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Systematic Review

Digital Twins in the Sustainable Construction Industry

Foad Zahedi [1], Hamidreza Alavi [2,*], Javad Majrouhi Sardroud [3] and Hongtao Dang [1]

1 School of Design and Construction, Washington State University, Pullman, WA 99164-2220, USA; foad.zahedi@wsu.edu (F.Z.); hongtao.dang@wsu.edu (H.D.)
2 Department of Engineering, University of Cambridge, Cambridge CB3 0FA, UK
3 Department of Civil Engineering, Faculty of Civil and Earth Resources Engineering, Central Tehran Branch, Islamic Azad University, Tehran 1469669191, Iran; ja.majrouhi@iau.ac.ir
* Correspondence: sa2194@cam.ac.uk

Abstract: Digital Twin (DT) technology, as the evolution of Building Information Modeling (BIM), has emerged to address global concerns regarding the environmental impacts of the construction industry and to meet sustainability indicators. Despite numerous studies targeting the integration of DT and sustainability, there is a noticeable gap in creating a comprehensive overview of the efforts and future directions in this field. Therefore, this research aims to provide both a scientometric analysis and a thematic review of 235 papers extracted from the Scopus database. These papers, all published between 2017 and 2024, focus on previous efforts, current trends, and future directions of using the Digital Twin for construction sustainability. In addition, 34 papers that were cited more than 20 times were classified by the application into four categories: simulation, technology integration, smart systems, and literature review. Furthermore, regarding the application of smart systems in sustainability, the authors discussed applications of BIM-DT in smart construction, smart buildings, smart infrastructures, and smart cities based on the most-cited papers. Subsequently, five research gaps were identified and suggested for future investigation. The research gives a holistic insight into the current trend of DT among researchers, previous achievements, and future directions.

Keywords: BIM; construction; critical review; Digital Twin; scientometric analysis; sustainability

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1. Introduction

Global warming and the rapid, human-driven destruction of the environment have led to a surge in attention on producing corrective solutions. One of the pivotal industries exacerbating ecosystems is the construction industry, which is a major source of urban pollution [1]. This industry accounts for 40% of energy consumption, one-third of carbon emissions, and a quarter of global waste generation [2,3], with construction and demolition waste (CDW) being its most pollutant byproduct [1]. Therefore, the construction industry has been compelled to find solutions to mitigate its negative effects. In the 1970s, automation was introduced to the construction industry through building information modeling (BIM) [4]. Since 1950, discussions in certain strains of thought have grown in popularity, including population growth, resource use, and pressure on the environment, all of which revolve around "sustainability" [5]. The United Nations have promoted the use of the term "sustainable development" since 1987, describing it as an idea that "meets the needs of the present generation without compromising the ability of future generations to meet their own needs" [6]. Incidentally, in recent years, sustainability has widely been related to environmental factors, and other dimensions should be considered in this regard, including economic and social indicators.

In the 1970s, Finland introduced a new approach to digitizing the construction industry [4], the n-dimensional (nD) model, including 3Dmodeling, 4D scheduling, 5D estimating, 6D sustainability, 7D operation and 8D safety [7]. Digital Twin (DT), the evolution of BIM, has been innovated to streamline construction project tasks during the entire project lifecycle and enhance sustainability [8]. DTs were initially used to simulate physical assets digitally, providing a platform for processing and managing information. Originally, DTs functioned primarily as monitoring tools but have since evolved to support control, optimization, and automation. Continuous improvements in learning and digital representation have enhanced DT capabilities. Today, DTs can integrate with advanced technologies such as artificial intelligence (AI), data analytics, the Internet of Things (IoT), and augmented reality (AR), revolutionizing engineering processes [9]. AI assists in modeling complex systems by leveraging data gathered from IoT sensors. With emerging technologies enhancing decentralized processes and reducing reliance on human tasks, while significantly minimizing errors, these innovations are now at the forefront of DT technological research. Although academic trends have primarily focused on the application of DTs in manufacturing and supply chain management, the construction industry is seeing an increasing number of studies in this area. These studies emphasize reducing errors and ensuring as-designed construction [10], which directly contributes to improving sustainability indicators.

BIM aimed to reduce the environmental impact while simultaneously reducing the associated time, costs, and risks [11]. Governments have collaborated with industry and academia to develop roadmaps for implementing and mandating BIM in the industry. BIM is a virtual representation of a built environment, covering the engineering and construction phases [12]. The evolution of BIM during the construction phase has led to the development of DT technology [13], which provides real-time feedback on structural, mechanical, and electrical elements using sensors [14]. The widespread utilization of BIM in the construction industry has led researchers to promote BIM integrated with sustainability, known as the 6D of BIM. During the engineering phase, BIM enables accurate energy consumption simulation. In the construction phase, it helps anticipate and measure energy usage. During the Operation and Maintenance (O&M) phase, DT technology provides occupant comfort and optimized energy consumption [15].

BIM could be used in sustainable construction through robust information delivery and better energy modeling [16]. Additionally, BIM contributes to reducing carbon emissions and material waste, thereby developing the principles of sustainable construction [17]. The endeavor to integrate BIM within the building lifecycle has yielded promising outcomes. The BIM-based design demonstrates efficiency in sustainable construction, with various research studies highlighting its positive impact on design and the concurrent reduction in environmental footprints. In a compelling case study, the application of BIM during building form design showcased a substantial 20% reduction in embodied carbon from construction materials [18]; this is in stark contrast with conventional design approaches, which, as evidenced, result in 2–3 times higher carbon and energy production compared to their BIM-based counterparts [19]. A proposed framework encompasses a sustainable BIM model, addressing aspects of retrofitting and improvement for both new and existing buildings [20]. The pivotal work of Ata et al. introduces a groundbreaking concept—the materials digital passport, meticulously structured to seamlessly integrate with BIM in the pursuit of sustainable construction. This tool serves as an invaluable resource for designers, providing qualitative and quantitative information about materials. In the qualitative realm, it imparts insights into circularity and disassembly practices, while the quantitative dimension precisely delineates destructibility, recovery, and environmental scores [21]. Several studies have explored models and approaches to reduce CDW and greenhouse gas (GHG) emissions. For instance, BIM implementation in case studies reduced waste by 4.3% to 15.2%, demonstrating the positive impact of engineering improvements [22]. Jalaei et al. developed a BIM plugin that successfully reduced CDW in high-rise building walls by 42.4%, emphasizing the potential of innovative tools in waste reduction [1]. A 2022 study proposed a framework to minimize CDW at the early design stage by addressing rework, design faults, and redesign possibilities [23]. Through a study focused on the Chinese construction market, 206 buildings and a construction project were investigated to develop a predictive model for waste generation across three phases: understructure, superstructure, and the finished stage. Waste types were categorized into five groups: inorganic nonmetallic, organic, metal, composite, and hazardous waste. Leveraging Big Data collected from this comprehensive study, the model effectively predicts the quantity of waste generated in each phase [24]. Despite the advancements and proven benefits of BIM to the construction industry, research shows that BIM still needs further developments to be exhaustively employed [11]. A critical issue is real-time data exchange between construction assets and the model, which prevents simultaneous monitoring. However, most recent research efforts have been allocated to integrating BIM with other technologies, including Radio Frequency Identification (RFID), AR, and Geographical Information Systems (GISs). Moreover, BIM lacks interoperability, which would aid in software utilization and data transfer for the engineering, construction, and operation phases [25]. Nevertheless, efforts are being applied to proposing innovations that provide project teams with real-time data exchange and condition monitoring of the built environment. The virtual counterpart [26], later called the DT, is created to not only provide a seamless flow of real-time information but also enhance the sustainability of the construction. Therefore, considering the progressive trend of studies emphasizing sustainability in the construction industry, it is crucial to have a clear vision of current trends and future directions. Therefore, this study is dedicated to providing information about the application of DT technologies in enhancing sustainability throughout the lifecycle of built environments. Several recent reviews have focused on DTs [14,27–29]. Among these, Albalkhy et al. reviewed 228 publications and classified DT applications into six categories: (1) sustainability and environmental performance; (2) facility management; (3) safety, health, and risk management; (4) structural performance; (5) construction management; and (6) architecture- and urban-related applications [27]. Various attempts conducted during the last five years have reviewed the effects of digitalization, specifically DTs, from different lenses. Huang et al. provided an extensive literature review and explored how DTs enhance sustainability in civil engineering in structural health monitoring (SHM) and full project lifecycle [30]. For successful DT implementation in the construction industry, several challenges need to be addressed. IT infrastructure must be enhanced to ensure a seamless flow of information. Data exchange must be reliable, with trustworthy data transmitted without interference or network failures. Security and privacy regulations must also be met, particularly concerning data sharing. Furthermore, organizations and end-users need to be informed about the benefits of DTs, and professionals require training to develop realistic expectations. A standardized modeling approach is currently lacking, and the domain of IoT data exchange during model development and maintenance must be improved to ensure reliable data analysis in a common data environment [31].

While the integration of DT technology with sustainability is progressing, further advancements are required to meet global needs. Emerging technologies such as AI and IoT are generating new forms of DTs, including cyber-physical twins, AI-driven DTs, and urban DTs, necessitating in-depth research to address sustainability concerns. Although the aforementioned reviews have explored DT applications, there remains a gap in focusing both qualitatively and quantitatively on how DTs function in promoting sustainability. To address this gap, this study reviews all published articles, encompassing 235 conference and journal articles published between 2017 and 2024, both qualitatively and quantitatively. The critical review applied in this research aims to extract current trends and future directions. The paper is organized as follows: In Section 2, the authors present their review methodology and strengthen the research methodology that is applied in this research. In Section 3, a quantitative analysis is performed. Section 4, the proposed definitions for DTs are reviewed, and previous endeavors on DT applications in sustainable built environment lifecycles are thematically discussed. Eventually, future research topics are proposed in Section 5.

The current research, therefore, emphasizes the importance of DT implementation in achieving a sustainable built environment. In doing so, the authors review the most-cited articles, DT applications, and the advancements that have been made in smart buildings over the past two years. Additionally, recent research efforts on smart infrastructures and smart cities are discussed using an extensive literature review. The paper is the first to profoundly consider advancements and practices in DTs within a single source.

2. Research Methodology

A systematic literature review was selected for this research as it is an effective method that provides a comprehensive perspective on previous research efforts [32,33] and builds upon the PRISMA checklist. This method also enhances our understanding of research trends and strengthens knowledge structures [34]. The research protocol, based on previous review-building development efforts [15,35–38], is presented in Figure 1. Initially, a preliminary search was performed on the database, followed by a double-screen review. The scientometric analysis in the second stage aimed to develop bibliographic networks. In the final stage, the lifecycle of built environments was divided into four phases, which were thematically discussed.

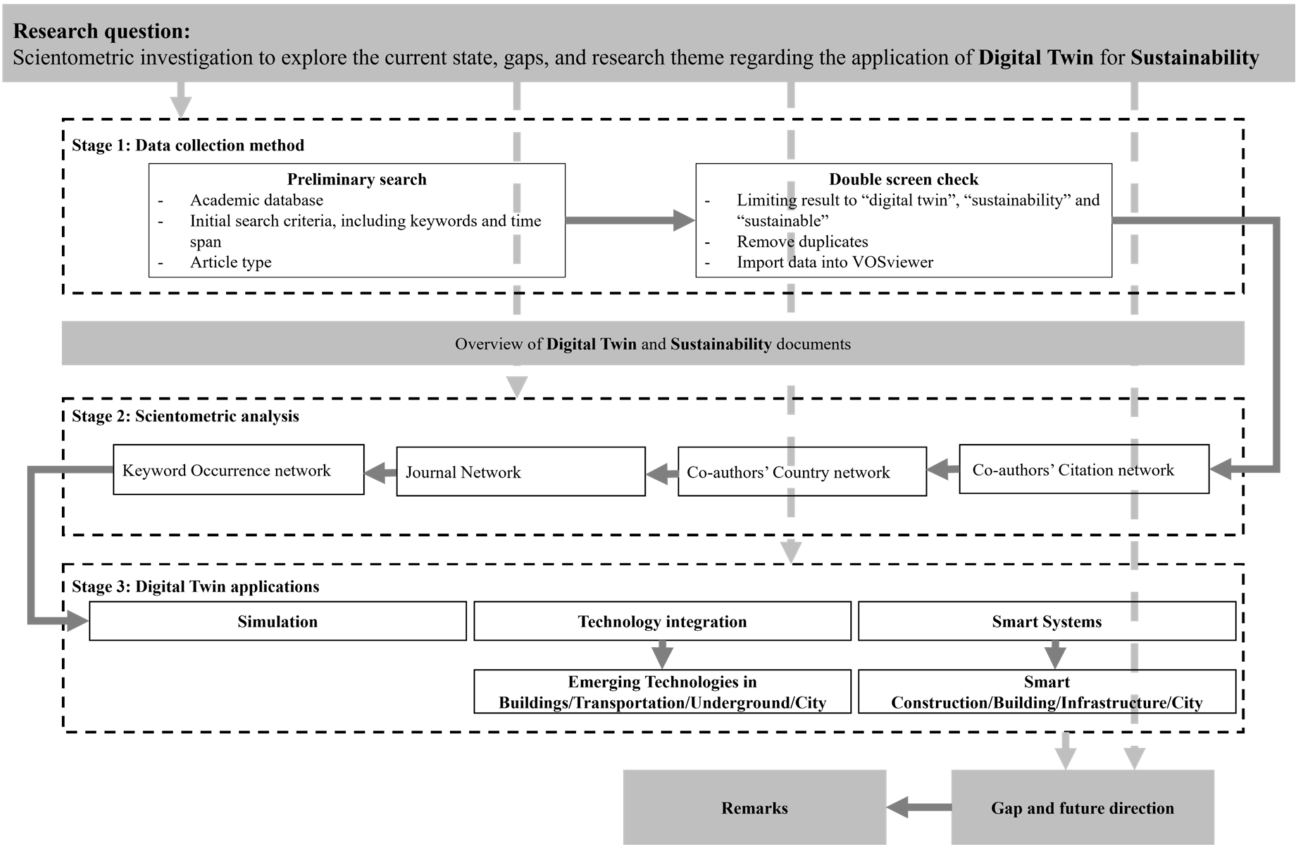

Figure 1. Scientometric analysis flowchart.

2.1. *Bibliometric Analysis*

Preliminary Search

The preliminary search was conducted to understand the boundaries of the research. The Scopus database is a primary source of abstracts; it indexes publications from more than 7000 publishers, including more than 91 million records from more than 17 million authors across the globe. The initial search encompassed "Digital Twin" as the keyword with unlimited timespan, language, and publishing stage. The search resulted in the retrieval of 25,257 publications (Table 1).

Double Screen Check

The double screen check was used with the aim of limiting the timespan, the type of publication, and the stage of publication, utilizing keywords that reflect the research goals. Related studies were exported through an extensive search, using the keyword

"Digital Twin" in journal articles and conference proceedings in the engineering subject area. The preliminary search resulted in 25,527 papers. Performing the double screen check, we limited the search through the use of the following keywords: "sustainability" OR "sustainable" AND "construction" OR "building" OR "built". These keywords were required to appear in the paper title, the keywords, or the abstract. Duplicates were removed. English language was required, and there was no limitation on publication time span. With these measures, 235 papers were found (after the removal of duplicates) (Table 1). This result was achieved on 7 July 2024.

Table 1. Bibliometric search criteria and results.

Stages	String and Filter	No. of Document
Preliminary Search	Database: Scopous Subject area: Engineering Keyword: "Digital Twin" (Title) Document type: journal article, conference proceedings	25,257
Double Screen Check	Keyword: Sustainability **OR** Sustainable **AND** Construction **OR** Building **OR** Infrastructure (title, abstract, keyword) Language: English Time span: All years (2017–2024)	235
Removing duplicates		235

As illustrated in Figure 2, the trend of publications shows a surge across all types of papers starting from 2017 and peaking in 2023, where 36.6% of the total publications (86 out of 235) were recorded. Furthermore, 80% of all 235 published papers were produced during the last three years. Before 2017, research had especially been focused on developing DTs and the transformation of BIM into DTs and the principles of these technologies; meanwhile, research concentrating on sustainability was lacking. Therefore, this review covers almost all the research efforts on DT applications in sustainable built environments.

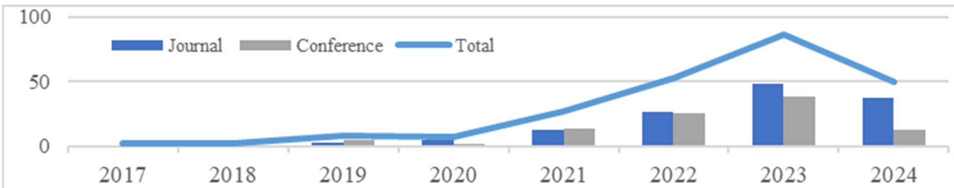

Figure 2. Distribution of papers published between 2017 and 2024.

2.2. Systematic Review

A systematic review analysis is defined as "a quantitative study of research on the development of science" [39]. This approach evaluates the impact of research and measures relationships between citations to construct a knowledge map using information extracted from academic databases. In this study, the Scopus database was selected as the primary source. While a manual literature review allows for a comprehensive mapping of a specific research area, there are debates concerning subjective interpretation [40]. Therefore, the systematic review technique was employed in this study to analyze DT projects within the architecture, engineering, and construction (AEC) industry and to construct a knowledge map of the area. This perspective on the DT field through a network helps researchers to understand the current research patterns and trends.

The bibliometric search scrutinized the title, abstract, and keywords to conduct a comprehensive review of the literature on Digital Twin and sustainability. The following analyses, as depicted in Figure 1, were performed to validate the research patterns: co-authors' citation network, co-authors' country network, and journal network. Before discussing future research directions, a keyword co-occurrence analysis was performed to identify trending research areas. This comprehensive approach helps in understanding the landscape of Digital Twin research within the context of sustainability and provides insights into emerging trends and collaborative networks.

3. Scientometric Analysis

VOS viewer software 1.6.18 was employed for the scientometric analysis to create a network among the 235 publications identified in the Scopus database. All publications were defined within the software to facilitate a comprehensive bibliometric analysis. This approach allows for the visualization of relationships and patterns among research papers based on citations, co-authorships, keywords, and other relevant factors.

3.1. Most-Cited Papers

Table 2 presents the first five most-cited papers; these were all journal articles, collectively accounting for 846 citations, which constitutes approximately 27.3% of the total citations analyzed. This indicates a significant impact of these journal papers within the field under study.

Table 2. Top five most-cited publications.

N	Author and Year	Type	Article Title	Journal/Conference	Cited	Ref.
1	Zaheer et al., 2022	Article	The Metaverse as a Virtual Form of Smart Cities: Opportunities and Challenges for Environmental, Economic, and Social Sustainability in Urban Futures	*Smart Cities*	237	[41]
2	Shim et al., 2019	Article	Development of a bridge maintenance system for prestressed concrete bridges using 3D Digital Twin model	*Structure and Infrastructure Engineering*	174	[42]
3	Kaewunruen and Lian, 2019	Article	Digital Twin aided sustainability-based lifecycle management for railway turnout systems	*Journal of Cleaner Production*	164	[43]
4	Li et al., 2020	Article	Sustainability assessment of intelligent manufacturing supported by Digital Twin	*IEEE Access*	151	[44]
5	Xia et al., 2022	Article	Study on city Digital Twin technologies for sustainable smart city design: A review and bibliometric analysis of geographic information system and building information modeling integration	*Sustainable Cities and Society*	120	[45]

3.2. Co-Authors' Country Analysis

A co-authorship country network (Figure 3) was developed to discuss the countries with the highest contribution to knowledge in the field. Countries with more than five published conference and journal papers were explored without specific restrictions on citation numbers. A total of 20 countries were identified to have contributed to the construction of the network. In this network visualization, each node represents a country, and the links depict collaborations between countries. The size of each node reflects its contribution, with larger nodes indicating a higher number of published papers. Additionally, the analysis revealed that the University of Cambridge has published 13 papers focusing on Digital Twin–sustainability integration, making it the most prominent organization in this area. Following closely are Politecnico di Milano, the University of Birmingham, and

Rheinisch-Westfälische Technische Hochschule Aachen, each with six publications. The University of Hong Kong follows with five publications (Figure 4).

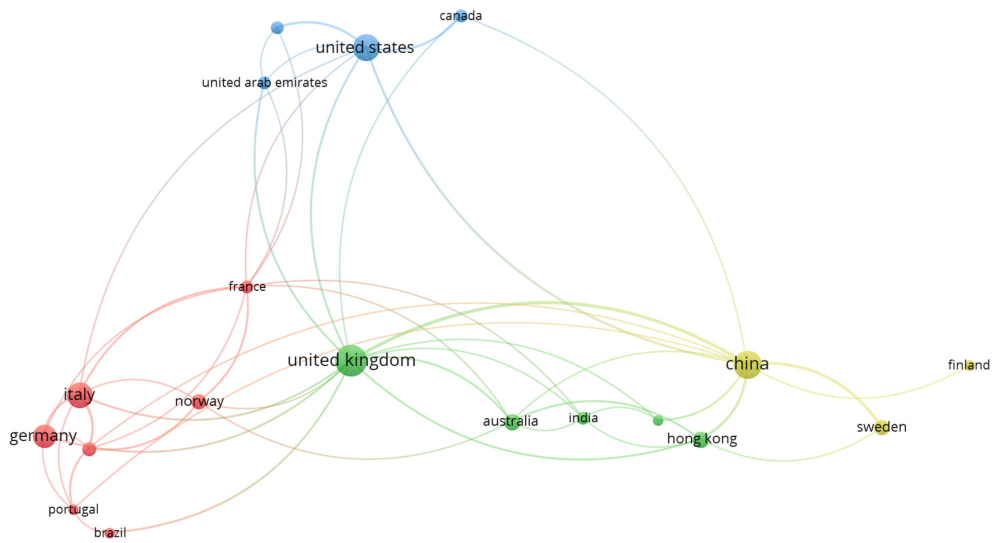

Figure 3. Co-authorship country network.

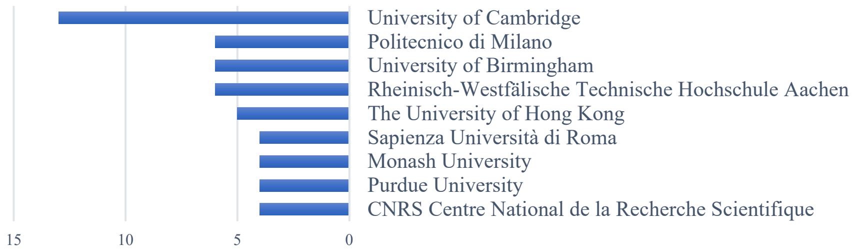

Figure 4. Publications arranged by organization.

Table 3 provides detailed information about each country's achievements in terms of citations and documents related to Digital Twin–sustainability knowledge. The United Kingdom emerges as the most active country in developing this knowledge domain, with 40 publications, 839 citations, and a total link strength of 23. Following closely are the next four active countries, including China (32 documents, 744 citations, and a total link strength of 22), the United States (30 documents, 172 citations, and a total link strength of 14), Italy (27 documents, 90 citations, and a total link strength of 12), and Germany (22 documents, 165 citations, and a total link strength of 7).

Table 3. Countries' contributions to the knowledge area.

Country	Documents		Citations		Total Link Strength
	Count	Percentage	Count	Percentage	
Total	**301**	**100%**	**4978**	**100%**	
United Kingdom	40	13.29%	839	16.85%	9
China	32	10.63%	744	14.95%	12
United States	30	9.97%	172	3.46%	1
Italy	27	8.97%	90	1.81%	0
Germany	22	7.31%	165	3.31%	0
Australia	11	3.65%	389	7.81%	4
Hong Kong	11	3.65%	315	6.33%	4
Others	*128*	*42.53%*	*2264*	*45.48%*	

"Others" advocates the countries that published equal to and less than 10 papers.

3.3. Journal Network

Table 4 provides a report on the journals that have achieved the most significant number of citations in this context.

Table 4. Productive journals and conferences arranged by the number of citations.

Source	Citations	Percentage	Total Link Strength
Total	**5449**	**100%**	
Sustainability	200	3.67%	3696
Automation in Construction	153	2.81%	4028
IEEE Access	145	2.66%	1313
Sustainable Cities and Society	105	1.93%	2050
Buildings	98	1.80%	2006
Automation in Construction	78	1.43%	1452
Energies	77	1.41%	1590
Energy and Buildings	75	1.38%	2508
Sensors	74	1.36%	990
Energy	70	1.28%	2455
Journals with citations < 70	*4374*	*80.27%*	

Among the most impactful journals, *Sustainability* is cited 200 times, equal to 3.67%, with a total link strength of 3696. *Automation in Construction* has 153 citations, 2.81% of the total, and it has the highest total link strength (4028). The next highest-ranking cited journals are *IEEE Access* (citation: 145; 2.66%; total link strength: 1313), *Sustainable Cities and Society* (citation: 105; 1.93%; total link strength: 2050), and *Buildings* (citation: 98; 1.80%; total link strength: 2006).

Table 5 lists the journals and conferences that have hosted the highest number of papers in the field of Digital Twin applications in sustainability. The Scimago Journal & Country Rank was used to determine the H-Index of these journals and conferences. Journals with more than three publications and conferences with more than two publications are included in the table. The five selected journals collectively published 21 papers, contributing 24.7% of the total publications. Additionally, the three conferences featured in the table contributed 7.4% of the publications, making up 32.1% of the overall total. Specifically, the *Sustainable Cities and Society* journal hosted six papers (12.5%), and the *Buildings* journal hosted five papers (10.4%). These findings highlight the significant contribution of these journals and conferences to the dissemination of research on Digital Twin applications in sustainability.

Table 5. Productive journals and conferences arranged by the number of published papers.

Source Publications	Host Country	Count	Percentage	H-Index
Regular journals (Total)		**133**	**41.96%**	
Sustainable Cities and Society	The Netherlands	14	10.5%	130
Buildings	Switzerland	11	8.3%	55
Frontiers in Built Environment	Switzerland	6	4.5%	35
Journal of Cleaner Production	UK	6	4.5%	268
Energies	Switzerland	5	3.8%	152
Energy and Buildings	The Netherlands	5	3.8%	232
IEEE Access	United States	5	3.8%	242
Others (number of publications < 5)		*81*	*60.9%*	

Table 5. *Cont.*

Source Publications	Host Country	Count	Percentage	H-Index
Conference proceedings (Total)		**101**	**31.86%**	
IET Conference Proceedings	UK	5	5.0%	47
Procedia CIRP	The Netherlands	3	60.0%	103
Proceedings—2023 IEEE International Conference on Big Data, BigData 2023	Italy	3	3.0%	NA
Others (number of publications < 3)		*90*	*89.1%*	

H-Index extracted from Scimago Journal & Country Rank "https://www.scimagojr.com/" (Accessed on 7 July 2024). NA: Not available.

3.4. Keyword Co-Occurrence Analysis

A total of 889 keywords were identified across the explored papers, with 49 of them appearing three times or more. Figure 5 illustrates the relationships between keywords used by authors, showing each node and their co-occurrence in papers. According to Figure 5, the keyword "Digital Twin" has the highest frequency, appearing 90 times and having a total link strength of 115.

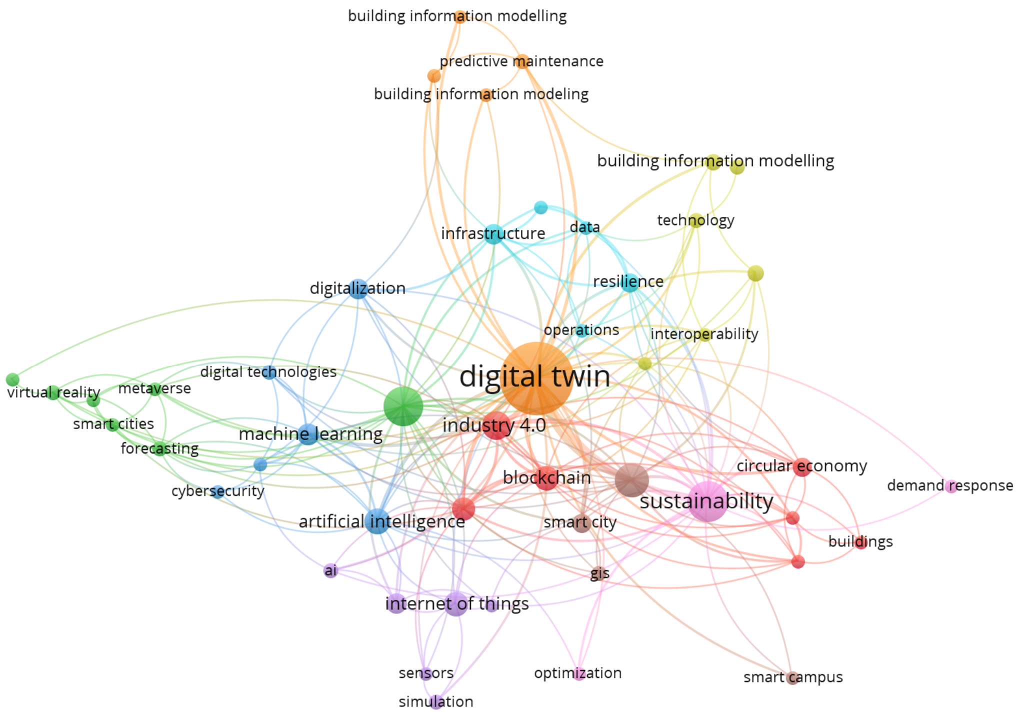

Figure 5. Keyword co-occurrence network.

Based on Table 6, which provides information about the occurrence of each keyword and their network parameters, "Digital Twin" stands out with the highest frequency at 90 occurrences and a total link strength of 115. Following this, the next most frequent keywords are "Sustainability" (occurrence: 27; total link strength: 49), "Digital Twins" (occurrence: 26; total link strength: 31), "BIM" (occurrence: 19; total link strength: 39), and "Industry 4.0" (occurrence: 14; total link strength: 30). However, "Digital Twin" emerged in different terms, including "Digital Twins" and "Digital Twin (DT)", and "BIM" was repeated through the phrasing of "building information modelling (BIM)", "building information modeling (BIM)", and "building information modelling", emphasizing the leverage of the keywords.

Table 6. Highly occurring keywords with network parameters.

Keyword	Occurrences	Total Link Strength	Keyword	Occurrences	Total Link Strength
Digital Twin	90	115	Technology	4	7
Sustainability	27	49	Virtual Reality	4	7
Digital Twins	26	31	Asset Management	3	9
BIM	19	39	Building Information Modeling (BIM)	3	4
Industry 4.0	14	30			
Artificial Intelligence	11	19	Building Information Modelling	3	5
Blockchain	10	20			
Internet of Things	10	8	Buildings	3	4
IoT	9	24	Built Environment	3	12
Machine Learning	8	15	Climate Change	3	5
Digitalization	7	12	Construction	3	12
Energy Efficiency	7	8	Cybersecurity	3	4
Infrastructure	7	16	Data	3	12
Circular Economy	6	14	Deep Learning	3	6
Resilience	6	18	Demand Response	3	2
Smart City	6	11	Digital Transformation	3	9
Building Information Modelling (BIM)	5	7	Interoperability	3	9
			Maintenance	3	2
Sustainable Construction	5	8	Metaverse	3	9
AI	4	7	Operations	3	6
Digital Technologies	4	7	Optimization	3	4
Digital Twin (DT)	4	2	Sensors	3	5
Forecasting	4	11	Smart Building	3	5
GIS	4	4	Smart Campus	3	4
Predictive Maintenance	4	9	Smart Cities	3	6
Simulation	4	4	Smart Infrastructure	3	8

4. Content Analysis

4.1. Digital Twin Definitions

In 2012, the term "Digital Twin" was first utilized in the context of the NASA Apollo 13 mission, as described in the following quote: "An integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [46]. However, since then, scientists and researchers have not reached a consensus on a unique definition of "Digital Twin". Various definitions of DTs have been proposed across different industries. A comprehensive table of DT definitions is available in Appendix A (Table A1), along with the corresponding references in the text.

Since the introduction of DTs in 2002 [47], DTs have been demonstrated to have advanced applications through integration with emerging technologies and systems, ranging from preventive decision-making to the development of autonomous systems.

DTs represent an evolution from BIM, as they simulate the physical condition of a project within a virtual environment. They can also integrate with IoT technologies, enabling efficient energy consumption through optimized energy modeling during the engineering phase. This optimization leads to efficient energy management and enhanced occupant comfort during the operational phase [14]. Consequently, developments in DTs are significant advancements for the industry.

Adding the automated decision-making feature to DTs, which enables real-time data collection of the state of a built environment to provide accurate predictions of future states and take reliable actions, is interpreted as a cyber-physical twin [48]. This innovation facilitates intelligent and automated processes by employing computing technologies such as sensing, analyzing, predicting, and understanding, along with communication strategies that include interaction and interface management and control mechanisms like interoperability, evolution, and evidence-based certification [49].

4.2. Digital Twin Applications

Considering the 235 papers explored with the mentioned keywords, all papers cited more than 20 times until 7 July 2024 were selected for review, totaling 40 papers. Articles are categorized based on application in simulation, technology integration, smart systems, and literature review. Six papers that were deemed to be irrelevant to the construction industry were excluded, leaving a total of 34 papers for review that are categorized by application in Table 7.

Table 7. Highly cited DT papers divided by applications.

No	Title	Ref.	Application
1	The Metaverse as a Virtual Form of Smart Cities Opportunities and Challenges for Environmental, Economic, and Social Sustainability in Urban Futures	[41]	Simulation
2	Development of a Bridge Maintenance System for Prestressed Concrete Bridges Using 3D Digital Twin Model	[42]	Simulation
3	Digital Twin Aided Sustainability-Based Lifecycle Management for Railway Turnout Systems	[43]	Simulation
4	Sustainability Assessment of Intelligent Manufacturing Supported by Digital Twin	[44]	Smart systems
5	Study on City Digital Twin Technologies for Sustainable Smart City Design: A Review and Bibliometric Analysis of Geographic Information System and Building Information Modeling Integration	[45]	Simulation
6	Circular Digital Built Environment: An Emerging Framework	[50]	Technology integration
7	Digital Twin for Sustainability Evaluation of Railway Station Buildings	[51]	Simulation
8	Developing a Dynamic Digital Twin at a Building Level: Using Cambridge Campus as Case Study	[52]	Technology integration
9	Digital Twin Models for Optimization and Global Projection of Building-Integrated Solar Chimney	[53]	Simulation
10	Urban Digital Twin Challenges: A Systematic Review and Perspectives for Sustainable Smart Cities	[54]	Simulation
11	Interoperability Between Building Information Modelling (BIM) and Building Energy Model (BEM)	[55]	Simulation
12	Design and Assembly Automation of the Robotic Reversible Timber Beam	[56]	Technology integration
13	Unpacking Data-Centric Geotechnics	[57]	Technology integration
14	Digital Twin Enabled Sustainable Urban Road Planning	[58]	Technology integration
15	Future Landscape Visualization Using a City Digital Twin: Integration of Augmented Reality and Drones with Implementation of 3D Model-Based Occlusion Handling	[59]	Technology integration
16	Metaverse Supply Chain and Operations Management	[60]	Simulation
17	Digital Twin Simulation Tools, Spatial Cognition Algorithms, and Multi-Sensor Fusion Technology in Sustainable Urban Governance Networks	[61]	Technology integration
18	AI-Based Physical and Virtual Platform With 5-Layered Architecture for Sustainable Smart Energy City Development	[62]	Smart system
19	Renewable Energy System Controlled by Open-Source Tools and Digital Twin Model: Zero Energy Port Area in Italy	[63]	Simulation
20	Hybrid Learning-Based Digital Twin for Manufacturing Process: Modeling Framework and Implementation	[64]	Technology integration

Table 7. *Cont.*

No	Title	Ref.	Application
21	An Initial Model for Zero Defect Manufacturing	[65]	Smart systems
22	Efficient Container Virtualization-Based Digital Twin Simulation of Smart Industrial Systems	[66]	Smart systems
23	Digital Twin-Enabled Smart Modular Integrated Construction System for On-Site Assembly	[67]	Technology integration
24	Blockchain-Enabled Cyber-Physical Smart Modular Integrated Construction	[68]	Smart systems
25	A BIM-IoT and Intelligent Compaction Integrated Framework for Advanced Road Compaction Quality Monitoring and Management	[69]	Smart systems
26	A Framework for Using Data as an Engineering Tool for Sustainable Cyber-Physical Systems	[70]	Simulation
27	Adoption of Blockchain Technology Through Digital Twins in the Construction Industry 4.0: A PESTELS Approach	[71]	Technology integration
28	Project Data Categorization, Adoption Factors, and Non-Functional Requirements for Blockchain Based Digital Twins in the Construction Industry 4.0	[7]	Technology integration
29	Digital Twins in Infrastructure: Definitions, Current Practices, Challenges and Strategies	[72]	Smart systems
30	Collaboration and Risk in Building Information Modelling (BIM): A Systematic Literature Review	[73]	Technology integration
31	Digital Twin Framework for Automated Fault Source Detection and Prediction for Comfort Performance Evaluation of Existing Non-Residential Norwegian Buildings	[74]	Smart systems
32	Digital Twins for Managing Railway Bridge Maintenance, Resilience, and Climate Change Adaptation	[75]	Simulation
33	Design and Implementation of a Smart Infrastructure Digital Twin	[76]	Smart systems
34	Digital Twin with Machine Learning for Predictive Monitoring of CO2 Equivalent from Existing Buildings	[77]	Technology integration

Reviews conducted recently show further developments are required in Digital Twin applications and their integration with other technologies; the infancy level of DTs' developments is also highlighted, encouraging researchers to delve into the subject.

5. Simulation

DTs have emerged as powerful tools in both lifecycle management and urban development, offering simulation capabilities that provide insights into current conditions and future projections. As a part of Building Management Systems (BMSs), DTs enable stakeholders to access real-time data for better decision-making in long-term maintenance and operational prioritization. For example, studies have demonstrated the value of DTs in railroad turnout lifecycle management by integrating field data like time, cost, and sustainability metrics into a 3D BIM model, which enhances decision-making efficiency [42,43]. However, while these examples show potential, they often remain siloed in their application, focusing on specific domains without addressing broader, cross-functional opportunities. For instance, DT models that incorporate cost, scheduling, and carbon emission metrics (6D) have shown promise in improving sustainability and resilience for existing infrastructure [51,75], but there is limited discussion on how these methods could be standardized or scaled for widespread adoption in diverse infrastructure contexts.

This gap extends to the digital transformation of existing districts into zero-energy zones [63]. Although simulations demonstrate the feasibility of integrating renewable energy technologies, such as solar chimneys, to improve energy efficiency in both low-income and developed countries [53], questions remain about the scalability of such models across different climate zones and socioeconomic contexts. Furthermore, despite advancements in energy optimization using BIM-to-BEM simulations during the design phase, challenges like BIM-BEM interoperability in complex buildings persist, often resulting in errors (e.g., missing or incompatible data) [55]. These technical and interoperability issues highlight a critical need for more robust frameworks that can handle the complexity of real-world applications.

At the urban management level, DTs show significant potential for improving city planning and infrastructure management. By simulating networks of transportation systems, such as bridges and railways, DT can facilitate more sustainable decision-making [70]. Moreover, virtual sustainable city models are being explored within the Metaverse, with studies highlighting their potential to enhance governance, social interactions, and climate change mitigation efforts [41]. This concept is also beneficial for optimizing supply chains, further improving efficiency and sustainability [60]. However, the current literature highlights fragmentation, especially in the integration of GIS and BIM for smart city design. While some scholars emphasize the importance of developing holistic platforms with semantic attributes for real-time city lifecycle management [45], the path toward achieving this remains unclear, particularly given the barriers related to interoperability, infrastructure needs, and governance [54].

The existing literature clearly demonstrates the utility of DTs in simulating various aspects of infrastructure and urban management, yet significant gaps remain in the standardization, scalability, and integration of these technologies across different domains.

6. Technology Integration

The integration of various technologies with BIM and DTs has shown significant potential in enhancing efficiency, especially through the use of real-time data for decision-making and predictive maintenance. For example, incorporating BIM with IoT, BMS, and asset tagging platforms creates dynamic DT systems that improve asset tracking and enable predictive maintenance [52]. While such integration offers clear benefits, there are ongoing challenges related to data management and interoperability across these diverse technologies.

A growing body of research explores how these technologies can also contribute to sustainability and circularity in the built environment. For instance, material passports and BIM are emerging as key technologies to promote circular construction practices, with DTs providing critical support [50]. However, despite their promise, the practical implementation of these systems on a large scale is limited, particularly in the standardization of workflows and data-sharing protocols across projects. This is an area where future research could focus on harmonizing digital platforms to better support sustainable construction processes [56].

Other studies highlight the potential of DTs in modular construction. Jiang et al., for example, introduced the Digital-Twin-Enabled Smart Modular Integrated Construction System (DT-SMiCS) by combining DTs with RFID and ultra-wide band (UWB) devices, enabling real-time, multi-dimensional data collection [67]. This research points to a growing trend of making construction components "smart," but more work is needed to address how such systems can be generalized to different construction types and materials. Similarly, while blockchain integration with DT promises enhanced trust, information management, and automation [71], the complexity of these systems, particularly in relation to cybersecurity and data governance, remains an open challenge that requires further exploration. The integration of DTs and blockchain has also been shown to enhance collaboration, automate processes through smart contracts, and improve data exchange [7].

When it comes to achieving sustainability goals, digital technologies are proving to be transformative. Arsiwala et al. developed a framework combining BIM, IoT, and AI to predict and measure carbon emissions in existing buildings, showing promising results for net-zero renovations [77]. Their work highlights the potential of digital tools to optimize sustainability, but the lack of standardized data models and the need for high-level stakeholder engagement pose significant barriers to widespread adoption. Similarly, Ali et al. emphasized the critical role of DTs in overcoming barriers to integrating BIM with sustainability goals [73], yet there is limited discussion in the literature about how these systems can be made accessible to smaller construction firms with limited technological infrastructure.

At the urban management level, DTs continue to show transformative potential. For instance, combining city-level DT models with AR and drone technologies improves urban planning by allowing stakeholders to visualize complex construction environments in real time [59]. However, while visualization enhances decision-making, issues related to data accuracy and the integration of various technologies remain critical. Similarly, the integration of DTs with AI and BIM in geotechnical engineering has improved lifecycle management by offering more data for informed decision-making [57], yet scalability across different infrastructure types and geographies is still a challenge.

Research into sustainable infrastructure development has also benefitted from DT applications. For example, a DT-based approach integrating multi-criteria decision-making (MCDM) and GIS was validated in a case study for sustainable road development, where it helped balance stakeholder demands with environmental constraints such as air quality and noise pollution [58]. Nica et al. demonstrated how DTs can be integrated with other technologies for urban management and governance [61]. This type of multi-technology integration shows significant promise for urban management, but more work is needed to develop frameworks that can consistently address diverse stakeholder requirements and environmental considerations.

In the manufacturing sector, the integration of DTs with AI has proven to be highly effective in managing sustainable processes. A hybrid-learning-based DT system has been shown to enhance reliability and adaptability, particularly when handling uncertain conditions, leading to more efficient and resilient operations [64]. This integration underscores the potential of combining real-time data analysis with predictive capabilities to optimize resource use and operational decision-making.

While existing studies demonstrate the potential of integrating technologies such as IoT, AI, blockchain, and AR with BIM and DTs, significant gaps remain in terms of scalability, interoperability, and real-world implementation. Many of the current applications are highly specialized, and there is a need for more holistic frameworks that can support a wider range of construction practices and urban management scenarios.

Given the importance of emerging technologies in sustainable built environment lifecycle management, particularly in reducing costs, time, workforce requirements, and minimizing errors, further investigation has been conducted to analyze the application of various technologies integrated with DTs across different types of built environments.

6.1. Emerging Technologies in Building Lifecycle Management

Before the construction phase begins, BIM is employed for cost–benefit analysis and energy consumption predictions, contributing to sustainable design and LCA, with a focus on material carbon emissions. BIM also facilitates Integrated Project Delivery (IPD) implementation and the transition to Integrated Digital Delivery (IDD) in construction projects. Additionally, during the construction phase, BIM helps reduce design issues, costs, and time, and improve energy usage. The progress and processes of the construction phase can be monitored through BIM-IoT integration, allowing for risk prediction by simulating the project [78]. BIM–blockchain integration provides a reliable platform for recording project progress and resource consumption [79]. Data exchange via wireless and wired IoT sensors and actuators ensures high-quality services, enabling each component to maintain effectiveness and intelligence, contributing to occupant comfort, health, and efficient energy consumption, while boosting productivity [80]. During the O&M phase, BIM-IoT integration supports energy performance management, indoor environment monitoring, thermal comfort control, space management, hazard monitoring, and community monitoring. DT-IoT–computational fluid dynamic (CFD) simulation is expected to streamline resource planning and improve lifecycle monitoring. A Revit visualization interface, based on DT-IoT, enhances thermal comfort monitoring and estimation. Additionally, ANN (artificial neural network)-based DTs reduce the computational time required to predict thermal comfort by 98%, and an ANN–support vector machine (SVM)-based DT can estimate the future condition of MEP components. Machine learning (ML)-based DTs are projected to predict facilities' Life Cycle Cost (LCC) using real-time data [78]. Moreover, integrating BIM and blockchain securely stores IoT sensor data during the O&M phase, particularly ensuring the protection of private or confidential information [79].

Integrating BIM-based applications with cloud computing provides real-time access to data and resources, helping to mitigate common BIM challenges. This integration allows users to access information via Internet-based applications, enabling project stakeholders to communicate more effectively on a single decentralized platform. Combining Big Data with BIM/DT allows stakeholders to leverage data collected throughout the project lifecycle, improving project delivery efficiency and identifying hazardous areas on construction sites, thus reducing health, safety, and environment (HSE) risks. ML, a key Big Data mining technology, benefits the construction industry by predicting project costs in the early stages and identifying structural damage. BIM–unmanned aerial vehicle (UAV)– laser scanner integration facilitates the 3D surface method without requiring attributions, providing real-time updates on construction site conditions and work progression, which could support the development of construction DTs. Moreover, virtual reality (VR) can be used for risk assessments, layout, lighting, and landscape design; when integrated with BIM, VR enhances project understanding through walkthrough simulations, offering a safe training environment for workers and operators. Since AR provides better comprehension of the surrounding environment, BIM-AR integration facilitates information exchange between project team members and construction staff, improving overall project coordination and communication [81].

6.2. Emerging Technologies in Road and Transportation Infrastructure Lifecycle Management

BIM-GIS integration forms the foundation of an infrastructure DT for lifecycle management, providing crucial information on geometry, engineering monitoring, project timelines, costs, and energy consumption [82]. Additionally, BIM-GIS enhances the efficiency and performance of roads by monitoring utilities, including structural, geotechnical, and drainage data [83]. By installing IoT sensors, sensitive instruments, or other communication tools on infrastructure elements, DTs can report real-time updates on current conditions and changes in service loads [82]. To address the lack of IoT sensors and the insufficient data for predicting bridge damages, an adaptive simulated annealing particle swarm optimization (ASAPSO)–convolutional neural network (CNN) integration method has been proposed, which accurately identifies bridge damages [84]. However, IoT sensor malfunctions can cause missing data, as discussed by Zhang et al. [85], who reviewed and compared recent developments in data recovery methods. To tackle this issue, an advanced CNN–bidirectional gated recurrent unit (BiGRU)-based technique was proposed in [86], which reconstructs lost data for SHM and enables effective damage detection. Light Detection and Ranging (LiDAR) technology is versatile and capable of detecting human-made objects and transportation infrastructures. When combined with inertial measurement unit (IMU) and GPR (ground-penetrating radar), it can detect road defects, and when mounted on UAVs, it enhances surface inspections and facilitates comprehensive rehabilitation solutions. LiDAR–GNSS (Global Navigation Satellite System) integration is also used for pothole detection, revolutionizing maintenance management approaches [87]. LiDAR and ML have transformed the manual DT development of railroads into an automated process [82]. Although LiDAR provides accurate road surface scanning, red–green–blue (RGB) photos can capture images of the inspected paths, identifying defects such as cracks. RGB photos can be captured using less expensive tools and with minimal training, though the data are limited to a 2D environment, offering color-based insights on cracks, holes [87], and friction changes [82]. ML can process these photos, delivering a comprehensive report that is more accurate and cost-effective than human inspections. Drones equipped with high-quality cameras can detect and categorize defects, while RGB-D cameras offer a more precise perception of road surfaces by analyzing light pulses to calculate distances. For subsurface analysis, thermal imaging or infrared thermography can be employed to capture thermal gradients in both asphalt and concrete, providing insights into underlying conditions. Similarly, GPR uses electromagnetic waves to detect shallow subsurface conditions [87]. UAVs and drones also contribute to SHM, while unmanned marine systems (UMSs) are useful for post-disaster bridge inspections [83]. Furthermore, the effect of temperature on bridge bearings, which is often overlooked in predicting the functionality and potential defects of long-span bridges, can be accurately assessed using an integrated deep convolutional neural network (DCNN)– long short-term memory (LSTM) neural network [88].

6.3. Emerging Technologies in Underground Utilities Lifecycle Management

The use of IoT sensors in developing tunnel DTs during the construction phase enhances hazard prediction and warning capabilities, as demonstrated in a case study [89]. The Tunnels Defects Diagnosis System (TDDS), built upon BIM and semantic web technologies, automates defect detection and facilitates decision-making by identifying the causes of defects [90]. While finite element method (FEM)-to-BIM integration allows engineers to incorporate geotechnical information into BIM models, the reverse process, BIM-to-FEM, still requires manual work [91]. BIM-GIS integration significantly improves the management of underground infrastructure, both at the individual and network levels, as well as supporting the decision-making process [92]. This integration also creates an underground management system that optimizes designs and assists excavator operators with real-time spatial information, ultimately transforming it into an as-built database [93]. Additionally, BIM paired with AI-powered cameras for analyzing Big Data has proven to be a powerful tool for inspecting underground utilities [94]. In another study, Hu et al. developed a DT of a buried pipeline using mobile augmented reality and Brillouin fiber optic sensors, showing that the framework can accurately measure unpredictable and significant deformations [95].

7. Smart Systems

DTSs have evolved into smart systems with advanced decision-making capabilities, allowing them to autonomously manage operations and respond to real-time changes. Various studies have demonstrated the value of integrating DTs into different industries, highlighting their potential to enhance transparency, efficiency, and real-time monitoring. For example, integrating blockchain with DT in modular construction projects enables teams to automatically visualize and assess progress, while simultaneously measuring key performance indicators (KPIs) in real time. This approach has been shown to improve project reliability, transparency, and persistence [68]. However, despite the benefits, integrating blockchain into construction workflows poses challenges related to scalability and the complexity of adapting this technology to different types of projects.

Similarly, Lin et al. developed a DT simulator specifically tailored to improve construction processes by optimizing operations and decision-making [66]. While this innovation advances the automation of construction workflows, its generalizability to larger, more complex construction environments is still under exploration. In another study, researchers proposed a framework for the real-time detection and identification of facility faults, focusing on enhancing occupant comfort [74]. Although the framework proved effective in improving building management, further research is needed to address the data interoperability challenges that often arise when integrating DT into existing facility management systems, particularly in older buildings with legacy systems.

In the field of road construction, a BIM-IoT integration platform has been developed to create a DT of road prototypes, providing precise monitoring throughout the construction process and promoting sustainability [69]. Despite its advantages, such integration requires significant resources and expertise, presenting challenges for widespread adoption in the construction industry. Broo et al. [76] conducted a comprehensive review of literature and practice to identify the most effective DT architecture for smart infrastructures. Their proposed architecture, applied in a real case study, demonstrated the practical application of DTs in infrastructure projects, yet barriers related to technology adoption and the cultural readiness of organizations remain significant obstacles.

The development of smart energy cities has also benefited from DT integration. Park et al. introduced an AI-based digital platform designed to optimize energy consumption across interconnected objects in urban environments [62]. While this demonstrates the potential for improving energy efficiency, it also underscores the complexity of managing large-scale urban systems, where obstacles such as technological expertise and cultural resistance to change slow the adoption of DT technology [72].

In the manufacturing sector, Li et al. proposed an intelligent manufacturing assessment framework supported by multi-criteria decision-making (MCDM) and DT technology; the framework was designed with the aim of enhancing sustainability by streamlining decision-making processes [44]. This aligns with broader efforts to optimize production systems. Similarly, a zero-defect manufacturing (ZDM) model integrating physical and DT systems has been used to monitor and detect faults in real time, boosting both sustainability and operational efficiency [65]. Despite these advancements, the transferability of these systems to more complex sectors like construction, which involve diverse data environments and regulatory requirements, remains an open question.

Challenges related to scalability, interoperability, and technology adoption continue to hinder broader applications of DTs in construction and infrastructure projects. For example, although Broo et al. [76] made significant strides in identifying the optimal DT architecture for smart infrastructure, the practical implementation of such models across different sectors is still in its early stages. Similarly, while blockchain integration with DTs has proven valuable for enhancing transparency and efficiency [68], questions remain about its long-term sustainability, particularly in smaller or less technically advanced firms.

DT/BIM Integration for Sustainable and Smart Built Environments

As has been discussed, options provided by smart systems enable automated operations and reactive responses that enhance sustainability; this section also advocates for various smart systems.

During the design phase, BIM equips sustainability measurement tools and facilitates multidisciplinary data and information exchange. This integration allows for the superimposition of various disciplines within a cohesive model, enabling effective sustainability assessments that guide designers toward creating energy-efficient buildings. To achieve sustainability, a range of BIM applications has been developed, including tools for analyzing energy performance and carbon emissions, simulating lighting, and optimizing overall building performance. BIM visualizes building performance during the early design phase. BIM addresses several environmental issues associated with the construction industry, including emissions, construction and demolition waste, noise pollution, and resource consumption. The 3D BIM model optimizes construction time and costs, thereby enhancing sustainability indicators in building construction. Notably, BIM's role in circular economy (CE) management has led to a 60% reduction in waste generated at the Shanghai Center in China, and it also minimizes waste generation by preventing rework [96]. A Digital Twin–BIM–Internet of Things–data mining framework has been proposed for advanced project management, promoting a seamless flow of information, improved understanding, and predictive optimization of construction processes. A BIM-IoT framework is discussed in [97] that aims to support the assembly of modular construction by enhancing decision-making, assisting stakeholders, and improving collaboration and supervision. Additionally, a BIM-RFID integration framework has been modeled in [98], demonstrating improvements in risk management and reductions in completion schedules. BIM has also been utilized in automated contract and payment processes via blockchain, achieving successful outcomes in real-world applications [99]. When applied to virtual construction, DTs enable the testing of assumptions prior to actual construction. The integration of DTs and AR assists project teams in visualizing construction details in real time. When combined with RFID technology, it enhances safety by providing real-time location data for workers and alerts to potential hazards [100], as well as facilitating automated design reviews [101]. DT leverages real-time data to evaluate various design options while ensuring compliance with local regulations [102]. During the construction phase, BIM-GIS integration facilitates early project takeoff for procurement management and supports preparation and decision-making for retrofitting initiatives [103].

Deng et al. summarized the applications of DT in buildings, emphasizing real-time monitoring of the built environment, predictions derived from real-time data gathered using IoT sensors to facilitate decision-making processes, and automatic feedback mechanisms for identifying necessary interventions [78]. These applications significantly enhance disaster response and management, helping to avoid human errors and accelerate evacuation procedures [104]. Investigations into the integration of BIM and GIS [103] reveal applications in crisis and risk management, energy and facility management, and heritage maintenance. The integration of IoT and BIM enhances the intelligence of existing buildings through Big Data analysis, leading to optimized operations and the implementation of BMS. By monitoring real-time data gathered from BMS, BIM enables energy analysis and management, which optimizes energy consumption. Moreover, this integration reduces the amount of waste generated in renovation projects compared to traditional on-site approaches [105]. A proposed BIM-IoT framework focuses on predicting energy consumption and enhancing occupant comfort [106]. Additionally, a DT model comprising BIM, IoT, the Internet, and SVM can detect the type and level of indoor dangers, as demonstrated in a case study that validated its applicability [107]. A separate case study on the use of BIM in LCA highlighted its effectiveness in accurately measuring emissions from various materials, making it suitable for low-carbon design initiatives [108]. During the facility management phase, DTs facilitate data-driven asset management by relying on data exchange between the physical facility and its digital replica [102]. Similarly, DTs reflect real-time structural and facility behavior through continuous data collection, enhancing predictive capabilities and enabling informed decision-making [100]. In [109], smart electricity meter data are utilized for real-time energy management in smart buildings. Alavi showed the utilization of BIM during O&M; providing high-quality data reduces the effort required by an O&M team to attain information and gather data. The proposed solutions were found to lead to an increase in occupants' satisfaction through integrating feedback into the BIM model. The BIM model, therefore, mitigates serious defects and improves living quality. A BIM-based facility management dashboard enables decision making [110].

DTs enhance infrastructure by gathering integrated data for intelligent building management and maintenance of these systems [72]. Edmondson et al. [111] proposed a real-time performance monitoring system for sewer systems through the integration of BIM and the IoT. A review of different DT architectures led to the development of a smart infrastructure asset DT specifically for bridge management based on best practices [76]. The integration of BIM and GIS enables the monitoring of the current state and future needs of infrastructure, both individually and as part of an interconnected network [112]. This integration also supports excavation and backfilling modeling, time management, construction machinery management, safety assessment, and facility management [103].

On a city scale, Deng et al. [78] argue that DT technology should not only possess the capabilities of a smart building but should also track individuals' movements to manage traffic and urban energy effectively, thereby contributing to the development of smart cities. Yammaura et al. [113] utilized the integration of BIM and GIS for smart city planning and development. Based on a comparison of various DT frameworks for urban development, a DT–city model has been proposed that integrates a range of technologies, including DT, IoT, 5G wireless systems, blockchain, simulation, collaborative computing, and AI to facilitate automatic city management [114]. Additionally, a BIM/construction information modeling (CIM) reconstruction framework has been successfully tested in creating a digital representation of a high-density city using topographic maps [115]. To establish a holistic city DT, a

2020 study presented an integrated system where each component represents a specific urban element [116]. The use of DT combined with AI in infrastructure management has been explored, demonstrating its effectiveness for real-time monitoring, problem identification, issue resolution, efficiency improvements, and loss reduction [117]. A conceptual smart city DT has also been proposed and tested for disaster management, employing sensing and simulation capabilities within community management contexts [118]. Ang et al. [119] introduced an urban–BEM workflow that encompasses the necessary data and processes, integrating personal behavior into urban planning based on real case studies. Furthermore, a literature review discussed the applicability of DT simulation tools, multi-sensor fusion technology, and spatial cognition algorithms in sustainable urban management, concluding that IoT-based smart cities could effectively integrate these technologies [61].

8. Research Gaps: Potential Research Directions

While the authors have reviewed the current trends, this section aims to anticipate future research trends, focusing on the application of Digital Twins in sustainability, particularly within the construction industry.

Structural Health Monitoring

The research indicates that while numerous studies highlight the use of DTs for predicting structural conditions and inspections, the integration of emerging technologies such as IoT, VR, UAV, and ML for SHM is still in its early stages and requires further development. The expected outcome of such research is an improvement in both the sustainability and resilience of individual infrastructures and interconnected networks.

Efficient Water Consumption and Analysis

The application of DTs for efficient energy consumption and enhancing occupants' comfort has been thoroughly investigated, with various methods proposed. However, there is a noticeable gap in strategies aiming to achieve efficient water consumption. Therefore, the development of DT-based approaches for water efficiency remains a critical area for future research.

Urban Development and Management

The Metaverse creates a virtual world that is interconnected with the real world, evolving alongside it while redefining the concepts of time and space within the physical realm [120]. Currently, the Metaverse is utilized in various domains, including gaming, simulation, marketing, education, and social interactions [121]. It holds significant potential as a tool for digitally modeling urban environments, including infrastructure [41]. However, its applicability has primarily been assessed conceptually, with limited practical examination. Therefore, there is a need to develop a modeling framework for creating a realistic urban–DT that accurately reflects the current state of the city and facilitates real-time information exchange between the physical city and its digital counterpart. This framework must also address existing challenges identified in various studies, such as those discussed in [120,121]. To evaluate its pragmatic functionality, case studies are essential for simulating a physical city within the Metaverse.

Integrated Source of Energy and Energy Efficiency

Research has been conducted to explore net-zero electricity storage solutions for a limited number of houses [122]. This research focuses on the decision-making capabilities of cyber–physical twins that balance energy production from renewable resources with energy consumption, all while ensuring occupant comfort. The concept of integrating energy storage systems to cover a neighborhood, an area, or an entire city in order to achieve a net-zero energy system is identified as a topic that requires extensive investigation and practical applications.

Furthermore, the authors advocate for the utilization of this technology for energy management at the national level, particularly in countries that experience diverse weather patterns across their territories.

Underground Projects HSE Considerations

Studies focusing on the application of DTs in the sustainable lifecycle management of underground projects are limited. However, such projects, including tunnels and deep excavations, are prone to significant risks from unpredictable events. Developing DTs integrated with IoT, cloud computing, and wearable sensors can enhance hazard prediction and recognition, while also improving communication between office teams and workers on-site. Additionally, these technologies contribute to more effective evacuation and crisis management strategies.

Inspection of Existing Underground Infrastructures

Previous studies have developed robots for inspecting stormwater channels, allowing for real-time data collection and visualization of defects and blockages. These data enable O&M teams to make predictive and corrective decisions to prevent near- and mid-term crises [123]. Therefore, the integration of robotics with IoT, AR, VR, Global Positioning Systems (GPSs), and DT technologies provides a reliable overview of the current state of underground infrastructures, including channels, pipelines, and water transmission tunnels. This integrated approach helps O&M teams identify issues, particularly in inaccessible locations. The integration is expected to ensure continuous operation while addressing global climate change and associated natural disasters, thereby enhancing the sustainability and resilience of infrastructure. Additionally, this study will facilitate the planning of rehabilitation and strengthening activities through ongoing monitoring of the condition and behavior of infrastructure.

Cyber–Physical Infrastructure/Building

Smart infrastructures provide data feedback and enable decision making based on a comprehensive and continuously evolving set of data [124]. Related concepts have been developed and discussed over several decades. However, cyber–physical twins, which rely on automated decision-making features, represent a significant advancement in DTs and smart infrastructure concepts. They are expected to facilitate automatic defect detection and enable control or preventive decisions through the integration of computing technologies, communication strategies, and control mechanisms. Cyber–physical infrastructures and buildings are anticipated to enhance their lifespan and prevent the escalation of structural defects.

CE-DT Integration Case Study

As discussed, DTs contribute to enhancing sustainability. Çetin et al. studied DT applications in circular construction and supply chain management [50]. Salmenperä et al. focused on advancing circular twins [125]. However, there is a notable lack of studies specifically examining case studies in circular construction.

9. Conclusions

The destructive impacts of the construction industry on various aspects of life require urgent action to mitigate these consequences leveraging DT technology. While digitalization has improved the sustainability indicators of the industry, significant challenges remain. This research aims to explore previous efforts and trending research paths regarding the application of BIM/DT in sustainable construction. Therefore, a comprehensive literature review was conducted to highlight current trends and research directions among academics. In this process, 34 journal and conference papers with the highest citation counts were selected and categorized based on their focus, including simulation, technology integration, and smart systems. Given the importance of technology integration and smart systems in achieving sustainability, further investigations were carried out. Recent advancements in integrating emerging technologies with DTs for sustainable lifecycle management of buildings, infrastructures, and underground utilities were examined. Additionally, smart systems, crucial for creating a sustainable built environment, were analyzed and discussed, focusing on DT-based smart construction, buildings, infrastructure, and cities. This review provided insights into research trends, showing that, although many studies have been published, and the effectiveness of DT in areas such as smart construction, building and infrastructure O&M, and urban management has been demonstrated, further development is needed.

Finally, based on the review, potential areas for future research were identified and summarized into eight subsections.

Although the research aims to present recent developments and future directions, it has certain limitations. The Scopus database was used for exploration, and only English-language journal articles and conference papers were considered, resulting in the exclusion of other potentially relevant publications.

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Abbreviations

List of Abbreviations

AEC	Architecture, Engineering, and Construction	GPR	Ground Penetrating Radar
AI	Artificial Intelligence	GPS	Global Positioning System
ANN	Artificial Neural Network	HSE	Health, Safety, and Environment
AR	Augmented Reality	IMU	Inertial Measurement Unit
BEM	Building Energy Modelling	IoT	Internet of Things
BiGRU	Bidirectional Gated Recurrent Unit	KPIs	Key Performance Indicators
BIM	Building Information Modelling	LiDAR	Light Detection and Ranging
BMS	Building Management System	LSTM network	Long Short-Term Memory Neural network
CDW	Construction and Demolition Waste	MCDM	Multi-Criteria Decision Making
CE	Circular Economy	ML	Machine Learning
CFD	Computational Fluid Dynamic	O&M	Operation and Maintenance
CIM	Construction Information Modeling	RFID	Radio Frequency Identification
CNN	Convolutional Neural Network	RGB	Red–Green–Blue
DCNN	Deep Convolutional Neural Network	SHM	Structural Health Monitoring
DT	Digital Twin	SVM	Support Vector Machines
DT-SMiCS	Digital-Twin-enabled Smart Modular integrated Construction System	UAV	Unmanned Aerial Vehicle
FEM	Finite Element Method	UMS	Unmanned Marine Systems
GHG	Greenhouse Gas	UWB	Ultra-Wide-Band
GIS	Geographical Information System	VR	Virtual Reality
GNSS	Global Navigation Satellite System	ZDM	Zero-Defect Manufacturing

Appendix A

Table A1. Definitions of Digital Twins in the reviewed papers.

Row	Authors	Year	Definition	Ref.
1	Lehner et al.	2024	A Digital Twin prototype (DTP) portrays all possible products that can be made, is reusable, and consists of all the information necessary to describe, resemble, and create a physical twin. The resembled physical twin does not exist as described by the DTP until the decision for its creation is made. A connection to the physical twin transforms the DTP into a DTI.	[126]
2	Ghorbani and Messner	2024	A Digital Twin of an asset is a fit-for-purpose and intelligent virtual representation that is synchronized at specific frequencies, with an existing or planned connection between the virtual and physical twin that may include analysis and the ability to actuate physical changes from the virtual twin.	[127]
3	Tripathi et al.	2024	A data-driven network of interconnected instances of a digital twin or different digital twins, along with different organizational and individual stakeholders, that will create value for one another, enabled by new technologies.	[128]
4	Cureton and Hartley	2023	A digital representation at a set fidelity of a physical element, including its behavior, which is connected and integrated for efficiency.	[129]
5	Emmert-Streib	2023	A mathematical model with an updating mechanism that generates data which are indistinguishable from its physical counterpart.	[130]
6	Baidya et al.	2022	A Digital Twin framework involves a "physical entity" consisting of objects, processes, interacting ambience, and exogenous conditions, which are digitally reproduced in a counterpart "digital entity", and a bidirectional information flow between the physical and digital entity ensures the state and control information exchanges between them, supporting synchronous or asynchronous behavioral influence on each other.	[131]
7	Singh et al.	2022	A Digital Twin is a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data. It is not just the Digital Twin which mimics its physical twin but any changes in the Digital Twin are mimicked by the physical twin too.	[132]
8	De Lepper et al.	2022	the term digital twin might seem to refer to an all-encompassing model, realistically it is more likely that multiple different digital twins will be created for concrete use cases, such as specific diseases and treatments.	[133]
9	Venkatesh et al.	2022	Health digital twins are defined as virtual representations ("digital twin") of patients ("physical twin") that are generated from multimodal patient data, population data, and real-time updates on patient and environmental variables	[134]
10	Area et al.	2022	An evolving digital profile of the historical and current behavior of a physical objector real process that helps optimize the performance of the real process.	[135]
11	Opoku et al.	2021	Real-time representation of the building or structure that is fully or partially completed and developed for the purpose of representing the status and character of the building or structure it mirrors.	[136]

Table A1. *Cont.*

Row	Authors	Year	Definition	Ref.
12	Gillette et al.	2021	Digital replicas of patient hearts derived from clinical data that match like-for-like all available clinical observations.	[137]
13	Budiardjo and Migliori	2021	A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity.	[138]
14	Semeraro et al.	2021	A set of adaptive models that emulate the behaviour of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system.	[139]
15	ISO	2021	Fit for purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation	[140]
16	Serbulova	2021	A digital twin is a virtual prototype of a real object, group of objects or processes. It is a complex software product that is created from a variety of data. The digital twin is not limited to collecting data from the product engineering and production stages—it continues to collect and analyze data throughout the lifecycle of the real object, including through the use of numerous IoT sensors	[141]
17	Fotland et al.	2020	A digital copy of a physical asset, collecting real-time data from the asset and deriving information not being measured directly in the hardware.	[142]
18	DoD	2020	A dynamic virtual representation of a physical system that is continually updated using data from the real-world operational system.	[143]
9	AIAA	2020	A set of virtual information constructs that mimics the structure, context and behavior of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realize value	[144]
20	Rasheed, San, and Kvamsdal	2020	A virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making.	[145]
21	Lu et al.	2020	The digital representation provides both the elements and the dynamics of how a physical 'thing' operates and lives throughout its life cycle.	[146]
22	Moyne et al.	2020	A purpose-driven dynamic digital replica of a physical asset, process, system, or product.	[147]
23	Luo et al.	2019	A multi-domain and ultrahigh fidelity digital model integrating different subjects such as mechanical, electrical, hydraulic, and control subjects. It connects multiple product activities, and is a consistent model supporting design, production, operation, maintenance, and recycling lifecycle stage.	[148]
24	Leng et al.	2019	An exact and real-time cyber copy of a physical manufacturing system that truly represents all of its functionalities.	[149]
25	Nochta, Badstuber, and Wahby	2019	City Digital Twins are realistic digital representations of physical city systems, assets and processes providing digital simulation and management environments to aid decision-making.	[150]

Table A1. *Cont.*

Row	Authors	Year	Definition	Ref.
26	Madni, Madni, and Lucero	2019	A virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle.	[151]
27	ARUP	2019	The combination of a computational model and a real-world system, designed to monitor, control and optimise its functionality. Through data and feedback, both simulated and real, a digital twin can develop capacities for autonomy and to learn from and reason about its environment.	[152]
28	Nikolakis et al.	2019	Rich digital representation of real-world objects/subjects and processes, including data transmitted by sensors.	[153]
29	Ding et al.	2019	Digital Twining is a process of building a Digital Twin in the cyber world of the physical objects and systems, and establishing data channels for cyber-physical interconnection and synchronisation.	[154]
30	Xu et al.	2019	Simulates, records and improves the production process from design to retirement, including the content of virtual space, physical space and the interaction between them.	[155]
31	Kannan and Arunachalam	2019	A digital representation of the physical asset which can communicate, coordinate and cooperate the manufacturing process for an improved productivity and efficiency through knowledge share	[156]
32	Tao et al.	2019	A real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them	[157]
33	Wang et al.	2019	Essentially a unique living model of the physical system with the support of enabling technologies including multi-physics simulation, machine learning, AR/VR and cloud service, etc.	[158]
34	Tomko and Winter	2019	A cyber–physical–social system with coupled properties.	[159]
35	Brilakis et al.	2019	A digital twin is a digital replica of a physical built asset. What a digital twin should contain and how it represents the physical asset are determined by its purpose. It should be updated regularly in order to represent the current condition of the physical asset. A digital twin should be standardised yet extensible, able to address key use cases directly and specialty use cases with extensions, cloud and computationally friendly, scalable and verifiable.	[160]
36	Bolton et al.	2018	A realistic digital representation of assets, processes or systems in the built or natural environment	[161]
37	Kunath and Winkler	2018	The sum of all logically related data, i.e., engineering data and operational data, represented by a semantic data model.	[162]
38	Scaglioni and Ferretti	2018	A near-real-time digital image of a physical object or process that helps optimize business performance.	[163]
39	Zhuang, Liu, and Xiong	2018	A virtual, dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behavior, life, and performance in a timely fashion.	[164]
40	Batty	2018	A mirror image of a physical process that is articulated alongside the process in question, usually matching exactly the operation of the physical process which takes place in real time.	[165]
41	Qi and Tao	2018	Brings together the data from all aspects of product lifecycle, laying the data foundation for innovative product design and the quality traceability.	[166]

Table A1. *Cont.*

Row	Authors	Year	Definition	Ref.
42	Zheng, Yang, and Cheng	2018	a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level.	[167]
43	He, Guo, and Zheng	2018	A dynamic digital replica of physical assets, processes, and systems, which comprehensively monitors their whole life cycle	[168]
44	Tharma, Winter, and Eigner	2018	A virtual reflection, which can describe the exhaustive physical and functional properties of the product along the whole life cycle and can deliver and receive product information.	[169]
45	General Electric	2018	Dynamic digital representations that enable companies to understand, predict, and optimize the performance of their machines and their business.	[170]
46	Haag and Anderl	2018	A comprehensive digital representation of an individual product that will play an integral role in a fully digitalized product life cycle.	[171]
47	El Saddik	2018	Digital replications of living as well as nonliving entities that enable data to be seamlessly transmitted between the physical and virtual worlds.	[172]
48	Eisenträger et al.	2018	A digital model of a real object containing lifecycle records and dynamic status data, which are synchronized in real-time.	[173]
49	Alam and El Saddik	2017	An exact cyber copy of a physical system that truely represents all of its functionalities	[174]
50	Stark et al., 2017	2017	A digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases.	[175]
51	Grieves and Vickers	2017	A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.	[47]
52	Söderberg et al.	2017	Using a digital copy of the physical system to perform real-time optimization	[176]
53	Weber et al.	2017	The digital representation of all the states and functions of a physical asset.	[177]
54	Chen	2017	A computerized model of a physical device or system that represents all functional features and links with the working elements.	[178]
55	Schluse and Rossmann	2016	Virtual substitutes of real world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services.	[179]
56	Canedo	2016	A digital representation of a real world object with focus on the object itself.	[180]
57	Schroeder et al.	2016	A DT is a virtual representation of a real product.	[181]

Table A1. *Cont.*

Row	Authors	Year	Definition	Ref.
58	Kraft	2016	An integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by Digital Thread, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin.	[182]
59	Boschert and Rosen	2016	The linked collection of the relevant digital artefacts including engineering data, operation data and behaviour descriptions via several simulation models. The Digital Twin evolves along with the real system along the whole life cycle and integrates the currently available knowledge about it.	[183]
60	Rosen et al.	2015	Very realistic models of the current state of the process and their own behavior in interaction with their environment in the real world.	[184]
61	Ríos et al.	2015	The product digital counterpart of a physical product	[185]
62	Grieves	2014	A virtual representation of what has been produced. Compare a Digital Twin to its engineering design to better understand what was produced versus what was designed, tightening the loop between design and execution.	[186]
63	Reifsnider and Majumdar	2013	The ultra-high fidelity physical models of the materials and structures that control the life of a vehicle.	[187]
64	Shafto et al.	2012	An integrated multiphysics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor up- dates, fleet history, etc., to mirror the life of its corresponding flying twin.	[188]
65	Tuegel	2012	A cradle-to-grave model of an aircraft structure's ability to meet mission requirements.	[189]
66	Gockel et al.	2012	An ultra-realistic, cradle-to-grave computer model of an aircraft structure that is used to assess the aircraft's ability to meet mission requirements.	[190]
67	Glaessgen and Stargel	2012	A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.	[46]

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