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Review

Opportunities and Threats of Adopting Digital Twin in Construction Projects: A Review

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Abstract: Digital twin (DT) is recognized as a pillar in the transition from traditional to digital construction, yet the risks (opportunities and threats) associated with its implementation have not been thoroughly determined in the literature. In addition, there is a scarcity of research relating the risks of DT implementation to DT maturity levels, which has hindered the optimum consideration of such risks when DT is adopted at different maturity levels. To address these gaps, this study conducted a literature review of 1889 documents from Scopus and Web of Science databases. After rigorous filtration, 72 documents were selected and comprehensively reviewed. A total of 47 risk factors (RFs) were identified and categorized into opportunities (economic, technical, environmental and sustainability, monitoring and safety, and management) and threats (economic, technical, and policy and management). Subsequently, these RFs were mapped onto the five-level DT maturity model, providing users with insights into opportunities and threats on each level. The exhaustive list of RFs and proposed integration of a DT maturity model with corresponding RFs enables stakeholders to identify the risks in their specific use cases and facilitate the decision-making and success in transition across various levels of DT in real-life construction projects.

Keywords: digital twin; maturity level; construction risk; digital model; automation

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1. Introduction

The advent of digital technologies is reshaping the execution of construction projects. One such technology is digital twin (DT), which enables dynamic bidirectional data exchange between the physical assets and the digital model, showcasing its high potential in improving the performance of construction projects [1,2]. The projected size of the DT market is expected to reach USD 184.5 billion by 2030, with approximately 15–20% of the total market share attributed to the construction context [3]. Being capable of representing the near real-time status of the physical assets throughout the project lifecycle, DT has been recognized to provide significant benefits to the construction industry, such as enhanced safety monitoring, improved productivity, reduced costs, improved decision-making, and optimization [4–7]. In addition, DT provides solutions to the fragmentation concerns of the construction industry, such as information silos, isolated stakeholders, and decentralized on-site labor caused by the slow adoption of digitization [8–12]. Therefore, the practice of DT in the construction industry has emerged as an inevitable tendency.

Over the years, numerous definitions (e.g., [10,13–19]) of DT have emerged with the continuous evolution of DT-enabling technologies. Still, there is no unified definition of DT within the construction industry since the purposes and requirements of utilizing DT technology vary in different use cases. The Digital Twin Consortium [20] defines a digital twin as "*a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity*". Therefore, Seaton et al. [21] outlined that key elements of

DTs within the construction context include real-world entities, virtual representations, synchronization, fidelity, and frequency. Notably, the real-world entities could be both entities (e.g., construction equipment and products, workers, construction sites, and assets) and processes (e.g., design, construction, operation and management, and demolition) in the construction projects. Virtual representation is a digital duplicate of construction objects and processes, which includes various linked digital assets (e.g., digital models, images, documents, and videos) and supporting data [21]. Synchronization, which ensures that the status of the DTs is consistent with that of their physical counterparts [22], is a key element that differentiates a digital twin from other digital models. At the same time, synchronization is affected by both frequency and fidelity, which determines the timing of updates and precision of the virtual representation, respectively.

Research focusing on DT practice in the construction industry has gained momentum recently [23–29], showcasing that further improvement and broad adoption of DT within construction are crucial [30]. Nonetheless, the implementation of DT technology in the construction industry is full of risks due to the complexity of the construction projects and the inherent risks associated with adopting any emerging technology. According to the PMBOK [31], the term "risk" denotes the uncertainty that may lead to deviations from a project's planned objectives. Such deviations can result in either positive outcomes, referred to as "opportunities", or negative consequences, known as "threats", affecting the achievement of these objectives. In this review, both opportunities and threats are investigated and referred to as risk factors (RFs).

When it comes to reviewing articles, based on a thorough review of the literature reviews pertaining to the practice of DT in the construction industry, it has been revealed that the focus of these reviews is on four categories, including (1) exploration of DT-enabling technologies (e.g., AR, AI, and IoT), (2) differentiation of DT from other similar concepts (e.g., digital shadow, BIM, and cyber-physical systems), (3) identification of barriers or challenges associated with DT adoption, and (4) investigation of DT's applications in construction projects (e.g., sustainability, fault detection, and monitoring). This indicates the lack of a comprehensive review of RFs associated with DT implementation in construction projects. In research articles, although there is some research that, to a certain extent, has reviewed the RFs to DT implementation (e.g., [6,26,32–35]), the majority of them have focused on exploring some RFs of implementing DT within the construction context, while overlooking connecting them with the DT maturity levels. Regarding the maturity levels of DT, the literature has introduced it based on the sophistication of the implemented DT, outlining the progressive levels of DT development [36]. Since not all RFs are applicable to every level of DT maturity, it is necessary to provide meaningful insights for stakeholders in their DT practice to investigate the RFs' relevance at each DT maturity level.

Given the significance of the topic and the above-mentioned gap in research on a holistic review of RFs associated with DT implementation in construction projects, there is a need for a study that comprehensively identifies such RFs and map them onto specific DT maturity levels—as each level provide different opportunities and threats. This will enable the stakeholders to identify the risks in their current practices according to the adopted level of DT and to have a clear insight into RFs for the potential visioned DT level. To address this gap, the following research questions were formulated to guide this review:

1. What is the current situation of DT implementation in the construction sector?
2. What are the existing risks associated with DT practice in the construction industry?
3. How are the risks associated with DT implementation in the construction industry mapped onto the five DT maturity levels?

To answer the above questions, this study aimed to conduct a comprehensive review of the risks related to DT practice in the construction industry and map them onto corresponding DT maturity levels, thereby offering the stakeholders insights into opportunities and threats at each level. The remainder of this review is organized as follows: Section 2 introduces the background of DT maturity models in the literature; Section 3 demonstrates the comprehensive literature review approach; Section 4 shows the scientometric outcomes of the review; Section 5 shows the results of identified RFs and discusses the developed conceptual DT maturity level-based risk model; Section 6 illustrates the limitations and future directions; and Section 7 concludes with the contributions of this study.

2. Digital Twin Maturity Model

There are several DT maturity models proposed in different domains. In the manufacturing industry, Kritzinger et al. [37] outlined three hierarchical tiers of DTs based on the degree of data integration: digital model, digital shadow, and digital twin. Building upon this framework, Liu et al. [38] introduced two additional levels: Cognitive DT and Federated DT. Another model specific to manufacturing was developed by Hu et al. [36], including Basic, Connection, Integration, Perception, Interaction, and Autonomy. In the field of systems engineering, Madni et al. [16] proposed a four-level model based on the sophistication of the virtual model: Pre-digital Digital Twin, Digital Twin, Adaptive Digital Twin, and Intelligent Digital Twin. Similarly, Kumar et al. [39] proposed a more comprehensive model, including the Digital model, Digital Twin, Adaptive Digital Twin, Technical and functional DT, and Autonomous DT. In the Aerospace area, Medina et al. [40] introduced a four-level maturity model comprising Monitoring, Diagnostic, Prediction, and Prescription.

Several maturity models have also been developed in the construction industry. ARUP [41] proposed a five-level evolution model based on four metrics, Autonomy, Intelligence, Learning, and Fidelity, which are expected to increase as the DT progresses. According to the characteristics of each level, the five levels are named Linked, Feedback and Control, Predictive and Analytic, Learning, and Autonomous. Chen et al. [42] developed their six-level model grounded in asset management maturity stages: Unaware, Identifiable, Aware, Communicative, Interactive, and Instructive and Intelligent. Furthermore, models by Boje et al. [2] and Naderi et al. [43] emphasize technical advancements, while some models focus on functional completeness. For instance, Wagg et al. [44] proposed a five-level model for asset management: Supervisory, Operational, Simulation, Intelligent, and Autonomous Management. Similarly, Autodesk [45] introduced a tailored five-level model for the Architecture, Engineering, and Construction (AEC) industry—Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, and Autonomous twin—which was also adopted by Seaton et al. [21]. The different DT maturity models are listed in Table 1.

Table 1. Digital twin maturity model in the literature.

Domain	Reference	Levels	Name of the Levels
General	[38]	0~4	Digital model, Digital shadow, Digital twin, Cognitive DT, Federated DT
	[39]	1~5	Digital model, Digital twin, Adaptive digital twin, Technical and functional DT, Autonomous DT
Manufacturing	[36]	1~6	Basic, Connection, Integration, Perception, Interaction, Autonomy
	[37]	1~3	Digital model, Digital shadow, Digital twin
Systems engineering	[16]	1~4	Pre-digital twin, Digital Twin, Adaptive Digital Twin, Intelligent Digital Twin
Aerospace	[40]	1~4	Monitoring, Diagnostic, Prediction, Prescription
Construction	[41]	1~5	Linked, Feedback and Control, Predictive and Analytic, Learning and Autonomous
	[44]	1~5	Supervisory, Operational, Simulation, Intelligent, Autonomous management
	[2]	1~3	Monitoring Platform, Intelligent Semantic Platform, Agent-driven socio-technical platform

Table 1. *Cont.*

Domain	Reference	Levels	Name of the Levels
Construction	[45]	1~5	Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, Autonomous twin
	[21]	1~5	Descriptive twin, Informative twin, Predictive twin, Comprehensive twin, Autonomous twin
	[42]	1~6	Unaware, Identifiable, Aware, Communicative, Interactive, Instructive and Intelligent
	[43]	0~4	BIM, Digital twin, enhanced DT, Metaverse

Given the relevance and comprehensiveness of the five-level model proposed by Autodesk [45] and Seaton et al. [21], as shown in Figure 1, it was adopted in this review paper. At the Descriptive level (level 1), DTs represent the digital model connected to real-world systems but lack intelligence, learning, and autonomy [46]. At the same time, the Informative level (level 2) involves converting data into valuable insights. This is achieved with computer vision techniques, which are supported by artificial intelligence (AI) (i.e., deep learning technologies) [47]. The Predictive level (level 3) employs operational data for prediction. Specifically, with AI-based technologies (e.g., process mining), DTs can utilize large volumes of data to make valuable analytics and predictions [47,48]. At the Comprehensive level (level 4), DTs learn from diverse data sources within the surrounding environment and are able to conduct real-time analytics through what-if simulations. Using AI techniques such as machine learning, DTs can analyze historical data and real-time information to simulate various what-if scenarios. Finally, at the Autonomous level (level 5), with the help of AI, DTs can learn and minimize reliance on human inventions through automatic analytics and decision-making. Obviously, AI and AI-based technologies play a significant role throughout the DT levels.

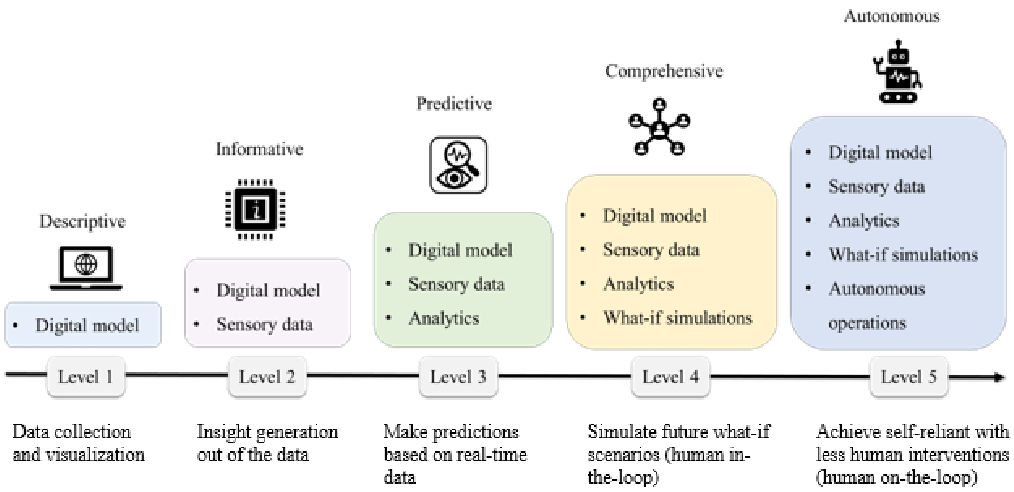

Figure 1. DT maturity model (adopted from [21,45]).

3. Methods

A comprehensive literature review, as a methodical and reproducible technique [49], is used in this research to identify, assess, and synthesize the existing body of research. Elsevier's Scopus and Web of Science (WoS) were selected as bibliographic databases for their respective strengths [50]. Scopus offers broader coverage, higher precision, and user-friendly article retrieval procedures [51], while WoS is recognized for its credibility, reliable publication data derived from a robust peer-review process, and inclusion of authoritative literature [52].

In addition to conducting a qualitative analysis of articles to identify risks associated with DT implementation in the construction industry, this study also utilized two prominent tools for quantitative visualization of the current scientific landscape: Bibliometrix and VOSviewer, which are widely employed for scientometric analysis [53]. It is worth noting that since relying on individual databases may not provide a comprehensive picture of the topic [54], this research adopts the innovative approach proposed by Caputo and Kargina [55] to effectively combine bibliometric data from both Scopus and WoS.

For the purpose of this research, the novelty of DT and its relatively limited number of publications specifically focusing on risks associated with DT was considered. As a result, to ensure a comprehensive inclusion of relevant literature, two broad search terms, namely "Digital Twin" and "Construction", were selected without applying any time filter. These terms were searched in May 2023 within the "Title, Abstract, and Keywords" field in Scopus and the "All Fields" field in WoS. The initial search, as depicted in Figure 2, involved a three-round filtering procedure. First, several filters were applied to refine the query further, including subject area, source type, language, and document type. Additionally, duplicates from both databases were removed. This process resulted in 530 articles remaining, which were then exported from Scopus in comma-separated value (CSV) format and from WoS in Excel (.xlsx) format. The second round involved a manual evaluation of the titles and abstracts of the retrieved articles, considering their research scope and relevance to the topic. Next, the results were exported in BibTex format for subsequent scientometric analysis. In the third round of screening, the selected articles underwent a full-text assessment to identify the risks associated with DT. The findings are outlined in the results section. Overall, 72 articles were deemed eligible for further exploration and analysis.

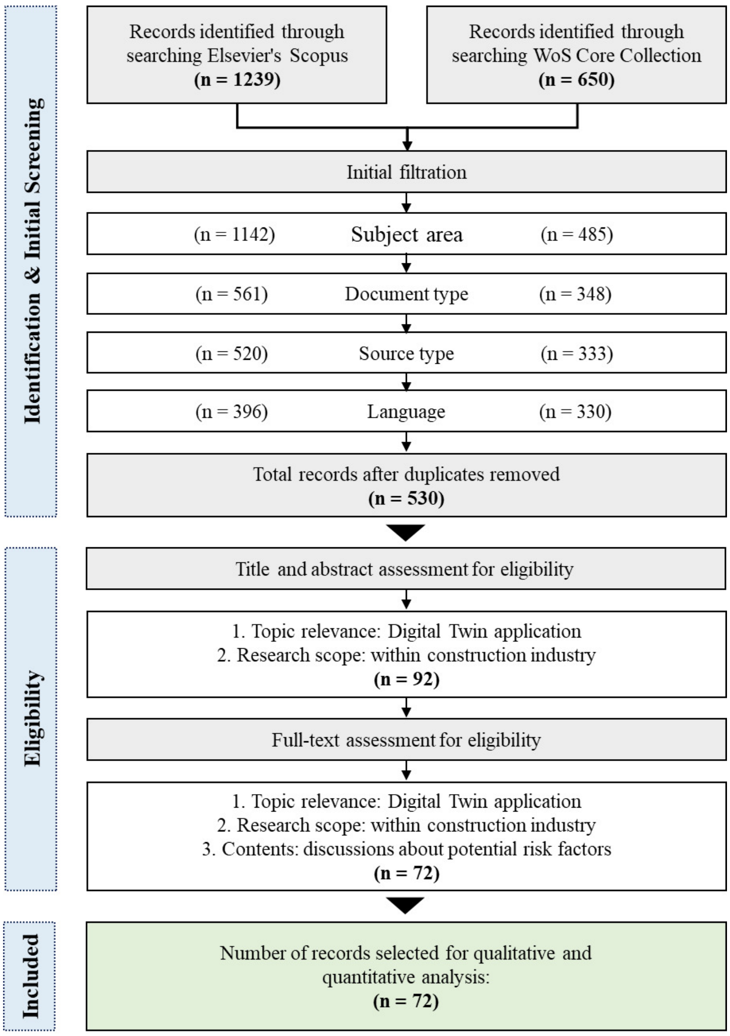

Figure 2. Data collection procedures.

4. Scientometric Analysis

This section reveals the findings of the scientometric analysis. As depicted in Figure 3, a comprehensive investigation was conducted to determine the number of publications within the scope of DT and construction for each year during the study period. Notably, the first study related to the implementation of DT technology in the construction field was published in 2018, and there has been a steady rise in the number of publications on this subject. It is significant to mention that there are only 14 publications recorded for 2023, which can be attributed to the timing of the publication search being conducted in May 2023.

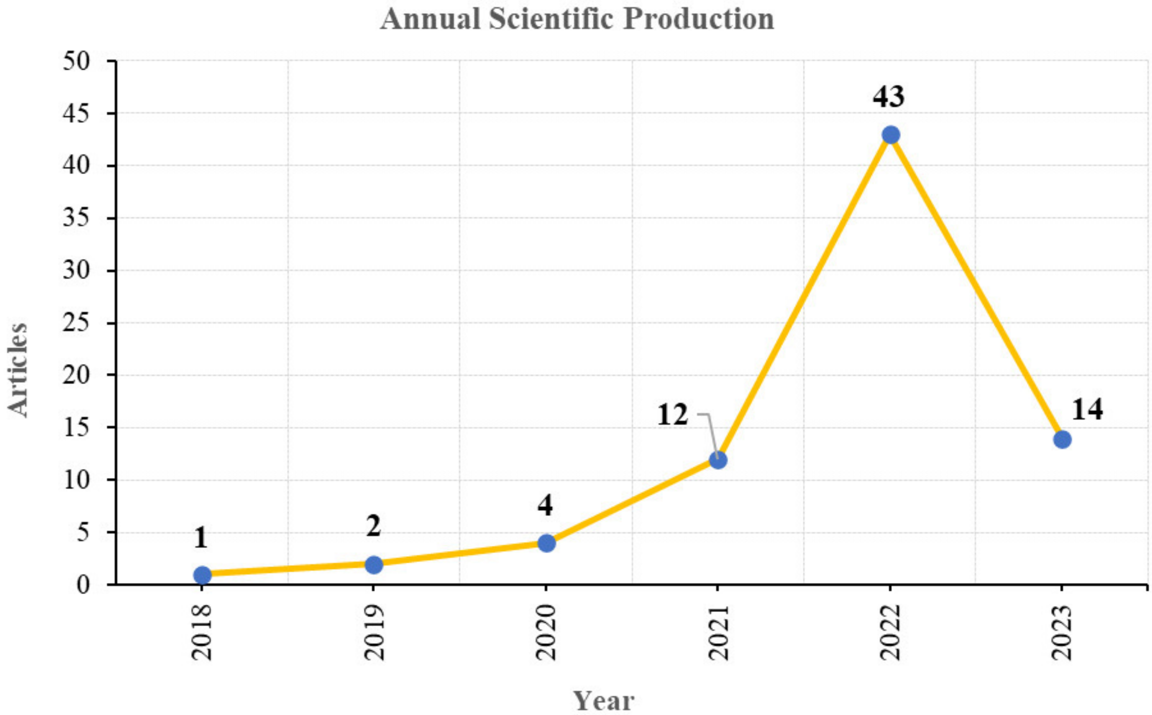

Figure 3. Distribution of the publications by year.

Figure 4 presents the distribution of the publications by source, revealing that the top three journals are *Automation in Construction*, *Buildings*, and *Journal of Construction Engineering and Management*. According to Bradford's law, the identified core journals are *Automation in Construction* and *Buildings*, which contribute about one-third of the total collection [56]. It is crucial to emphasize that the surge in the number of researchers engaged in studying and implementing DT in construction signifies an important shift toward more advanced and efficient practices within the construction sector. As more scholars contribute to this field of study, it will undoubtedly drive further progress and advancements in the practice of DT in the construction industry. In addition, the most globally cited documents are shown in Table 2; details about the number of citations and average citation per year that the document has received and the journal in which the document has been published are illustrated. This table provides researchers insights into the most influential works and significant trends within the field of DT practice in the construction industry.

To provide an overview of the distribution of publications by country, as presented in Figure 5, only the countries that have produced a combined number of more than 10 articles are presented. This figure reveals that China is a great example showcasing quick growth and development in this regard. It is significant to highlight that the implementation of DT technology in the construction industry is still in the preliminary stage worldwide. While developed countries such as the United States and Europe embarked on DT exploration earlier, considerable work remains to be accomplished before this technology attains sufficient maturity for widespread implementation. The global interest in DT technology presents a promising opportunity for continuous growth and development within the construction industry.

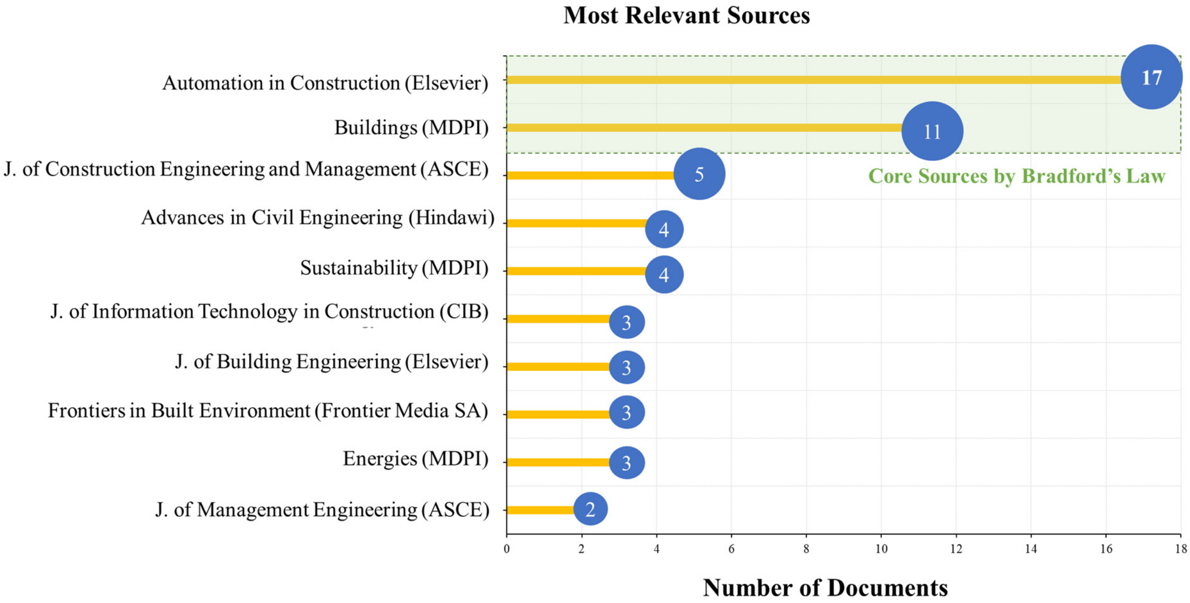

Figure 4. Distribution of the publications by source.

Table 2. Most globally cited documents.

Documents	Journal of Documents	Total Citations	Average Citations per Year
[47]	*Automation in Construction*	220	73.33
[17]	*Data-Centric Engineering*	117	29.25
[8]	*Automation in Construction*	112	37.33
[57]	*Journal of Building Engineering*	105	35
[58]	*Structure and Infrastructure Engineering*	92	18.4
[59]	*Journal of Information Technology in Construction*	83	27.66
[60]	*Mechanical Systems and Signal Processing*	76	25.33
[61]	*Automation in Construction*	72	14.4
[5]	*Automation in Construction*	64	21.33
[62]	*Developments in the Built Environment*	54	13.5
[63]	*Frontiers in Built Environment*	51	8.5
[64]	*Journal of Construction Engineering and Management*	36	18
[65]	*Automation in Construction*	35	17.5
[24]	*Journal of Building Engineering*	33	11
[66]	*Buildings*	31	10.33
[67]	*Engineering, Construction and Architectural Management*	30	7.5
[68]	*Automation in Construction*	25	12.5
[69]	*Journal of Management in Engineering*	16	8
[70]	*Journal of Building Engineering*	15	7.5
[71]	*Journal of Engineering, Design and Technology*	15	

Figure 6 depicts a three-field Sankey plot indicating the relations between countries, sources, and Keywords Plus. Keywords Plus, which is more comprehensive than Author Keywords, is generated by a computer algorithm based on the phrase or words most frequently used in the titles of an article's reference list [72]. Author Keywords were not used since there were many varying spellings of the same term (e.g., 'Building Information Modeling', 'BIM', 'Building Information Modeling (BIM)', and others). As can be seen, China, the United Kingdom, Australia, and the United States are the leading countries in contributions. Meanwhile, *Automation in Construction* and *Buildings* stand out as the most prominent journals for publishing articles on this topic, establishing their significance in disseminating knowledge and insights. Moreover, the utilization of Keywords Plus analysis highlights the current research hotspots in this field, such as construction, architectural design, lifecycle, and building information modeling. Table 3 represents the top 20 most cited sources within the collection of reviewed studies, and they are ranked based on the number of citations. *Automation in Construction* is the most prominent journal with the highest citations. Moreover, compared with the other journals, *Automation in Construction* has the highest h-index (which measures both the productivity and impact of the publications), g-index (which considers the distribution of citations among the articles), and m-index (which takes into account the median of the h-index distribution of the journal's articles), illustrating that it has the most significant impact among the journals. The details are shown in Table 4, which ranked the journals according to their h-index.

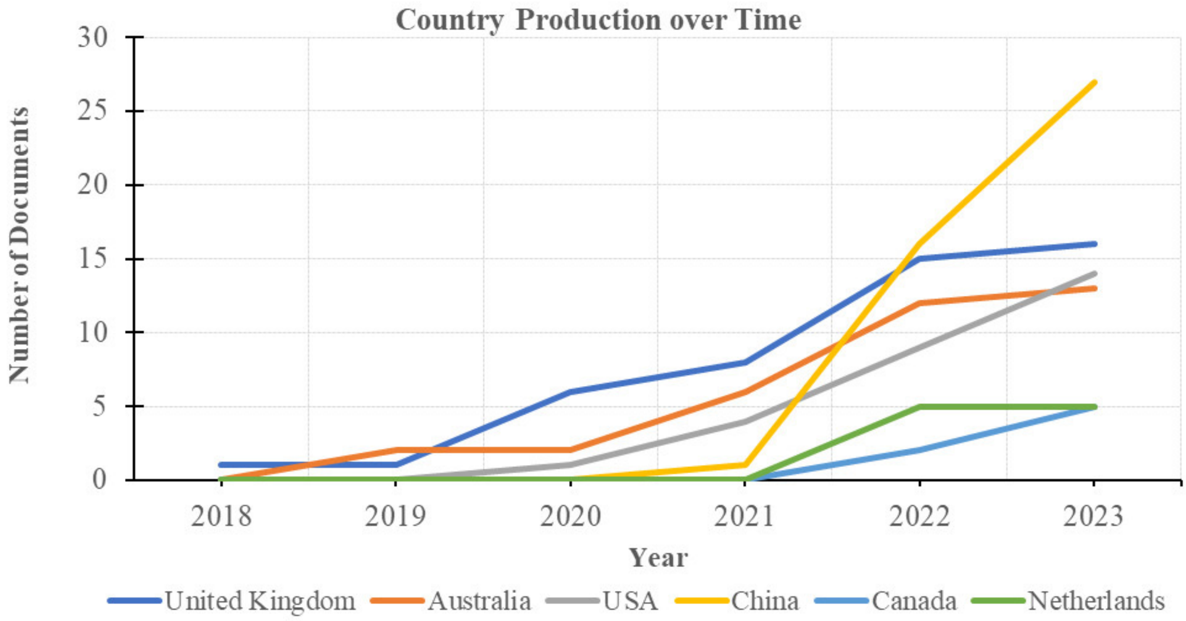

Figure 5. Distributions of publications by country.

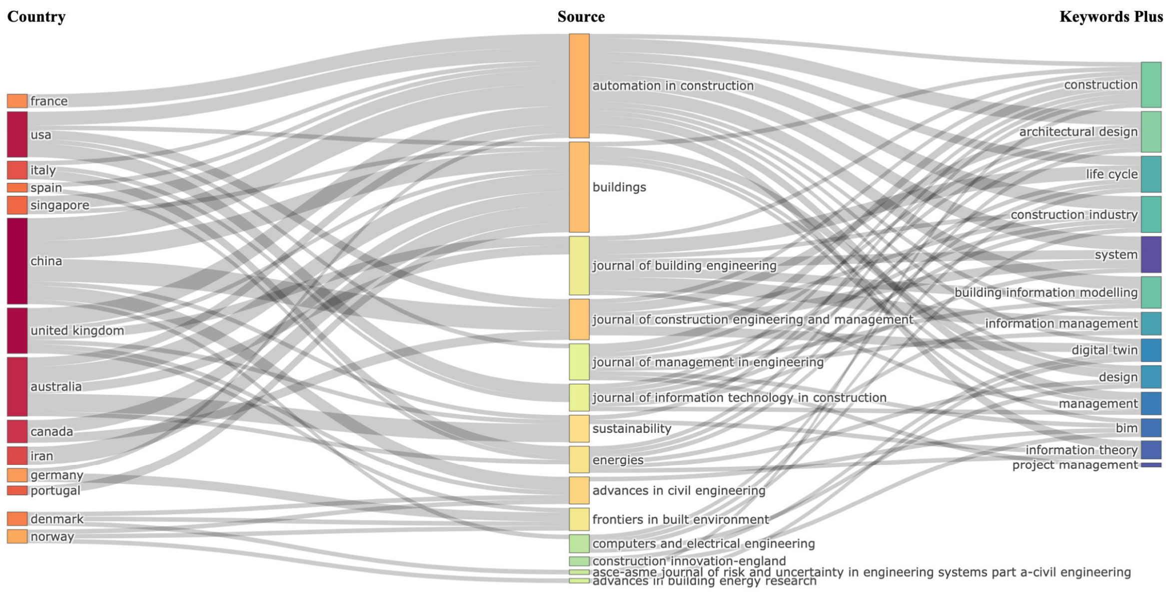

Figure 6. Three-field Sankey plot showing the relationship between countries, sources, and Keyword Plus.

Table 3. Most local cited sources.

No.	Cited Source	No. of Citations
1	*Automation in Construction*	501
2	*Energy and Built Environment*	40
3	*Sustainability*	40
4	*Buildings*	30
5	*IFAC-Papers Online*	28
6	*Sensors*	28
7	*IEEE Access*	27
8	*Journal of Building Engineering*	24
9	*Journal of Cleaner Production*	24
10	*Journal of Construction Engineering and Management*	24
11	*Journal of Manufacturing Systems*	23
12	*Computer in Industry*	21
13	*International Journal of Advanced Manufacturing Technology*	20
14	*Journal of Computing in Civil Engineering*	20
15	*Advances in Civil Engineering*	19
16	*Procedia CIRP*	19
17	*Advanced Engineering Informatics*	18
18	*International Journal of Project Management*	18
19	*Journal of Construction Engineering and Management*	18
20	*Journal of Management in Engineering*	18

Note: The term "local" means the collection of articles in this review.

Table 4. Sources' local impact.

No.	Source	h-Index	g-Index	m-Index	Total Citations	No. of Articles	Publication Year Start
1	*Automation in Construction*	8	17	1.6	580	17	2019
2	*Advances in Civil Engineering*	4	4	1	30	4	2020
3	*Buildings*	4	8	1.33	64	11	2021
4	*Frontiers in Built Environment*	3	3	0.5	58	3	2018
5	*Journal of Building Engineering*	3	3	1	153	3	2021
6	*Journal of Construction Engineering and Management*	2	5	1	45	5	2022
7	*Journal of Information Technology in Construction*	2	3	0.66	89	3	2021
8	*Journal of Management in Engineering*	2	2	1	24	2	2022
9	*Advances in Building Energy Research*	1	1	1	2	1	2023
10	*ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems Part A-Civil Engineering*	1	1	0.5	4	1	2022
11	*Computers and Electrical Engineering*	1	1	0.5	8	1	2022
12	*Data*	1	1	0.5	2	1	2022
13	*Data-Centric Engineering*	1	1	0.25	117	1	2020
14	*Developments in the Built Environment*	1	1	0.25	54	1	2020
15	*Dirección y Organización*	1	1	0.5	1	1	2022
16	*Energies*	1	3	0.33	13	3	2021
17	*Energy and Built Environment*	1	1	1	9	1	2023
18	*Engineering Construction and Architectural Management*	1	1	0.25	30	1	2020
19	*International Journal of Applied Earth Observation and Geoinformation*	1	1	0.5	4	1	2022
20	*Journal of Engineering Design and Technology*	1	1		15	1	

Figure 7 illustrates the co-occurrence of (a) Keywords Plus and (b) Author Keywords, in which the size of the circle reflects its frequency of occurrence, while the thickness of the lines represents the extent of co-occurrence of the circles. Also, each of the color in Figure 7 represents different keywords clusters that are frequently co-occurring together.

From Figure 7a, it is obvious that the top three keywords are "architectural design", "construction", and "building information modeling". These keywords represent their high relevance and popularity among scholars in this field, and they are useful for researchers to identify emerging trends in this field. In Figure 7b, it is obvious that the term "digital twin" emerges as a prevalent topic among researchers in this field. Notably, its occurrence is consistently observed with keywords such as "construction", "blockchain", "building information modeling", and "internet of things". These keywords reflect prominent areas of interest within the authors' publications, providing valuable insights into the research themes for the following researchers.

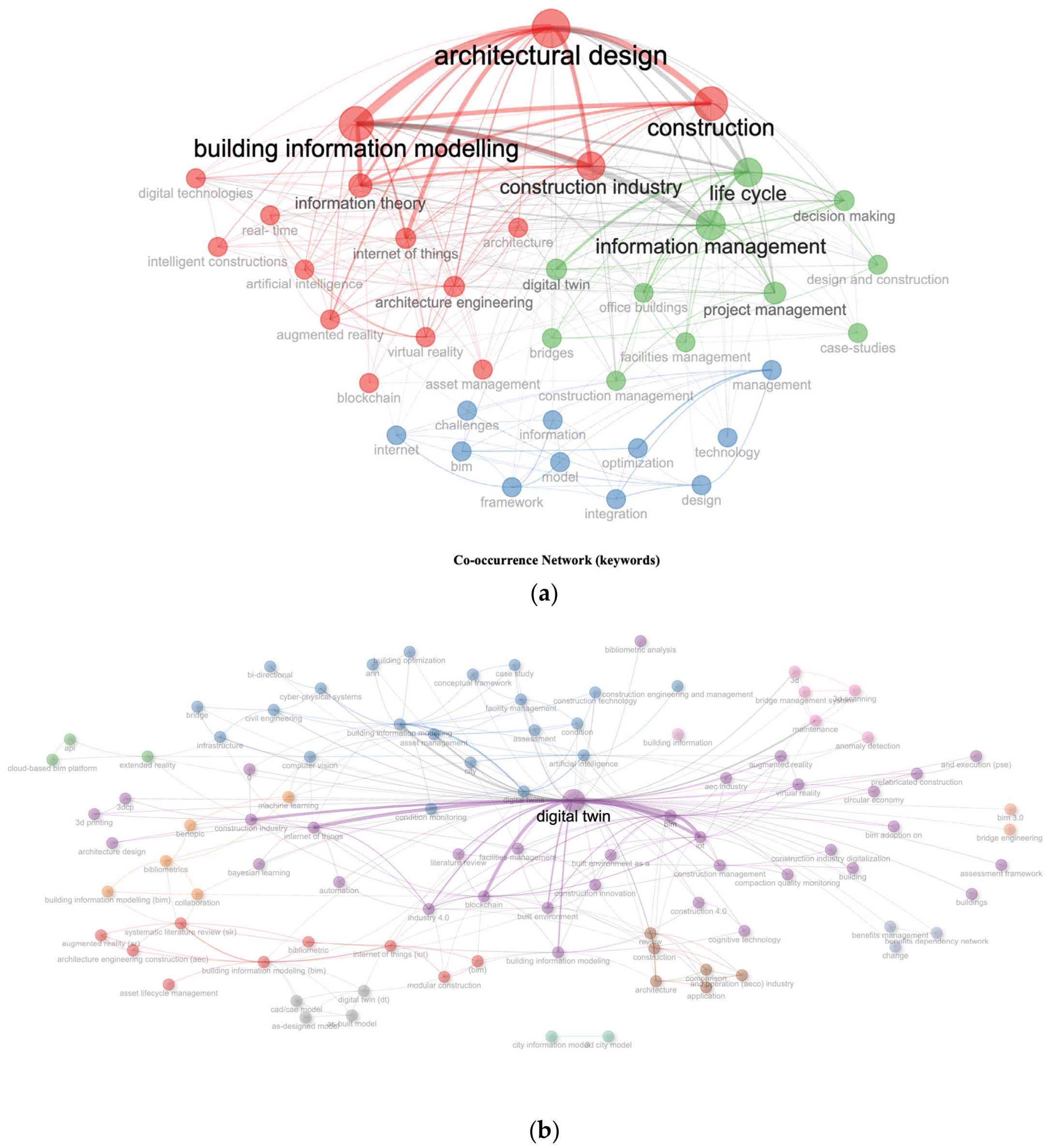

Figure 7. Co-occurrence of (**a**) Keywords Plus and (**b**) Author Keywords.

Figure 8 presents a visual representation of the collaboration network among countries and institutions. The size of the circles in the graph indicates the number of citations, while the line thickness reflects the extent of collaboration between the circles. Also, each of the color in Figure 8 represents different clusters of institutions or countries that are frequently collaborating together. Specifically, in Figure 8a, it is evident that the University of Cambridge is prominent both in terms of citation count and active engagement in collaboration with other institutions. From Figure 8b, it is apparent that China, the United Kingdom, and the United States are the top three countries in citation volume.

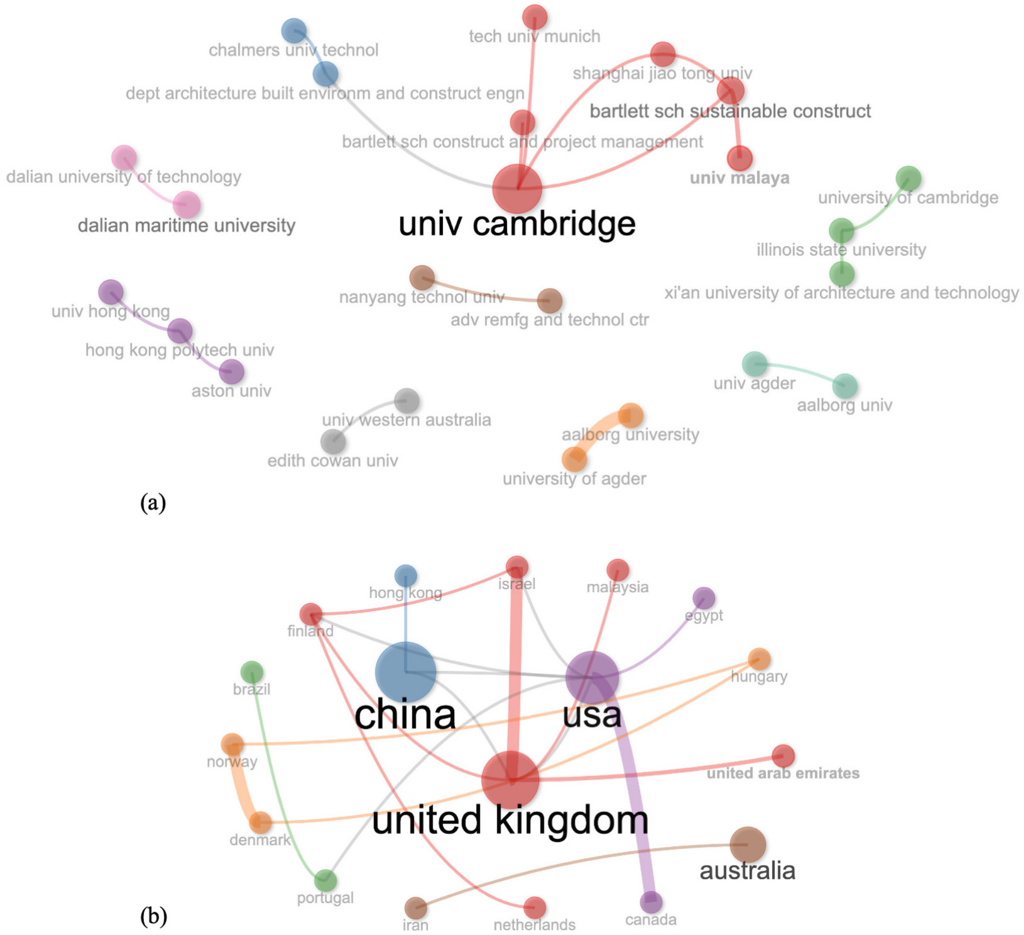

Figure 8. Collaboration network among (**a**) institutions and (**b**) countries.

Several pieces of Appendix information are available online regarding the reviewed papers in Appendix materials, including most relevant authors and most locally cited authors (Appendix A), most relevant affiliations (Appendix B), most cited countries (Appendix C), most relevant keywords (Appendix D), most global cited reviewed articles (Appendix E), and summary of reviewed articles (Appendix F).

5. Discussion

In the first step of this research, a thorough overview of the previous literature reviews pertaining to the practice of DT in the construction industry was conducted, and a total of 45 published reviews from the last decade were explored. This was to justify the gap in research for conducting a comprehensive review of the RFs, and it was shown that there is no such review article in the body of the literature to investigate the RFs associated with DT implementation in construction projects. To keep the focus of this review article on the RFs, the results of this investigation are provided in Supplementary Section S1.

When it comes to the RFs, a total of 47 RFs regarding the practice of DT in construction projects were identified through an analysis of filtered publications and the reference lists of those publications. Tables 5 and 6 offer an overview of the RFs. The identified RFs were classified into opportunities and threats, with 32 and 15 RFs, respectively. Following [32,73], the opportunities were further divided into five sub-categories: Economic (4), Technical (9), Environment (2), Monitoring and Safety (7), and Management (10). Similarly, the threats were grouped into three categories: Economic (3), Technical (6), and Policy and Management (6). An overview of categories in opportunities and threats is shown in Figure 9. A summary of the reviewed publications is presented in Supplementary Section S2, while subsequent sections provide greater details about each category and its associated RFs.

Table 5. List of opportunities derived from the reviewed papers.

Category	Code	Factors	Explanation	Reference
Economic	OE1	Energy reduction	DT can provide precise energy monitoring analysis and promotion of energy-saving habits.	[74,75]
	OE2	Cost optimization	e.g., Connecting to the cloud system to effectively reduce overhead costs; eliminating the costs associated with physical simulation and diagnosis.	[17,57,76–79]
	OE3	Project time reduction	DT's real-time simulation and analysis capability facilitates faster decision-making and more efficient resource allocation, resulting in a shorter construction timeline.	[9,69,80–83]
	OE4	Higher productivity	DT offers increased productivity by monitoring the progress of the project and identifying potential issues before they become costly problems.	[11,47,69,84]
Technical	OT1	Real-time bi-directional communication	DTs are continuously updated with real-time data from various sources (e.g., sensors and IoT devices), and feedback is sent to the physical asset.	[74,81,82,85–87]
	OT2	Design optimization	e.g., DT technology can be used to create models with higher accuracy.	[5,28,74,76]
	OT3	Improved data navigation and synchronization	DT facilitates data communication and provides all stakeholders with seamless access to siloed data.	[8,28,74,88]
	OT4	Enhance cyber security	All transactions taking place in the DT can be securely and permanently tracked in the blockchain network, enhancing the security and trust in all project data.	[9,66,80,85,89]
	OT5	Anomaly detection	DT can anticipate abnormal actions and handle ambiguous circumstances using effective troubleshooting abilities.	[5,8,90,91]
	OT6	Deformation correction	DT can simulate corrective scenarios to make accurate adjustments to the virtual model and align it with the current state of the physical asset.	[5,91]
	OT7	Automatic updates of the digital representation	Web services were utilized to handle the automatic updating of the model, ensuring the accuracy of the DT through a real-time information model.	[61,80,83,86,92]
	OT8	Improved IT integration	Within a project, DT can seamlessly integrate with existing IT systems, software, and data resources.	[84]
	OT9	Enhancement in key digital enablers	The integration of DT with key digital enablers, such as IoT, blockchain, and AI, drives innovation and efficiency in the construction industry.	[29]

Table 5. *Cont.*

Category	Code	Factors	Explanation	Reference
Environmental and Sustainability	OEn1	Emissions tracking (including greenhouse gas and carbon emissions to air, water, etc.)	DT can track emissions with its capabilities of data collection, emissions modeling, and real-time monitoring.	[74,75,93]
	OEn2	Reduce waste generation	DT can reduce waste production and enhance resource efficiency by optimizing the projects' processes.	[74,93]
Monitoring and Safety	OMS1	Inform and update worksite hazards	DT can align data in unpredictable and intricate settings to address potential accidents.	[74,93]
	OMS2	Automatic construction site monitoring	DT can track construction advancement, assess construction excellence, ensure construction safety, and monitor personnel, equipment, and materials.	[5,8,17,47,57,66, 69,73,74,76,79,80, 89,94–97]
	OMS3	Construction progress monitoring	Data obtained through laser scanning, photographs, and videos of the asset is gathered and utilized to monitor the progress of the project using DT.	[74,79,86,98]
	OMS4	Risk control and safety management	In the construction stage, DT can inform and update worksite hazards, and workers can get automatic navigations and alerts. In the O&M stage, DT can also address risks through the simulation of what-if scenarios.	[8,69,74,76,80,85, 93,96,99–101]
	OMS5	Structural health monitoring (SHM)	DT can offer promising models for immediate and ongoing SHM utilization, including recognizing damage to the structure, evaluating safety, assisting in failure prevention, and aiding maintenance procedures.	[74,75,84,93,102]
	OMS6	Building occupancy monitoring	DT can enhance space utilization and sensor system effectiveness and precision through real-time occupancy tracking and advanced algorithms.	[74,76]
	OMS7	Enhance safety training efficiency	The virtual practice platform can effectively reduce the potential accidents associated with on-site training.	[74]
Management	OM1	Real-time tracking	DT can track information on materials, the movement of heavy equipment, and in-house prefabrication processes.	[30,74]
	OM2	Construction logistic	Stakeholders can optimize the planning and management of construction logistics activities utilizing DT, which has capabilities like site planning, material tracking, equipment tracking, and resource allocation.	[74,94]
	OM3	Improve configuration and workflow efficiency	DT can improve the two-way cooperation between the virtual and physical assets and build up environment-aware abilities to optimize the workflow process.	[74]

Table 5. *Cont.*

Category	Code	Factors	Explanation	Reference
Management	OM4	Lifecycle management	DT has cognitive capabilities to identify intricate and unforeseeable actions and develop rational strategies for optimizing dynamic processes that aid in decision-making for building lifecycle management.	[74]
	OM5	Smart city development	DT can facilitate the demonstration and openness of administrative tasks, urban planning, and policy through visualization and digital prototype analysis.	[74,79]
	OM6	Improved decision-making	Employing VR technology throughout the lifecycle of a building improves the communication of data to relevant stakeholders, leading to better decision-making.	[5,17,19,57,76,85,89,92]
	OM7	Enhanced predictive maintenance	DT can monitor the present operational condition and performance of a physical asset to pre-schedule maintenance activities, such as calibration management.	[5,67,85,103]
	OM8	Facility management	DT can obtain, produce, and display the asset's context, evaluate data irregularities, and optimize services.	[47,58,59,70,75,84,85,89,102,104]
	OM9	Quality assurance	Using DT in the design stage can effectively enhance the quality of the projects in the subsequent stages.	[66,80]
	OM10	Increase user engagement	DT can promote information sharing and facilitate communication between stakeholders	[8,9,84,85,94]

Table 6. List of threats derived from the reviewed papers.

Category	Code	Factors	Explanation	Reference
Economic	TE1	Potential needs for additional resources in the design stage	It requires the purchase of the necessary hardware and software, as well as the development of the DT model. Additionally, the implementation of DT technology requires additional training and resources to ensure that the technology is used correctly.	[30,76,105]
	TE2	High maintenance cost	The cost of maintenance of software and hardware is high.	[62]
	TE3	Increase of cost on human resources (recruit and training)	It requires more experienced staff who possess the relevant knowledge with regard to DT technologies.	[105]
Technical	TT1	Threat of software incompatibility	There is a lack of a unified platform used by all stakeholders for real-time data integration.	[30,106,107]
	TT2	Threat of inadequate data processing ability	There is a wide range of data workflows, which necessitates a high demand for computing. Additionally, various software is used for data processing, leading to an overload of data.	[30,89,106,108]

Table 6. *Cont.*

Category	Code	Factors	Explanation	Reference
Technical	TT3	Inadequate information management	It is difficult to achieve transparency and interconnectivity in the information management database, which may hinder data integration and interoperability among different data sources.	[24]
	TT4	Data deficiency issues	Inadequate data between physical and virtual space would lead to a series of problems, such as analytic inaccuracies and flawed decision-making.	[24]
	TT5	Data security issues	DT necessitates a substantial amount of data flow, making it difficult to safeguard data security and privacy.	[80,89,107,108]
	TT6	Data quality issues	Without reliable and accurate data, DT may produce inaccurate results.	[109]
Policy and Management	TPM1	Human errors	This can be caused by a lack of professional experience. For example, in the modeling phase, the personnel may include too much detail or omit necessary information.	[104,107]
	TPM2	Staff's resistance to DT adoption	They are afraid that DT technology is taking away their place.	[76,80]
	TPM3	Lack of client demand	The perceived dangers, scarcity of knowledge, and time expenses of long-term surveillance are the primary obstacles to the widespread acceptance of DT.	[80,105]
	TPM4	Inadequate collaboration among stakeholders	Due to the complexity of the construction projects, it is hard to integrate all the participants to work as a team.	[30,80]
	TPM5	Difficulties in recruiting qualified staff/personnel	There are limited qualitative staff who can handle DT, which increases the difficulties of hiring.	[10]
	TPM6	Absence of interoperability standards and guidelines	There is a lack of unified standards for DT; this may pose issues such as fragmentation, data compatibility, data integration, and data sharing.	[66]

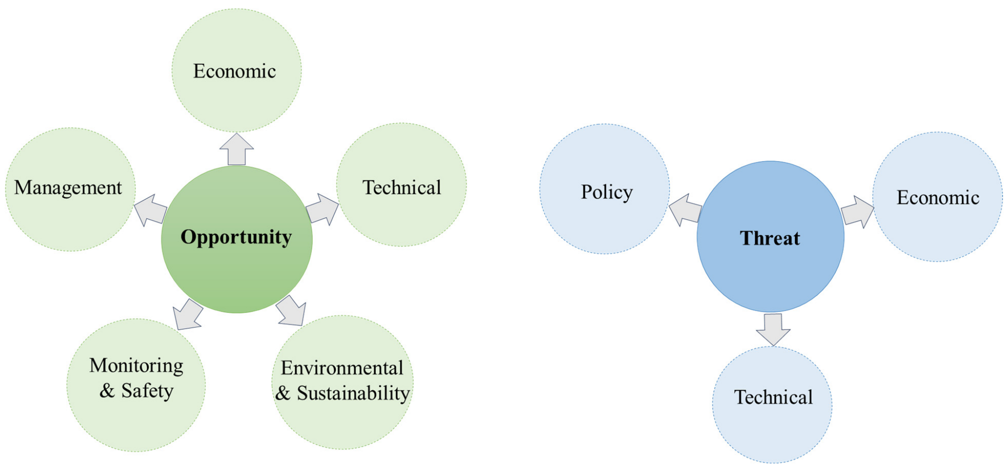

Figure 9. Overview of risk factor categories.

5.1. Opportunity

In this research, the term "opportunity" refers to the positive uncertainties that DT may introduce to projects. After a comprehensive literature review, the identified opportunities were sorted into five clusters: Economic, Technical, Environmental and Sustainability, Monitoring and Safety, and Management. Detailed introductions of each category are presented in the subsequent paragraphs.

5.1.1. Economic

The economic potentials of DT technology present a highly attractive opportunity for project stakeholders, including cost reduction, project time reduction, energy efficiency, and increased productivity [10,11], and numerous studies have explored the economic benefits associated with its implementation [110,111]. It is estimated that by 2025, cost savings caused by DT could reach approximately USD 950 million during the design and construction stages, as well as USD 400 million during the O&M phase [24,112]. In addition, by optimizing the construction process schedule and resource allocations, DT can accurately predict energy consumption [10,11], enabling project managers to exercise better control over budgetary considerations during the design and planning stage of the building process. Moreover, through real-time data acquisition facilitated by reliable techniques such as BIM, AI, blockchain, and IoT sensors, DT enables the automation of construction processes, preventive operation, and maintenance, as well as monitoring [2,24,75]. As a result, errors and rework can be effectively minimized, leading to increased productivity and decreased costs and time [113].

5.1.2. Technical

DT has emerged as a powerful technical support to enhance the efficiency of construction projects. DTs are often referred to as cyber-physical systems that establish bidirectional communication between the physical and digital realms, characterized by the seamless flow of data [95,97]. Therefore, DT can facilitate effective data communication, providing stakeholders with access to previously siloed data [9,17]. Furthermore, the implementation of blockchain networks can significantly enhance cybersecurity within the DT framework, ensuring transparent and traceable data flows [66,114]. Liu et al. [115] emphasize that DT enables the tracing of historical product design steps and continuous monitoring for achieving optimization. Adopting a DT-based approach facilitates an iterative design optimization process spanning from static configuration to dynamic execution [116]. At the same time, the accuracy of DT is ensured by the automatic update of BIM models utilizing web services [86,117]. By harnessing these features, the construction industry can benefit from improved efficiency and effectiveness in project execution.

5.1.3. Management

DT technology is significant in project management by enhancing overall project efficiency. Firstly, DT fosters increased user engagement by promoting information sharing and facilitating seamless communication between stakeholders [9,85,97]. Taking advantage of its robust information communication abilities, DT enables real-time tracking of various project aspects, including material information, movement of heavy equipment, and in-house prefabrication processes [30]. This functionality extends to resource dispatching, encompassing tasks such as resource scarcity detection, demand analysis, decision-making, resource allocation, and database updates with the assistance of AI [118]. Meanwhile, the virtual model enables DT to simulate and understand the construction logistics, which leads to comprehensive data analysis and better communication with the physical system [87]. Opoku et al. [6] highlight the predictive capabilities of DT in identifying potential hazards related to construction logistics, which subsequently improves coordination efficiency within the supply chain and supports decision-making during activities such as silo distribution and restocking [94]. Continuous data acquisition further enhances DT's potential to support efficient asset management, enabling immediate surveillance and more intelligent decision-making for smart buildings [24,76].

5.1.4. Environmental and Sustainability

DT technology is able to improve the sustainable performance of construction projects; for example, DT minimizes construction waste throughout the project lifecycle and facilitates material recycling during decommissioning stages [93]. Furthermore, DT's continuous tracking of greenhouse gas emissions enables the development of energy efficiency and pollution reduction plans. Sepasgozar [119] also proposed that DT, combined with AR, IoT, blockchain, and digital 3D modeling, has the potential to monitor energy and water consumption, air quality, carbon dioxide emissions, and noise. Additionally, by utilizing cognitive capabilities, DT allows for the identification of intricate and unforeseeable actions, enabling the development of rational strategies for dynamic process optimization that assist in the decision-making of a building's lifecycle management [120].

5.1.5. Monitoring and Safety

DT is highly regarded for its robust monitoring and safety management capabilities within construction projects. During the construction phase, DT informs and updates worksite hazards, providing workers with automatic navigations and alerts [74,93,121]. Moreover, DT enables the autonomous detection and monitoring of construction sites by tracking advancements, assessing excellence in construction, ensuring safety, and monitoring personnel, equipment, and materials [95,97]. Xie et al. [86] highlighted the ability of DT to monitor assembly progress in the prefabricated building sector by analyzing data obtained through laser scanning, photographs, and videos based on BIM. In addition, DT offers promising models for immediate and ongoing utilization of SHM, including damage recognition, evaluating safety, preventing failure, and aiding maintenance operations [74,93]. Through consistent collection of data from sensors throughout the building's operational lifespan, DT provides a comprehensive reflection of the building's condition, generating predictive warnings that help prevent potential hazards and conflicts.

5.2. Threats

In this research, the term "threat" refers to the negative uncertainties that DT may introduce to projects. The identified threats were grouped into three categories: Economic, Technical, and Policy and Management. Further discussions will be presented in the following sections.

5.2.1. Economic

Concerns have been raised regarding DT's associated economic costs [62,105]. Lei et al. [33] highlight two primary economic threats related to DT implementation: equipment costs and human resource expenses. Implementing DT requires substantial investment in both hardware and software, as well as significant expenses for data acquisition. These costs can pose challenges to organizations seeking to adopt DT technology. Additionally, the human resource aspect incurs various expenses, including recruiting and hiring specialists with expertise in DT [33,105]. Another significant economic threat arises from the absence of a unified program for the collaboration of DT technologies; this results in increased development costs for specialized software [62]. In light of these concerns, it is necessary for stakeholders to carefully consider the potential economic implications of embracing DT, weighing the benefits against the associated costs.

5.2.2. Technical

There are also technical gaps that need to be addressed to achieve DT's potential completely. Lei et al. [33] identify data as a key technical factor in the implementation of DT, including data accuracy, availability, standardization, integration, and complexity. Ensuring the high quality of data remains a challenge in current implementation efforts, limiting the real-time update of twin models. Moreover, DT currently falls short of achieving real-time data communication due to technical gaps associated with enabling technologies like AI, blockchain, and IoT [106]. These constraints hinder the ability of DT to provide real-time updates of twin models, limiting its potential impact on decision-making processes. Furthermore, the uneven dispersion of DT hardware devices, such as smart sensors, poses an additional challenge, making it difficult to capture real-time data from various locations [33]. In addition, overload data workflows in construction projects require various software for data processing and computing, while the accessibility of the software is also a significant challenge [33]. The insufficiency of data flow between physical and virtual spaces in FM is another critical concern highlighted by Honghong et al. and Ozturk [24,106], leading to errors in construction process control.

5.2.3. Policy and Management

While there is growing recognition by governments worldwide regarding the significance of DT, including the UK's establishment of the Gemini Principles for DT, practical guidelines and frameworks for its development remain lacking [11]. The extensive flow of data required by DT also raises concerns about data security and privacy [107]. Specifically, the exchange of data between various devices and software presents a risk of potential exposure or leakage of sensitive information [33]. Consequently, these issues significantly impede effective information sharing among stakeholders. Practical guidelines would facilitate the adoption of DT technologies while ensuring regulatory compliance, data protection, and secure information sharing. The practice of DT in construction projects is also significantly impacted by management-related factors that pose threats. One key challenge is the need for effective collaboration among stakeholders, which proves difficult due to the inherent complexity of the construction projects [80]. Furthermore, practitioners in the field exhibit reluctance to embrace DT, primarily because they harbor doubts about its ability to yield benefits during the design and construction stages within the construction industry [6,17]. Simultaneously, there exists an apprehension that this innovative technology may render their roles redundant [76,80]. Another challenge lies in the limited number of faculty members proficient in handling DT, which potentially leads to issues in subsequent project stages. In summary, perceived dangers, lack of knowledge, and the time-consuming nature of long-term monitoring are primary obstacles to the widespread adoption of DT.

5.3. Conceptual DT Maturity Level-Based Risk Model

This conceptual model was developed based on mapping the RFs on different DT maturity levels, as illustrated in Figure 10. Each level of DT maturity provides a certain number of opportunities, and such opportunities are also relevant to the next levels. For instance, DT maturity level 3, in addition to all benefits of levels 1 and 2, provides OEn1, OEn2, OMS1, OMS2, OMS6, OM2, and OM7, given the capability of real-time analysis and prediction. At level 4, which leverages the advancements from level 3, stakeholders can perform insightful analysis through what-if scenarios, thus leading to improved decision-making (OM6). For example, by running simulations, DTs can identify energy inefficiencies and potential structural issues and optimize resource allocation and construction schedules, thereby helping stakeholders make informed decisions to achieve opportunities like Energy reduction (OE1), Cost optimization (OE2), Project time reduction (OE3), and Structural health monitoring (OMS5).

At the most sophisticated level (level 5), DT is expected to comprehend the impact and performance of assets, enabling autonomous decision-making. Therefore, certain opportunities can only be exploited when DT is implemented at its full capability. For instance, Anomaly detection (OT5) and Deformation correction (OT6) are categorized into level 5. Here, DTs utilize unsupervised learning to assess the condition of physical assets and identify anomalies [41]. Additionally, the DTs learn from historical feedback and information to develop optimal strategies for addressing deformations. Level 5 DTs exhibit high accuracy, making them valuable for Risk control and safety management (OMS4). With their advanced intelligence and fidelity, Level 5 DTs can operate safely with minimal human intervention. Moreover, for Smart city development (OM5), fully semantic DT systems at the highest level can be connected and provide feedback to support city-level decision-making processes.

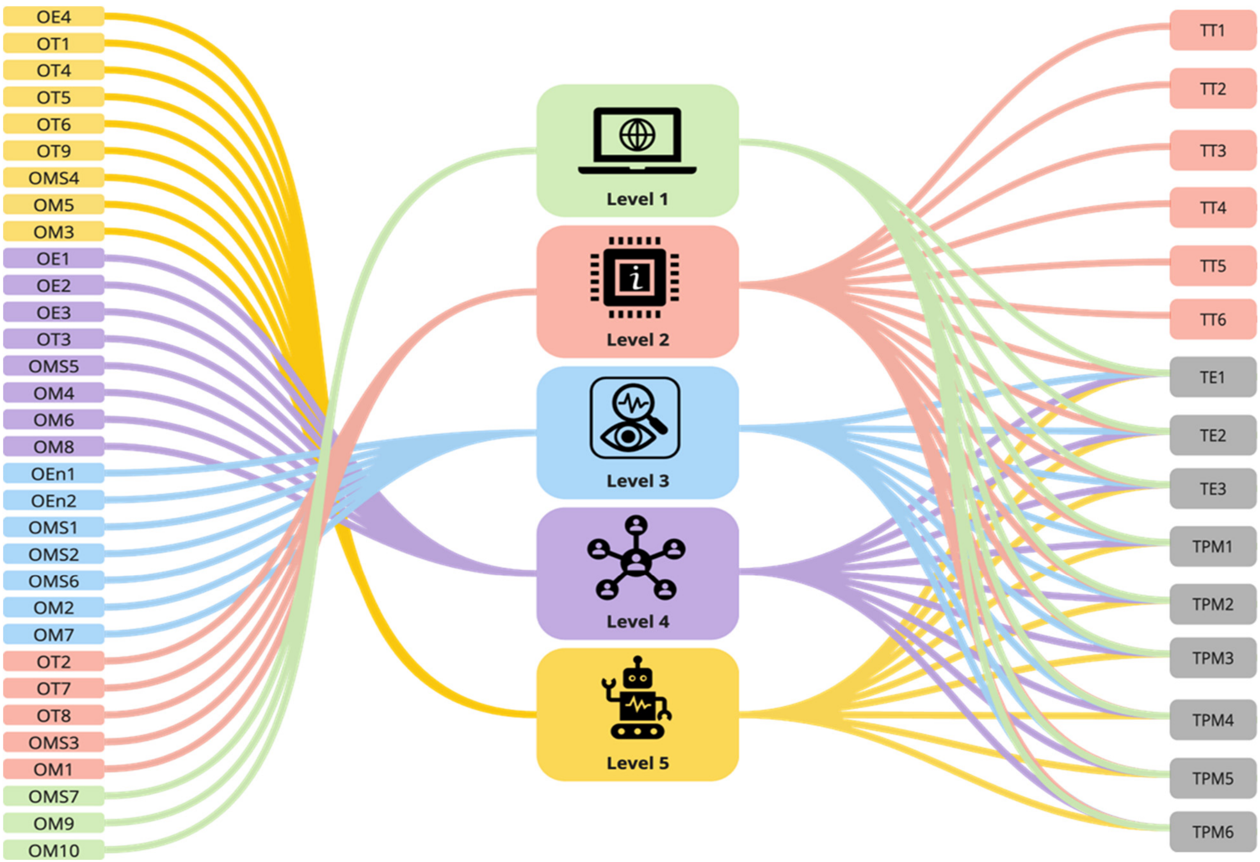

Figure 10. DT maturity model with mapped opportunities and threats.

When it comes to threats, in contrast with the opportunities, it is perceived that not all threats of lower levels are applicable to higher levels. For instance, technical threats (TT1-TT6) that were identified in this review are primarily related to data, once addressed at level 2, and are expected to be no longer a concern for upper DT levels. In contrast, Economic threats (TE1-TE3) are universal across all five levels due to the increased demands for qualified software, hardware, and human resources, leading to higher investments. Similarly, Policy and Management threats (TPM 1–5) must be addressed across all five levels, as stakeholder involvement is essential even at the Autonomous level (Level 5), where human supervision remains necessary [2]. Therefore, threats such as Human errors (TPM1) and Poor collaboration among stakeholders (TPM4) persist from levels 1 to 5. The significance of these threats varies across various levels. For instance, with increasing autonomy of DT from level 1 to 5, it tends to replace more manual work in the construction projects (e.g., structure design, anomaly detection, and construction site monitoring), thereby intricating an increasing resistance from the staff (TPM2) toward DT. However, at the same time, the effect of lacking client demand (TPM3) diminishes as the DT level develops.

Overall, similar to other technologies and processes, higher levels of DT maturity offer increased opportunities. However, the highest level of DT is not a necessity for every project. In other words, DT implementation should be purpose-driven, and the required maturity level of DT is informed by the requirements of the projects, the capabilities needed, and the readiness of the company. Notably, although the highest level is autonomous, human intervention is still required. From levels 1 to 4, humans are actively involved in operations (human-in-the-loop), while at level 5, human oversight is primarily for supervision in most cases (human-on-the-loop).

6. Limitations and Future Directions

Due to the novelty of the topic and the limited available discussions on DT-associated risks, there were only a relatively small number of publications available for analysis. Furthermore, in this study, conference proceedings and grey literature were excluded to ensure that the selected articles had undergone rigorous peer review. Despite the challenges, the present work remains significant as it contributes to the accumulation of knowledge in this area. From a theoretical perspective, the RFs list provides an in-depth overview of the potential positive and negative impacts of DT on construction projects. However, most previous research addressed the opportunities of DT, giving little attention to its threats. Therefore, further exploration of DT is necessary to understand its implications fully. Having reviewed all the related works, the following future directions are put forward:

- To identify and address potential missing risks related to DT implementation in the construction industry across various contexts because both opportunities and threats may differ in diverse contexts. Developing a comprehensive list of risks will establish a robust foundation for future context-based research;
- To identify the most important RFs and evaluate their potential impact on construction projects considering the DT maturity levels. This will, in turn, assist in cultivating response plans and help optimize risk management efforts, eventually enabling practitioners to effectively manage the risks associated with DT implementation at various maturity levels;
- To investigate the relationships among the identified RFs. This helps researchers to better understand the complex relationships between them. Investigating these relationships provides a foundation for conceptualizing research projects and enables practitioners to better anticipate and manage potential opportunities and threats associated with DT implementation;
- Given the significance of the economic aspects of adopting a new technology, one interesting future direction is to develop predictive cost-related risk models/tools/decision support systems that can be adopted on a project-based basis to assess the financial implications of DT adoption at any maturity level.

7. Conclusions

This study conducted a comprehensive review to investigate the RFs associated with implementing DT in construction projects. The novel contribution of this review is twofold. First, comprehensive identification of both positive and negative risks linked to DT implementation within the construction projects. Second, the development of a conceptual risk-mapped DT maturity model provides new insight into adopting any level of DT and making risk-informed decisions on the transition from a certain level to a higher one. According to the findings of this review, it was concluded that (1) there are 47 RFs affecting the implementation of DT at various maturity levels; (2) all opportunities of lower DT maturity levels are observed in higher levels; (3) some threats apply to certain DT maturity levels while they will not necessarily observe at higher levels; (4) some threats apply to all DT maturity levels while their significance at each level and their mitigation strategies are not necessarily the same across the levels.

This comprehensive literature review highlights the importance of understanding both opportunities and threats associated with implementing DT in construction projects. In addition, the categorization of the RFs in this review provides clear perspectives on the uncertainties in adopting DT. Finally, the conceptual DT maturity level-based risk model that is developed for the opportunities and threats provides research and practical implications to inform the decision-making process for adopting any level of DT and transition from conventional DT low levels to higher levels and also to be used by academics as a novel model for further developments in this research area.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/buildings14082349/s1. References [122–127] are cited in the supplementary materials.

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

Appendix A

Table A1. Most relevant authors and most local cited authors.

Most Relevant Authors		Most Local Cited Authors	
Author	**No. of Articles**	**Author**	**No. of Local Citations**
BRILAKIS I	3	LI M	12
LIU H	3	LIU H	10
SVIDT K	3	TEISSERENC B	9
ZHANG Y	3	AL-HUSSEIN M	8
CHEN K	2	BARKOKEBAS B	8
DING L	2	HAMZEH F	8
GIROLAMI M	2	SEPASGOZAR SME	8
HOSAMO HH	2	ANNAN J	7
LEI Z	2	GANG Y	7
LI H	2	HAIJIANG L	7
LI L	2	HAN S	7
LI M	2	HONGHONG S	7
LI X	2	TIAN Z	7
LU Q	2	ZHU Z	7
NIELSEN HK	2	HUANG GQ	6
PAN Y	2	JIANG Y	6
SACKS R	2	LIU X	6
SVENNEVIG PR	2	NABIZADEH AH	6
TEISSERENC B	2	PAN W	6

Appendix B

Table A2. Most relevant affiliations.

Affiliation	Articles
Shanghai Jiao Tong University	7
National University of Singapore	6
University of Cambridge	6
University of Twente	5
Curtin University	4
Dalian Maritime University	4
University of Granada	4
University of Western Australia	4
University of Hong Kong	4
Aston University	3
Bartlett School of Sustainable Construction (UCL)	3
Beijing University of Technology	3
Dalian University of Technology	3
Hong Kong Polytechnic University	3
Islamic Azad University	3

Table A2. *Cont.*

Affiliation	Articles
Mangosuthu University of Technology	3
Technical University of Munich	3
University of Malaya	3
University of Texas at Austin	3
Aalborg University	2
Aarhus University	2
Advanced Remanufacturing and Technology Centre	2
Bartlett School of Construction and Project Management (UCL)	2
Cardiff University	2
Chalmers University of Technology	2
Cornell University	2
Edith Cowan University	2
Illinois State University	2
Nanyang Technology University	2
Northumbria University	2
RMIT University	2
Ruhr-University Bochum	2
Stanford University	2
Swiss Federal Institute of Technology	2
Thammasat University	2
The University of New South Wales	2
University of Agder	2
University of Birmingham	2
Univ New South Wales	2

Appendix C

Table A3. Most cited countries.

Country	Total Citations	Average Article Citations
Australia	227	28.4
Singapore	225	56.2
United Kingdom	195	19.5
Israel	171	85.5
USA	132	22
Korea	92	92
China	79	5.3
Turkey	40	20
France	35	35
Switzerland	25	25
Hong Kong	16	16
Norway	16	5.3
South Africa	15	15
Italy	13	6.5
Iran	11	11
Malaysia	10	5
Germany	8	4
Canada	7	2.3
Spain	7	1.8
Portugal	5	2.5
Denmark	4	4
Netherlands	4	4
Sweden	1	1
Thailand	0	0

Appendix D

Table A4. Most relevant keywords.

Keywords	Occurrences
Architectural Design	13
Construction	13
Building Information Modeling	11
Construction Industry	10
Life Cycle	9
Information Management	8
Design	7
Digital Twin	7
Management	7
BIM	6
Information Theory	6
Project Management	6
System	6
Virtual Reality	6
Architecture Engineering	5
Decision Making	5
Framework	5
Future	5
Internet of Things	5
Artificial Intelligence	4
Augmented Reality	4
Facilities Management	4
Industry	4
Information	4
Optimization	4
Real-Time	4

Appendix E

Table A5. Most globally cited reviewed articles.

Article	Journal	Total Citations	Average Citations per Year
[47]	*Automation in Construction*	220	73.33
[17]	*Data-Centric Engineering*	117	29.25
[8]	*Automation in Construction*	112	37.33
[57]	*Journal of Building Engineering*	105	35
[58]	*Structure and Infrastructure Engineering*	92	18.4
[59]	*Journal of Information Technology in Construction*	83	27.66
[60]	*Mechanical Systems and Signal Processing*	76	25.33
[61]	*Automation in Construction*	72	14.4
[5]	*Automation in Construction*	64	21.33
[62]	*Developments in the Built Environment*	54	13.5
[63]	*Frontiers in Built Environment*	51	8.5
[64]	*Journal of Construction Engineering and Management*	36	18
[65]	*Automation in Construction*	35	17.5
[24]	*Journal of Building Engineering*	33	11
[66]	*Buildings*	31	10.33
[67]	*Engineering, Construction and Architectural Management*	30	7.5
[68]	*Automation in Construction*	25	12.5
[69]	*Journal of Management in Engineering*	16	8
[70]	*Journal of Building Engineering*	15	7.5
[71]	*Journal of Engineering, Design and Technology*	15	—

Appendix F

Table A6. Summary of reviewed articles.

Reference	Context	Scope	Method	Aim	Key Findings
[112]	USA	The AEC industry	Virtual design and construction (VDC) and digital twin approaches	To demonstrate VDC and DT's main benefits and applications, and anticipate cost savings in the AEC industry globally	The global demand and utilization of these DT enabling technologies, such as BIM, IoT, VR and AR, will largely save the cost in the AEC industry.
[69]	Hong Kong, China	The construction industry	Questionnaires and interviews	To utilize DTs and improve the existing level of details (LoDs) of BIM for construction site management.	The framework proposed in this study can be utilized to monitor and manage construction sites, enhance quality and efficiency, and improve construction safety.
[128]	Spain	Construction industry	Case study of a wind farm under construction	To explore the application of DT on construction monitoring	DT can assist in mitigating the risks that may occur during construction
[81]	China	Foundation pit excavation (FPE)	Bow-tie model	To establish an intelligent DT framework for risk prognosis and control to ensure reliable and efficient FPE processes.	The established model is able to support prognosis and control of negative deviations during FPE
[82]	Canada	Offsite construction	Discrete-event and continuous simulation	To improve production on offsite construction shop-floors through increasing labor flexibility	Although the multiskilled workers are perceived to reduce productivity, the increased labor flexibility actually enhances the movements of shop-floors and reduces its cost.
[9]	Australia	The construction industry	Qualitative interview	To develop a software architecture and framework of smart contracts for blockchain-based digital twin decentralized applications through the lifecycle of projects in Construction 4.0	The proposed BCDT architecture and smart-contract framework effectively met the requirements in the literature. By utilizing the non-fungible token (NFT) standard, the framework was developed to address the identified key use cases, industry issues, and functional requirements.
[89]	UK	The AEC industry	Case study based on the Clifton Suspension Bridge in Bristol (UK)	To develop a DT for an existing asset in the built environment and present a case study that demonstrates its feasibility.	There are five steps in the workflow of building DT in the built environment: data and demands acquisition, construction of the digital model, the transmission of real-time data, data/model synchronization, and operation.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[90]	Hongkong, China	Prefabricated construction	Numerical experiment and robotic testbed demonstration	To enable panning, scheduling, and execution (PSE) by utilizing real-time resource status and construction progress information extracted from high-fidelity DTs.	The developed digital twin-enabled real-time synchronization system (DT-SYNC) has the capability to simplify PSE decision-making, and DT-SYNC allows for the efficient and seamless execution of construction tasks, even in narrow urban areas and small cities.
[78]	Australia	Civil infrastructure	Semantic modeling	To develop a DT for intelligent infrastructure maintenance	The proposed DT concept enables predictive maintenance to avoid operational disruptions and subsequent financial loss.
[105]	UK	Civil and structural engineering	Questionnaire survey	To investigate current views of long-term monitoring in civil and structural engineering	Although long-term monitoring is generally regarded as a beneficial tool in the engineering design process, there is a significant difference in its actual implementation. Furthermore, there is little consensus on how it can provide the most benefits to this area, and there is currently no direct financial motivation to encourage its use in the industry.
[129]	China	Structural safety monitoring	Multi-fidelity surrogate model	To enhance the accuracy of real-time monitoring and prediction for the structural safety of a crane boom.	This study proved that the proposed DT can enhance the accuracy of DTs built by single-fidelity surrogate models and reduce the computational costs of numerical methods. Furthermore, the uncertainty of the lightweight DT was quantified.
[130]	Italy	Building management	Case study building in Italy	To define a novel approach in order to properly manage the retrofitting intervention.	The deep renovation of the current building stock plays a vital role in reducing greenhouse gas emissions. The outcomes of this renovation project in this research effectively demonstrate the efficiency of innovative modular prefabricated systems.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[108]	Portugal	Ocean engineering	Realistic virtual models of structural systems	To fill the gap between design and construction and to mirror the real and virtual worlds	The key advantages of improved trust management using the DT include data standardization and contextualization, automated anomaly detection, and the ability to constantly learn through sharing. Main challenges: collection, translation and sharing of data, and the threat of cyber-attacks.
[131]	China	Tower crane hoisting safety	Tower crane hoisting experiment based on DT	To realistically simulate different hoisting behaviors and dynamically analyze their influence on the tower crane.	The results of the DT-based experiment showed tilt hoisting is most likely to threaten the stability of the tower crane. Also, both the foundation and masts of the tower crane are weak and easy to be influenced by dangerous hoisting factors.
[70]	UK	FM in the AEC industry	Illustrative case studies	To analyze and make comparisons between the traditional FM and the DT-driven FM during the O&M phase through four geospatially representative cases.	By providing dynamic data on the building assets, DT technologies are able to efficiently make reactions to FM activities.
[88]	Canada	Offsite construction	Offsite construction DT model and case study with a Canadian company	To improve offsite construction productivity by utilizing the concept of DT.	The resulting assessment framework sets the foundation for an offsite Construction DT and enables easier technology application in practice by offering a holistic DT framework.
[101]	China	Prefabricated construction hoisting	Intelligent safety risk prediction framework and construction hoisting case study	To create a real-time updating model for predicting the behaviors of assembly building hoisting based on DT.	The framework can provide reliable solutions to the problems, including high risks caused by hoisting, difficulty in prediction, and low intelligence degree, by utilizing DT in hoisting risk prediction.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[132]	China	Road construction industry	Prototype system and case demonstration	To establish a foundational platform that utilizes BIM, IoT, and intelligence compaction (IC) to enable advanced monitoring and management of compaction quality.	The proposed framework enables the seamless integration of BIM and IC, allowing for the effective monitoring of road compaction quality by combining IoT data. Based on the monitoring results, the construction schedule can be adjusted and optimized accordingly.
[133]	Germany	Modularized construction	Case study for detailed design sub-model and quality control	To create the initial template for an asset administration shell (AAS) for precast concrete elements and establish a methodology for generating AASs using the BIM model of a modularized building.	The research demonstrated the use of the DT concept to organize and structure data and information to realize the purposes of ensuring production and quality. By implementing the DT based on the AAS, advanced communication methods are enabled, both within individual DTs and between multiple DTs.
[134]	China	Construction of subway station	DT- and IoT-based automatic multi-information monitoring system	To provide a digital solution to the monitoring of constructing dome method station	The DT system effectively reproduces and accurately describes the construction status of subway stations, offering advanced technical capabilities for the information and visualization management of arch cover method construction in subway stations.
[118]	China	The construction industry	Hybrid DT-BIM model	To enable rapid decision-making recommendations for the dispatching system based on advanced data analysis	The hybrid DT-BIM technologies can effectively assist in the dispatch systems for construction projects.
[8]	USA	Construction industry	Case study for DT-blockchain integration framework	To develop and test an integrated DT- blockchain framework to make the data communication traceable.	The integrated DT–blockchain framework has high potential in tracing all data transactions.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[60]	Brazil	Structural damage detection	Physics-based models integrated with ML	To maximize the potential of the proposed DT framework by investigating the integration of physicals-based models with ML techniques.	To solve a dynamic structural damage problem, this paper introduces a DT conceptual framework. Moreover, the three key components of this framework are emphasized: computational model, quantification of uncertainty, and calibration utilizing data from the physical twin.
[17]	UK	Buildings and civil infrastructure	Conceptual analysis	To establish a comprehensive and practical workflow for the planning and control of design and construction stages, as well as other facilities, through using DT information systems.	This paper presents a workflow framework for a comprehensive digital twin construction (DTC) information system. Furthermore, it provides an in-depth review of the necessary research and development to implement this framework. DTC's approach to construction management relies much on data that utilizes information and monitoring technologies within a lean, closed-loop planning and control system.
[61]	Australia	Construction industry	Case study-based System Information Modeling research	To highlight the importance of organizations establishing a benefits management process before investing in digital technology; thus, they can understand how digital technologies can combine to create economic value and enhance their competitiveness.	The changes brought about by digital technologies include three categories: automation, extension, and transformation.
[58]	South Korea	Bridge engineering	Digital twin model with digital inspection system	To enhance the bridge maintenance process	The DT-based framework simplifies access and management of information within the bridge maintenance system (BMS). The DT model ensures seamless interoperability, efficient information exchange, and easy specification and delivery of data drops. Parametric modeling saves time in the design stage and reduces the complexity of the model.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[87]	Singapore	Construction project management	A data-driven DT framework	To propose a highly automated and intelligent framework based on the integration of BIM, IoT, and DM to control and improve complicated construction processes.	Tactic decision-making serves a dual purpose: it not only helps in proactively preventing potential failures but also enables rational organization of work and staffing to ensure adaptability to changing conditions.
[100]	Australia	Construction workforce safety	Visual warning system integrating DT, DL, and MR technologies.	To complete the existing body of knowledge related to construction safety	The developed real-time visual warning system based on the integration of DT, DL, and MR technologies enhances workers' accuracy in risk assessment, reinforces their safety behavior, and offers construction safety managers a fresh perspective to analyze construction safety status.
[103]	China	O&M of buildings	Fusion mechanism of the DT and ML	To address the gap in research regarding the application of DTs in various aspects of building O&M and enhance the intelligence level of the model.	The study highlights that applying DT technology and ML algorithms is an efficient approach to achieving intelligent prediction and diagnosis of building O&M status. This enables intelligent operation and maintenance of buildings.
[91]	China	Steel structure	Three-point positioning technique	To achieve full-loop tracking and control of the assembly and manufacturing process	Using a DT-based model is beneficial for inspecting and verifying the structure, making it easier to trace the causes of quality issues. It also enables timely problem resolution, ensuring consistent progress in quality control and assessment.
[95]	Singapore	Construction facility management	Digital twin model and experimental study	To create a BIM-based and IoT-driven digital twin that monitors and manages the condition of the built environment related to wellbeing. This includes effectively handling associated data and communicating valuable insights for informed decision-making in facility management.	The BIM-based and IoT-driven DT method supports real-time environmental monitoring and provides facility managers with more actionable insights for maintaining the daily operation of buildings.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[93]	UK	Buildings and infrastructures	A framework for a risk-informed digital twin (RDT)	To introduce a novel automated multidisciplinary technology called the risk-informed digital twin (RDT), which incorporates all five levels of DT and is specifically designed for the built environment.	This article offers a clear definition of DT and highlights its distinction from digital models and mirrors. It also explores the potential benefits of applying DT in enhancing sustainability and resilience within the built environment.
[92]	Spain	Structural engineering	A DT framework for structures	To place particular emphasis on the aspects that are overlooked in the civil engineering field, including autonomous communication between the physical and digital entities, as well as the construction of DT workflow.	The proposed DT has the capability to support decision-making in preventing failures. Through the virtual entity (VE), reliability and risk assessment can be conducted under damaged conditions, and automatic alarms can be triggered in case of failure scenarios. Additionally, the tests demonstrate that the DT enables automated decision-making to ensure structural integrity.
[135]	USA	Architectural design	DT approach with hands-on experiment	(1) To develop a user-friendly tool assistant in DT design. With this tool, users can communicate with CAD software and get feedback on design outcomes intuitively. (2) To explore the mixed physical and digital mode's opportunities and effectiveness when it is adopted as a new medium in the design phase. (3) To evaluate the tool's feasibility and acceptability in design education and architectural design practice by testing users.	The researchers integrate a DT platform, which provides an excellent opportunity for students to understand how design decisions influence different project outcomes. It the enables teaching of important aspects such as design concepts, detailed processing, layout ideation, function exploration, and energy consumption analysis. Additionally, it serves as an assistant to help students overcome the barriers to CAD software and introduces them to 3D modeling, digital analytics, and programming.

Table A6. *Cont.*

Reference	Context	Scope	Method	Aim	Key Findings
[1]	USA	The AEC industry	Digitization framework using design science research (DSR) methodology.	To drive and encourage the adoption of digital technologies in the AEC industry, which has been relatively slow in embracing these advancements, through a digitalization framework.	The digitalization framework supports practitioners in choosing a corresponding DT level by comparing the pros and cons of each level, defining the DT system's assessment criteria, and evaluating the impacts of the selected DT on the organizational workflows and value creation.
[67]	UK	Construction O&M	AR-enhanced inspection system	To explain the creation of an automated method for detecting and isolating environmental anomalies using augmented reality (AR) in order to support facility managers in effectively addressing issues that impact the thermal comfort of building occupants.	The case study illustrates the utility of the proposed AR-enhanced inspection system in improving the O&M management process. By comparing various anomaly detection algorithms, it is found that binary segmentation-based vary point detection is efficient and successful in identifying abnormal temperatures. The FTA (fault tree analysis)-based decision-making tree formalizes the connection between temperature issues and the corresponding faulty assets. Moreover, the AR-based model enhances the maintenance procedures by visually highlighting concealed faulty assets to on-site maintenance workers.

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