on the asset's aggregated data. To do so, an asset's performance throughout its entire life cycle must be monitored and managed. Hence, a digital twin can aid in such decisions over an asset's entire lifecycle. Table 3 shows the identified research on lifecycle analysis using digital twins.

Table 3. Digital Twin for Lifecycle Analysis.

Author	Methodology/Aim	Findings
[35]	Proposes power engineering digital twins using IoT and Big Data.	The proposed model can be used by the design, construction, and supervision companies for real-time information sharing and management of a project.
[36]	Proposes a framework for DTs of real estate through model-based system engineering.	Significant savings can be obtained from the use of DTs for lifecycle management.
[37]	Proposes 6D BIM for managing railway turnout systems throughout their lifecycle.	The most expensive phase in the lifecycle is the reconstruction phase.
[38]	Proposes a blockchain-based Digital Twin for asset lifecycle management	Several prerequisites are needed to enable this: BIM Level 3, scalable blockchains, and implementation manuals.
[39]	Proposed a case study for continuous lifecycle integration of a hospital.	Several benefits were observed including a reduction in energy consumption and requested repairs as well as improved quality of the maintenance work.

4.2.2. DT Applications

DT models can be used by design, construction, and supervision companies for real-time information sharing and management of projects [35]. Several benefits arise from using DT for life cycle analysis. These include significant savings that can be obtained throughout the lifecycle by reducing maintenance costs and even predicting power outages [36]. Digital twins have been used for the life cycle analysis of various assets. Ref. [37] proposed a 6D BIM for managing railway turnout systems throughout their lifecycle. They reported that the most expensive phase in the lifecycle is the reconstruction phase. Ref. [38] proposed a blockchain-based Digital Twin for asset lifecycle management. Ref. [35] proposed power engineering digital twins using IoT and Big Data. Ref. [36] proposed a framework for DTs of real estate through model-based system engineering.

4.3. Disaster Management

4.3.1. Significance of Research on Disaster Management

Hazards have caused damage to communities economically, socially, and environmentally [33]. They can lead to the relocation of people and disruptions in a community.

Disasters may affect one infrastructure or several due to their interdependence. Therefore, it is crucial to study disaster detection to manage the situations, streamline the handling of emergencies, and reduce any possible damage.

4.3.2. Issues in Disaster Management

It is difficult to predict infrastructure failures that occur during disasters due to the unpredictability of the situations [40]. During disaster events, it may be difficult to perform regular operations and access information related to the infrastructure, damage that occurred, and current operations. An autonomous system would be beneficial in this case to streamline data recovery and processing [41]. Additionally, it is important to manage existing systems as well as interactions among the systems and community for an effective management process [41]. It is important to understand the states of spatiotemporal flux in a city during and after a disaster to help in the recovery process [33].

4.3.3. DT Applicability

The purpose of a DT in the case of disasters would go beyond a visual projection of the physical image. Its purpose would be to process data, suggest best practices, and aid in making informed decisions. For example, it can provide egress routes and the best routes to take to avoid flooded areas [41]. It can measure the extent of distress caused by the disaster and inform about the best decision to take in each case using what-if scenarios. For example, a 4D model of Singapore was created for the Virtual Singapore project to understand potential disaster risks and understand evacuation scenarios [33].

4.3.4. Disaster Applications

One of the main uses of DT is to predict the health status of an asset and its current conditions [20]. Fan et al. (2020) [42] proposed a framework to incorporate social sensing into digital twins to detect infrastructure disruptions and disasters based on textual, visual, and geo-map information collected. The proposed framework was able to integrate social sensing elements to capture and analyze data during disasters. Ref. [33] proposed a virtual city model using digital twin and visual data for decision-making in the event of risks and disasters. Ref. [43] proposed a DT framework of a disaster in a city composed of four layers: data collection, data analytics, decision-making, and network analysis. The proposed framework aggregates data that can be used for real-time monitoring and simulation of the multiple resource streams. Ref. [41] proposed a conceptual model for smart cities with digital twins for disaster management.

4.3.5. Emerging Issues/Gaps

Several limitations were reported by previous research. Ref. [42] reported the inadequacy of data during the disaster event after evacuation occurred. Similarly, Ref. [43] reported that the situational data collected may have noise and false information, which will affect the accuracy of the analysis. Although smart technologies can collect data more accurately than humans, there is still an issue with the quality of data collected. Another problem is that DT models can miss community-level interdependencies that manifest during disasters [41].

Recommendations for future work in this area include developing damage recognition systems to incorporate in digital twins [42]. These systems can be adopted from structural health monitoring or infrastructure management research. Artificial intelligence can be integrated with the DT models and the entire process can be automated [43]. This would enable faster analysis and quicker response to immediate dangers. Disaster management can be seen as a microcosm for smart city digital twin creation, which can be expanded for other uses as well [41].

4.4. Education

4.4.1. Research on Education

The increase in the use of virtual technologies in education coupled with the global trend of digitalization has led to a need to develop novel teaching methods. Courses on online education and gamification have become prevalent in construction. For example, virtual and augmented reality have been used to improve the competence of students through a hands-on approach [44]. Using immersive and interactive methods enhances the learning process for students. It enables their hands-on learning of the interconnectivity between systems and subsystems in construction, which otherwise might be difficult through lectures only. It also enhances their motivation and memorization of subjects through immersion and activities [44].

4.4.2. DT Applications in Education

Several DT applications were observed in the area of education. For example, Ref. [44] used virtual and augmented realities as well as digital twins to deliver construction courses. The proposed modules were beneficial to both students and instructors in conveying construction work. Ref. [45] proposed a DT-based approach for teaching and experimented on it with students. Although the proposed method increased student learning of DT, it was faced with IT problems and a lack of teachers' expertise. Ref. [46] proposed educational tools using digital twins for structural engineering and digital fabrication applications. This enabled a hands-on approach for the students using low-cost electronics. It can be observed that research on DT for education has been sparse as compared to other areas.

4.5. Structural Health Monitoring (SHM)

4.5.1. Interest in Structural Health Monitoring

There has been growing interest in digital twin applications for structural health monitoring. This is due to the importance of examining the deterioration of structures to avoid functional or structural failures. Many of the previous studies have analyzed structures solely based on the design documents. For example, fragility assessment has been conducted using finite element models based on the design documents of bridges [47]. This limits the accuracy of the model since it assumes that a bridge's conditions have not changed over time. However, external conditions such as weather and extreme conditions like earthquakes can impact the structural integrity of a bridge as well as render the initial design documents incorrect and, in some cases, obsolete. Hence, analysis needs to be conducted in real-time to account for updates and changes that occur to structures over time [47].

4.5.2. Structural Health Monitoring DT Applications

Several research projects have proposed DT for structural analysis applications. Ref. [48] discussed the use of three-dimensional DTs for the maintenance of prestressed concrete bridges. Two difficulties were observed in this process, which were the creation of the 3D model and its inspection. The model needs to be based on accurate data that tackle a variety of structural components within the bridge and are constantly updated. To facilitate the process, researchers can create "partial DT models", which only focus on a specific aspect of the model and utilize a limited amount of information. It can be very useful to create partial DTs, since they require less information, achieve a specific purpose, and are much faster to generate. The upgrade of partial DTs would be the "clone" DT, a second-level DT that is made up of multiple partial DTs [48]. It would include more information, hence allowing for a larger scope while managing the asset.

In addition to that, there have been several cases of the use of DT in applications related to structural health monitoring as shown in Table 4. Ref. [49] developed a digital twin for structural dynamics systems, which was able to update and improve the model and learn from observed data. Ref. [50] developed a DT demonstrator for structural simulation and applied a bending beam bench test to demonstrate this. They reported the calculation time to be over half a minute, which hindered real-time capabilities. Ref. [51] proposed a system using augmented reality, Internet of Things, digital twin, and simulation to monitor stresses throughout an entire lifecycle. Ref. [52] analyzed the effect of creep and shrinkage on the Sydney Opera House by integrating BIM and finite element models to create a digital twin. Ref. [53] proposed a framework for structural health monitoring of bridges using digital twins. They used two bridges as a case study and utilized four different approaches. Finally, Ref. [47] proposed a method for collapse fragility assessment using DT to determine the seismic collapse resistance and the bridge's vulnerable areas. The DT model was able to predict the intensity and probability of collapse. The proposed models in this area aimed at creating a closed process for structural modeling, assessment, and continuous monitoring. This enables the automation of processes as well as data preservation.

Table 4. Digital Twin for Structural Health Monitoring.

Author	Methodology/Aim	Findings
[47]	Proposes a method for collapse fragility assessment using DT.	The proposed model was able to determine the seismic collapse resistance and the bridge's vulnerable areas.
[49]	Develops a digital twin for structural dynamics systems.	The DT was able to update and improve the model and learn from observed data.
[50]	Develops a DT demonstrator for structural simulation.	A bending beam bench test was applied to demonstrate the system. The calculation time was over half a minute, which hinders real-time capabilities.
[51]	Proposes a system using AR, IoT, digital twin, and simulation to monitor stresses.	The stresses can be calculated and observed for the entire lifecycle.
[52]	Analyzes the effect of creep and shrinkage on the Sydney Opera House.	Proposed the integration of BIM and finite element to create a digital twin.
[53]	Proposes a framework for structural health monitoring of bridges using digital twins.	Two bridges were used as a case study and four different approaches were utilized.

DT has proven to be useful in the area of structural health monitoring based on the previously discussed studies. Another area that would benefit from this technology is the monitoring of heritage buildings. This would enable the lifecycle management of important structures. UAVs can be used for the 3D scanning of these structures as proposed by [48]. Machine learning algorithms can be used for image processing and prediction.

4.6. Facility Management

4.6.1. Facility Management (FM) in Construction Projects

Construction is known to be a fragmented industry where multiple stakeholders are involved throughout the various project stages. To improve this issue, efforts expended in digitalization have enabled the consolidation of project data from inception to delivery and operation. This was made possible through the use of building information modeling (BIM) and digital twins powered by artificial intelligence and the Internet of Things [20]. Previously, as-built BIM was introduced to provide a representation of a commissioned building. The problem with them, however, is that they provide a static image, which is not updated depending on the current status [7]. Hence, adopting a digital twin would solve this issue by enhancing the facility management process through a dynamic real-time representation.

4.6.2. DT Applications for Facility Management

Digital twins have become popular for facility management. One aspect of application here is related to the safety of construction and operations. According to [18], DT research is divided into two main branches: (1) using sensors to collect and analyze real-time information; and (2) integrating the analyzed information with a virtual application to visualize and simulate construction. Creating a digital twin for a structure/infrastructure aids in data traceability and the possibility of optimization [54]. Additionally, it would enable anomaly detection, which is beneficial during the operation and maintenance of facilities [55]. Ref. [55] proposed a method using DT and extended industry foundation classes to create an anomaly detection system for assets. They classified anomalies into two categories: point and contextual anomalies. A point anomaly refers to an instance where data deviates from the norm. On the other hand, a contextual anomaly refers to a deviation under a specific context. To apply this classification, they required historical data that established the non-anomalous operating conditions. A large number of systems and their inherent complexities create a challenge that requires a system to investigate and maintain them. Hence, a baseline needs to first be identified to distinguish between these two behaviors. This baseline can be created using data collected from an asset, including facility records, maintenance records, work planning, energy and sustainability, location and space management, and human/worker records [55].

4.7. Digital Twins for Cities

4.7.1. DT Use for Cities

A digital twin city is a digital representation of the physical objects and assets of a city [56]. Digital twin applications for cities can be classified into three areas: pre-construction, during construction, and post-construction or operation. Creating a city digital twin will enable the holistic planning of a city, which will improve its resilience to disasters. Many city-level challenges have been raised within the context of the coordination and integration of planning and management in cities [57].

Recently, a shift towards the development of smart cities has been observed across the globe. This socio-technological transformation is characterized by an integration between the real world and the virtual world using sensors and other technologies. This has enabled visualization and streamlined decision-making. Studies related to smart cities indicate that BIM is the starting point of DT and is considered a “semantically rich 3D model” that can be used for conducting simulations related to the built environment [20]. A city can be seen as a system of systems consisting of various infrastructures [57]. Hence, a smart city DT is the digital representation of a city’s infrastructure, human dynamics, information flow, and virtual and physical connectivity [11,58]. Creating a smart city DT will enable not only the real-time monitoring of infrastructure and the entire city, but also the creation of what-if scenarios to study potential hazards and their impact on the community. This will improve cities socioeconomically by allowing them to manage their resources and energy more efficiently.

4.7.2. DT Applications for Cities

Several applications have been proposed for city digital twins. For example, the city of Rennes in France created a virtual replica of the city [33]. This allowed them to use sensors around the city to measure energy usage, traffic, pollution, and other metrics for early detection of anomalies. However, one challenge that faces the creation of multiple DTs is that they are not replicable among different cities. The unique attributes of each city necessitate that the physical, social, economic, and technological attributes be studied and modeled accordingly [59]. Another application of DT is for educational purposes that are not limited to only include students in a classroom, but also for the general population [33]. For example, Ref. [60] proposed a serious game to create a model for a smart city and was able to educate the residents on sustainable development and the consequences of certain actions.

Within a smart city, one of the applications observed was related to environmental safety. According to [18], construction safety can be classified into three areas of study: environment safety, worker behavior safety, and safety awareness. Environment safety can be improved through the use of a digital twin. This will link the virtual model with the physical model, which will enable the creation of simulated scenarios virtually as a test bed before applying them in real life. These simulations can test changing workflow patterns as well as equipment flow and material storage locations. This will help associate metadata with models of cities [61]. Another application of DT is for educational purposes, which not only include students in a classroom, but also the general population [33]. For example, Ref. [60] proposed a serious game to create a model for a smart city and was able to educate the residents on sustainable development and the consequences of certain actions.

4.8. Infrastructure Management

4.8.1. Importance of DT for Infrastructure Management

Another notable application of DT would be in the field of infrastructure management. Construction projects are known for their complexity since there are multiple stakeholders and assets involved. This makes it important to have both a holistic and detailed view of the entire process since any missing information can cause potential cascade effects on the asset management process [34]. Table 5 shows the identified literature in this area.

Table 5. Digital Twin for Infrastructure Management.

Author	Methodology/Aim	Findings
[48]	Proposes a DT model for bridge maintenance.	The proposed model combined 3D information with a digital inspection system and applied it to prestressed concrete systems.
[62]	Proposes a "DT Uses Classification System" for infrastructure program management.	The terminology developed here will contribute to the National Digital Twin strategy in the UK.
[63]	Proposes a DT of a reinforced concrete bridge.	The proposed model used a 'slicing-based object fitting method'.
[64]	Proposes a DT-based bridge management system.	The proposed model showed the behavior and future performance of cable-supported bridges.
[65]	Proposes an integration of DT with geospatial data for bridge infrastructure modeling.	The proposed model aided in creating a bridge maintenance system for a case study in Morocco.

4.8.2. DT Applications for Infrastructure Management

According to [62], the current DT literature lacks standardized terminology, classifications, and procedures. Therefore, they proposed a "DT Uses Classification System" for infrastructure program management. They highlighted the importance of having a shared system to avoid miscommunications. Ref. [63] proposed a DT of a reinforced concrete bridge using point clouds to model the irregular shape. They recognized that significant time is wasted due to the manual modeling of bridges, so they developed a slicing-based technique to develop the DT from point clusters. They concluded that it would be better to have some human assistance while creating the model to capture complex shapes. This is also because the final result is influenced by many parameters, such as the number of slices taken and the configuration of the bridge.

Other DT applications for infrastructure management include a DT-based bridge management system for cable-supported bridges [64]. The authors identified a challenge in the process, which is the difficulty of assessing the effects of deterioration and updating the DT's parameters accordingly. On the same note, Ref. [48] proposed a DT model for prestressed concrete bridge maintenance. The model would utilize a 3D model as well as a digital monitoring system to continuously update the status of the bridge. Ref. [65] proposed integration of DT with geospatial data for bridge infrastructure modeling. They used an automated mobile mapping system to build a 3D model of a bridge. One of the difficulties they reported was that different modeling languages showed higher reliability for different geometries, so they recommended implementing two different languages in unison. Ref. [66] developed a DT that utilized traffic load measurements to gain insights about bridge behavior when subjected to different loads. The paper focuses on the structural health monitoring (SHM) of bridges when multiple cars are passing simultaneously since that would represent a realistic situation.

Several issues appear while studying DTs for infrastructure management. DTs are case-specific and cannot be generalized for more than one project. For example, if several bridges exist, a DT needs to be created for each one. Several data collection techniques exist, including scan-to-BIM and taking field measurements from the infrastructure itself. Therefore, future work in this area should involve creating components and component types of certain infrastructure that can be used as a template or automating the data collection process. Additionally, machine learning or deep learning algorithms can be used to detect damage automatically in the infrastructure.

4.9. Miscellaneous DT Application Areas

The data-driven approach to project management has spurred the use of DT for several other applications. This section discusses seven papers related to the construction field that do not fit under any of the previous classifications. Table 6 shows the identified research in this section. Ref. [67] proposed a life cycle assessment for a subway station using digital twin. They calculated the carbon footprint throughout the life cycle and found it to be the highest during the operation and maintenance phase. They also found that DT can be a useful tool in evaluating the vulnerability of a subway station to explore retrofit options as well as communicating with various stakeholders about the risks due to natural or artificial disruptions. In addition to applications relating to risk management, DT can also be used simply to visualize a particular physical space. Ref. [68] proposed a semi-automatic method to create a DT of the University of Cambridge based on images and CAD drawings and were able to reach medium LoD (level of detail).

Table 6. Miscellaneous Digital Twin Applications.

Author	Methodology/Aim	Findings
[67]	Proposes a life cycle assessment for a subway station using digital twin.	The carbon footprint is calculated throughout the life cycle and found to be highest during operation and maintenance.
[68]	Proposes a semi-automatic method to create a DT based on images and CAD drawings.	The proposed model was able to achieve LOD 300, which can aid in the operation and maintenance phases.
[69]	Proposes a method to control complex business enterprises using digital twins.	The proposed method enables the quantitative assessment of operations in business enterprises.
[70]	Proposes a DSS for construction site logistics using DTs.	Using sensors enables silo tracking and threshold-based filling. The DT enables the collection of data on orders, silos, and trucks.
[71]	Proposes a DT framework using BIM, IoT, and data mining for advanced project management.	The proposed model enables the assessment of workflows, workloads, and worker tasks.
[72]	Develops a DT-driven sensor that ensures construction safety in the process of dredging.	Using a deep learning-based model to create the DT model provided environmentally friendly results while maintaining high accuracy in its predictions.
[73]	Uses DT with VR to involve citizens in the urban planning process.	Using 3D modeling, urban mobility simulation and other tools enabled the decision-making process while involving the public.
[74]	Develops a DT model that uses traffic data to provide feedback about traffic and environmental performance	The proposed model can be used to monitor real-time transportation system technologies.

Moreover, Ref. [69] proposed a method to control complex business enterprises using digital twins. This enabled the quantitative assessment of operations in business enterprises. Ref. [70] proposed a DSS for construction site logistics using DTs. Using sensors enabled silo tracking and threshold-based filling, which enabled the collection of data on orders, silos, and trucks. To further benefit from DT, additional data needs to be collected to improve the site for the workers and equipment. Worker data can include their location, motion, and compliance with safety rules [20]. Similarly, equipment data can include their location and path to determine any possible dangers. The condition of access roads must also be added, and updates made to the price changes in materials and their transportation over time. This application of DT can enable the real-time tracking of fleet, material storage, and movement, and allow for optimization of the site logistics.

Some researchers have proposed techniques that involve the use of machine learning or other technologies in tandem with the DT model. Using IoT devices can enable the creation of a continuous loop between the physical and virtual components [71]. Additionally, cloud storage can be used as a repository for the data collected. Ref. [72] incorporated machine learning technologies while developing a sensor-driven DT model to ensure safety in the process of dredging. They compared the performance of four deep belief networks, which are a type of deep neural network. Then, they selected the best one and used it in the DT-based sensors. The result was a model that had a high accuracy in its predictions while also being environmentally friendly. Ref. [73] used DT with VR to involve citizens in the urban planning process. They used 3D modeling, urban mobility simulation, and other tools to enable the decision-making process while involving the public.

5. Discussion

5.1. Digital Twin Applications in Construction

Digital twins have been proposed for use in many areas in the construction industry. They have been recommended for use for robust decision-making in construction, operation, as well as asset management. However, some challenges remain that hinder their widespread application. Two challenges facing the construction sector are the data integrity and interoperability issues that can occur when connecting DT sensors, simulation, and O&M data [21,49]. The use of ontologies and linked (rather than static) data is preferred to solve this issue of interoperability [61]. However, the absence of a robust, applicable, and data-rich model that matches each of the targeted assets is still a problem.

Another issue is the inaccessibility to real-life data in certain situations. Some researchers have overcome this problem by using data from simulations replicated to mimic real life. Although this method is useful in the DT creation and management of a real asset, the data used is not entirely accurate in its depiction of the asset [20]. Therefore, care must be taken when constructing these simulations, which can aid in the prediction but cannot be relied upon entirely for the decision-making and optimization for the asset conditions. This method can be used for early visualization but cannot be used to base decisions such as maintenance or retrofitting since they are not accurate representations of an asset. Multiple sources are needed to triangulate the data and ensure its integrity.

To develop an effective digital twin, several prerequisites are required such as BIM level 3 as well as implementation manuals. Other technologies such as blockchain can also be used. However, scalable ledgers would be needed [38]. Finally, one issue that plagues the construction sector is the segmentation of the lifecycle phases. This manifests in different optimization goals and targets for each phase [20]. If the goals for the construction and operation phases do not coincide, this would impact the lifecycle of an asset.

Finally, DT has proven its use throughout an asset's entire lifecycle from design to construction, operation and maintenance, retrofitting, or demolition. The level of detail and accuracy needed for each of these phases is different. Visualizing an asset requires different details than decision-making. One beneficial application would be using DT for condition-based maintenance of infrastructure such as railways [75]. This can reduce costs associated with unnecessary maintenance and optimize resources allocated to this task. Another application would be for the fatigue assessment of complex infrastructure such as railways [76].

5.2. Enabling Technologies for Digital Twins in Infrastructure

Several technologies were used by the identified articles as a coupling or supporting technology with digital twin. Among these technologies are artificial intelligence, blockchain, sensing technologies, and VR/AR/MR. These technologies can be used for certain phases of the project, such as design, construction, or operation, or used for the entire life cycle assessment of assets. The need to monitor and control assets has become an important direction in the construction industry. For example, artificial intelligence tools can be used for forecasting or back-casting. Sensing technologies have evolved over the years. IoT has been used as a means for sensor data capture and automation of the data collection process. VR has been combined with DT for asset visualization and to enable interaction and collaboration among participants [73]. Ref. [10] classify DT architecture into data-related technologies, such as sensors, IoT, cameras, and 3D scanning for data collection; high-fidelity modeling, such as machine learning or deep learning semantic models; and model-based simulation, such as finite element analysis and discrete event simulation. The use of these advanced technologies coupled with DT in construction can enable fault detection, quick response and decision-making, optimization of logistics, assessment of life cycle costs and performance, and the achievement of sustainability.

6. Recommendations

With the advent of Industry 4.0, there has been an increasing trend toward interconnectedness in neighborhoods, districts, and cities. Current research has focused on specific sectors, such as a DT for energy management of cities [77], or at a smaller scale such as a household digital twin for energy consumption and optimization [78]. However, no previous research has proposed a DT that integrates multiple sectors. A multi-level framework can enable governments to monitor and control interconnected assets. Hence, it is recommended to create a multi-sectoral and multi-level DT for a city's multiple layers. This can be achieved through a system-of-systems (SoS) approach since each infrastructure is an independent, complex system while their combination leads to emergent behavior [79]. This SoS will connect the many systems and enable the governing bodies to monitor the assets separately as well as monitor the entire SoS. Multiple scenarios can then be created for the stakeholders to show their different perspectives and check how this affects the other assets [77].

The creation of DTs for 'model-based control of future autonomous systems' would also be extremely beneficial [50]. It would enable the simulation and optimization of individual systems as well as systems-of-systems together. This DT will be able to reflect the characteristics and behavior of an asset at its current state and predict future states if AI/ML are used. This can also be done to support urban planning in a city with respect to energy use or even land use to optimize city services. Hence, a holistic platform that can encompass many of the identified areas (e.g., energy, disaster management, lifecycle, smart city, etc.) would be useful to decision-makers. Additionally, a citizen-centric approach can also be adopted here to enable users to manage their data and collect citizen feedback to improve future city plans. This would bridge the gap between the diverse stakeholders involved in urban planning from end-users to governmental entities.

Several recommendations can be made based on the design of DTs in the studied research. For example, for structural health monitoring, Ref. [52] proposes the integration of BIM with finite element models to create a digital twin. However, to create a model of a city, certain issues need to be observed. For example, semantic interoperability between different data is one challenge [61]. Spatial information on all aspects should also be identified. The heterogeneity of the available data could cause issues that need to be addressed before embarking on an entire city DT. Different nomenclature among different tools/technologies would also cause a major issue. Data acquisition could be a challenge since the modes of acquisition as well as data types need to be standardized. Hence, a formal process needs to be defined for CAD-DT creation to simplify it and streamline the process [50]. A common standardized language is suggested for DTs to enable the creation of a standard that can be used by all projects [62]. This will eliminate the issue of heterogeneity of data and the underlying interoperability issues that might ensue. Additionally, automating data acquisition in a formal, standardized way can reduce the aforementioned problems.

DTs can also be applied at the project level. Ref. [18] recommend creating a digital knowledge network for construction safety composed of workers, objects, and hazards. This digital knowledge network can be expanded beyond safety to include the entire construction workflow, which can then be linked to the digital twin. This will include the mapping of all physical objects to enable their control and optimization. Adopting a lean approach by focusing on the flow of material, equipment, and labor can benefit construction companies. Data analytics techniques, such as big data, cloud computing, artificial intelligence, and blockchain, can then be applied for the analysis of the workflow, conducting what-if scenarios, and proposing mitigation strategies. Data collected through the digital twin can then be harnessed to create predictions for the future using machine learning. This will ensure data traceability throughout a project or asset's lifecycle.

Moving beyond the replication of the physical and virtual worlds only, the addition of human cognitive processes can also be helpful [9]. Modeling these human cognitive processes can be observed in construction projects as well as during disaster situations. Several types of metadata are needed to determine the causality between observations to study them and make decisions accordingly. This metadata can be from diverse sources and in a variety of forms, such as on assets, in BIM, or spatial information [80,81]. Additionally, spatiotemporal data are of importance to DT in these cases. This data can be collected using various methods, including laser scanning and photogrammetry.

Digital twin can also benefit from other established methodologies. For example, DT can benefit from the area of system-of-systems, especially in terms of scalability and sustainability. Both technologies are composed of multiple diverse connected systems communicating together, which, when combined, form a larger system. This is especially beneficial when attempting to link multiple infrastructures together.

Future trends include applications of digital twins for renewable energy projects since previous research has focused on the energy sector in general. Additionally, it can be extended to different power supplies and sectors (e.g., commercial, residential, industrial) on a macro scale [82]. This will enable the utilization and optimization of clean forms of energy, thus reducing the current need for traditional resources. The DT can include all aspects of the product lifecycle from design to operation. During the design, it can be used for system evaluation and data generation while during the operation, it can be used for process monitoring, prediction, and optimization [82]. Over 90 cities in the United States have committed to switching solely to renewable energy by 2050 [28]. Implementing a DT that encompasses all forms of energy will aid in energy usage/need estimation and tracking of the reliance on renewable energy sources.

7. Conclusions

Applications of digital twins in construction have been on the rise since their origin in the aerospace industry. They have proven to be highly beneficial in many sectors in providing a digital replica and a two-way communication method for an asset or an entire city. This paper presented a review of digital twin use in the construction sector as well as recommendations for future research. It can be observed that the focus on digital twins has mainly been on the design and architecture of independent assets, especially for asset design, visualization, or management. Research has also addressed specific use cases for DTs, such as for structural simulation, 6D BIM application, or hospital or bridge management. Based on the reviewed research, eight streams of research were identified, which serve the construction sector. These areas are life cycle analysis, facility management, energy, disaster, structural analysis, DTs for cities, infrastructure management, and miscellaneous applications. All these areas have shown enormous potential for digital twin applications in the AEC sector. Although there have been many advances, DT applications are still nascent. Data acquisition and heterogeneity remain important barriers to the full automation of DT creation. The heterogeneity of data sources as well as their quality are also important issues to study. Economic aspects associated with data acquisition, processing, and sharing of Industry 4.0 tools are recommended for study. Industry 4.0 tools include the Internet-of-Things, blockchain, and application programming interfaces (APIs). The use of these tools can enable DT to reach its full potential. Additionally, virtual/augmented/mixed realities are important tools to enhance user experience and can be used in classrooms for effective content delivery as well as for industrial applications. DT use can be expanded for the monitoring and maintenance of various assets beyond their current use in infrastructure. For example, they can be used for inspecting and maintaining important structures such as heritage buildings as well. Future research should assess the barriers to the use of these tools and the current practice in the AEC sector as well as in other industries that are ahead in DT adoption. With the development of 5G, blockchain, and IoT in construction applications, digital twins can be coupled with these technologies.

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