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Review

Barriers to the Adoption of Digital Twin in the Construction Industry: A Literature Review

De-Graft Joe Opoku [1,*], Srinath Perera [1], Robert Osei-Kyei [1], Maria Rashidi [2], Keivan Bamdad [1] and Tosin Famakinwa [3]

[1] Centre for Smart Modern Construction (c4SMC), School of Engineering, Design and Built Environment, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia
[2] Centre for Infrastructure Engineering (CIE), School of Engineering, Design and Built Environment, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia
[3] Teaching and Research Technical Services (TRTS), Built Environment and Engineering Cluster, Western Sydney University, Locked Bag 1797, Penrith, NSW 2751, Australia
* Correspondence: d.opoku@westernsydney.edu.au

Abstract: Digital twin (DT) has gained significant recognition among researchers due to its potential across industries. With the prime goal of solving numerous challenges confronting the construction industry (CI), DT in recent years has witnessed several applications in the CI. Hence, researchers have been advocating for DT adoption to tackle the challenges of the CI. Notwithstanding, a distinguishable set of barriers that oppose the adoption of DT in the CI has not been determined. Therefore, this paper identifies the barriers and incorporates them into a classified framework to enhance the roadmap for adopting DT in the CI. This research conducts an extensive review of the literature and analyses the barriers whilst integrating the science mapping technique. Using Scopus, ScienceDirect, and Web of Science databases, 154 related bibliographic records were identified and analysed using science mapping, while 40 carefully selected relevant publications were systematically reviewed. From the review, the top five barriers identified include low level of knowledge, low level of technology acceptance, lack of clear DT value propositions, project complexities, and static nature of building data. The results show that the UK, China, the USA, and Germany are the countries spearheading the DT adoption in the CI, while only a small number of institutions from Australia, the UK, Algeria, and Greece have established institutional collaborations for DT research. A conceptual framework was developed on the basis of 30 identified barriers to support the DT adoption roadmap. The main categories of the framework comprise stakeholder-oriented, industry-related, construction-enterprise-related, and technology-related barriers. The identified barriers and the framework will guide and broaden the knowledge of DT, which is critical for successful adoption in the construction industry.

Keywords: barriers; construction industry; digital twin; review; technology

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1. Introduction

The advent of Industry 4.0 gave rise to an array of digital technologies, including digital twin (DT) technology. DT presents the opportunity to develop digital models, which can be continually updated using several sources of data to make predictions regarding the current as well as future states and conditions of the physical asset. These models can be simulated for real-time predictions, optimisation, monitoring, and controlling, as well as enhanced decision-making regarding the status of a physical asset. In addition, DT utilises other technologies, including artificial intelligence (AI), machine learning, and data analytics. Due to the prowess of DT, the construction industry (CI), with its numerous challenges, has started DT applications. Technologies such as building information modelling (BIM), wireless sensor networks (WSNs), and machine learning, together with data analytics are presently being used to support the adoption of DT in the CI. Several studies [1–3] have studied DT in the CI and established their relevance. For instance, Opoku, Perera, Osei-Kyei, and Rashidi [2] indicated that DT is necessary for facility management since they can be employed in "What-if" analysis in decision making relating to the building's operation and maintenance activities. Researchers and practitioners are currently discovering the numerous potentials of DT in the CI. There is, however, a misconception in the construction industry where DT are likened to BIM due to their similarities [2,4]. Khajavi, Motlagh, Jaribion, Werner, and Holmström [4] therefore reported their differences based on their purposes, technologies, and end-users.

Notwithstanding the advancement of DT in the CI, it is essential to respond to the following question, "What barriers impede the prompt adoption of DT in the CI?" Unfortunately, only minimal consideration has been given to the barriers hindering DT adoption in the CI. Although some reviews [2,5–7] have been conducted on DTs in the CI, these reviews paid little attention to the barriers to DT adoption. For instance, Alshammari, Beach, and Rezgui [5] reviewed the current cybersecurity landscape of the built environment and focused on the current state-of-the-art in the fields of BIM, IoT, DT, and cybersecurity. Deng, Menassa, and Kamat [6] also identified the development of emerging technologies facilitating the BIM to DT's growth and applications in the built environment. Further, Opoku, Perera, Osei-Kyei, and Rashidi [2] reviewed the current state of DT application in the CI and focused on project lifecycle phases' applications of DT. Opoku, Perera, Osei-Kyei, Rashidi, Famakinwa, and Bamdad [7] also investigated the drivers for adopting DT in the CI. Currently, no study has comprehensively reviewed the available literature on the barriers to adopting DT in the CI. This hinders the preparedness to fully embrace DT in the construction industry. Therefore, this research aims to conduct extensive as well as comprehensive literature review on the barriers to the adoption of DT in the CI. The objectives below are therefore formulated to aid in achieving the aim of this research:

1. To determine the status of DT in the CI.
2. To identify and incorporate the barriers into a classification framework to enhance the roadmap for adopting DT in the CI.

This current study is novel since it is one of the pioneering studies to comprehensively undertake a review of the literature to determine a categorised set of barriers to the adoption of DTs in the CI. In addition, the development of an innovative framework arising from the current study would propel the desire to successfully adopt DT in the CI. It is expected that the classification of barriers would enable DT developers to provide efficient solutions that collectively address a whole cluster of barriers. In practice, the study results will present a point of reference for improving industry practitioners' knowledge of the need to embrace DT in the CI. The rest of the paper is organised in the following order: the state of the art of DT is presented in Section 2. Section 3 addresses the methodology adopted for this study. The bibliometric analysis of studies that relate to DT in the CI is introduced in Section 4. Section 5 presents the results and discussion of the paper. Lastly, the conclusions together with practical implications of the research and recommendations for further investigation possibilities are presented in Section 6 of this paper.

2. State of the Art

2.1. Concept and Definition of Digital Twin

The concept of DTs has made several waves in various industries and presents an overwhelming desire to adopt this concept. The National Aeronautics and Space Administration (NASA) first used the term "digital twin" in the public domain [8]. The Apollo program of NASA's conceptualisation of "twins" resulted in the use of the concept in its space exploration missions in the 1960s. During these missions, two matching spaceships were designed to mirror the state of the spaceship that was on a mission [9]. Boschert and Rosen [9] reported that the spaceship that stayed on Earth was regarded as the twin of the ship in space. The Earth-remained ship could present an idea of the conditions that existed in space during an exploration mission. However, in scientific research, it is well documented that Hernandez and Hernandez [10] were the first to use the concept. In

2003, at the University of Michigan, Michael Grieves applied the DT concept in an industry presentation for the formulation of a Product Life Cycle Management (PLM) centre. The PLM led to the digital version of a physical product which was later expanded with the Information Mirroring Model [11]. In 2006, Hribernik et al. [12] introduced an alternative to the DT known as “product avatar”. The “product avatar” was utilised in the development of an architecture for managing information that supported a bidirectional product-centric flow of information. A white paper was published in 2014 by Michael Grieves to explain the DT concept.

Several definitions of DT are available in the literature. However, the definitions are based on its application without a limitation to any specific industry. Opoku, Perera, Osei-Kyei, and Rashidi [2] reported on the ambiguities in the definitions of DT due to its lack of connection to specific fields within the global industry. Notwithstanding, the concept of DT as a technology should possess three (3) distinct components that include a physical object, a virtual entity, and the data that create a linkage between the physical and virtual entities [13,14]. Fotland et al. [15] defined DT as a physical asset’s digital form that collects real-time data from the entity and presents information which is not directly gathered using hardware. Luo et al. [16] described DT as a multi-domain as well as ultrahigh fidelity digital model that integrates several domains which include mechanical, electrical, and hydraulic, as well as the subjects of control. Grieves and Vickers [17] defined DT as a full description of an actual or potential product that is physically created using a set of virtual information constructs from the micro atomic level to the macro geometrical level. Gabor et al. [18] also defined DT as the simulation of the physical entity itself to enable the prediction of system’s state in the future. Moreover, Rosen et al. [19] defined DT as very realistic model of the current state of the process as well as their behaviours in communicating with their environments in their real world. These definitions from subsequent years’ publications really indicate the fact that, irrespective of the industry of DT application, there should be a physical entity, virtual entity, and the data that connects them in order to ensure a bidirectional dynamic interaction between the physical object and virtual model [14]. It is also worth mentioning that, for the virtual entity to be identified as a DT, the physical component must be in existence. This is significantly different from virtual engineering where geometric models are integrated with their related engineering tools for simulation-based decision making.

Furthermore, the sophistication of the physical and virtual entities’ integration identifies the different classifications of DT. Kritzinger et al. [20] and Opoku, Perera, Osei-Kyei, and Rashidi [2] reported that there are digital models where there are no interactions between the entities themselves. The studies also stated that there are digital shadows where there is a self-driven one-directional movement of data from the physical object to the digital model. This is normally through the utilisation of the Internet of Things (IoT) and WSN devices including sensors, drones, and the like. Finally, the studies indicated that in terms of a complete DT, there is a fully integrated two-way communication and interactions between the physical object and its virtual counterpart or model. Table 1 below presents an ordered list of definitions relating to the development of the DT concept and the specific domains of their application. This is to give a clearer understanding of how the concept’s development has evolved over the period across different domains.

Table 1. Sample list of yearly DT definitions in the literature.

S/N	Year	Domain of DT Application	Definition of Digital Twin	Reference
1	2010	NASA's integrated simulations	A combined multi-scale, multi-physics, probabilistic simulation of a system that utilises the most readily accessible physical models, updates from sensor, fleet history, and the like to reflect its flying twin's life.	[8]
2	2012	Airframes	An aircraft structure's cradle-to-grave model that has the capacity to achieve mission requirements, including sub-models of the electronics, controls of flight, the propulsion system, and other subsystems.	[21]
3	2013	Predictive manufacturing	A coupled model of the real machine that operates in the cloud platform as well as simulates the health conditions with a combined knowledge from both data-driven analytical algorithms and other accessible physical knowledge.	[22]
4	2014	Structural health management	A certification paradigm together with life management whereby models and simulations comprise the state of the as-built vehicle, as-experienced loads and environments, and other vehicle-specific history to allow high-fidelity modelling of individual aerospace vehicles throughout their service lives.	[23]
5	2015	Industrial manufacturing	A very realistic model of the current state of the process as well as their behaviours in communicating with their environments in their real world.	[19]
6	2016	System design	A simulation of the physical entity itself to enable the prediction of system's state in the future.	[18]
7	2017	Product lifecycle management	A full description of an actual or potential product that is physically created using a set of virtual information constructs from the micro atomic level to the macro geometrical level.	[17]
8	2018	Smart manufacturing	A multi-domain and ultrahigh fidelity digital model incorporating various areas including mechanical, electrical, hydraulic, and various subjects of control.	[16]
9	2019	Architecture for cyber physical systems	A physical entity's digital version that is connected and synchronised to signify the system's elements and dynamics relating to its lifecycle operation within the system's environment.	[24]
10	2020	Work environment safety	DT is a physical asset's digital form that collects real-time data from the entity and presents information which is not directly gathered using hardware	[15]
11	2021	Construction	DT is similar to Building Information Model (BIM). However, their purposes, technologies, end-users, and data types are different. Digital twin utilises real-time data, whilst BIM works with static data.	[2]
12	2022	Construction	A fully or partially completed structure or building's representation in real time to reflect the character and status of the structure or building.	[7]

2.2. Application of DT in the CI

The growing interest in the DT concept and technology has seen a gradual implementation within the CI. Although the industry is recognised as being slow in terms of innovation and advancements in technology, over the past years, the technology has witnessed a slow adoption to tackle the wide array of challenges in the CI. Researchers in the CI have undertaken several studies relating to DT in the industry. Opoku, Perera, Osei-Kyei, and Rashidi [2] reviewed and reported on the applications of DT technology in the CI. The authors focused on the technology's applications across the various life cycle stages of a construction project. They reported that at a project's design and engineering stage, the utilisation of DT has been geared towards the use of BIM models. This aids in decision making regarding the inheritance or discarding of various components and information during the project's redesign as well as re-engineering activities. In the construction phase of a project, Opoku, Perera, Osei-Kyei, and Rashidi [2] reported that digital twins have been focused on cost reduction and the structural integrity of the project's system. Further, the authors indicated that during the project's operation and maintenance stage, the applications of the technology have been focused on the management and maintenance of facilities, monitoring, processing of logistics, and energy simulations of projects. This enables the facility managers to take vital decisions that relate to operating and maintaining the building project. Finally, the authors reported that there have been limited studies focusing on DT applications in the project's demolition and recovery phase. Notwithstanding, the authors mentioned that DT could be employed in the conservation as well as safeguarding heritage assets that may have to be demolished soon. These applications indicate that the CI is keen on utilising DT technology to provide solutions to most of the challenges confronting the industry.

2.3. DT Applications in Other Domains

DT technology has witnessed several applications in technology-advanced industries or domains including manufacturing [20,25], aeronautics and aviation, healthcare [26], automotives [27], the energy sector, education, and meteorology [28], among others. In manufacturing, DT has been utilised for real-time monitoring, control of production, production planning, predictive maintenance, and detecting faults, together with the monitoring of the state of various systems [29]. Tao et al. [30] mentioned that DT ensures the healthcare management of products and provides their digital footprint through their geometry, structure, behaviour, and functional properties. In the healthcare domain, Kamel Boulos and Zhang [31] indicated that DT is employed in enhancing the diagnostics, prognostics, and treatment of patients. Further, Bruynseels et al. [32] reported that DT is used for disease prediction, well-being management, and the provision of precise medication. In the aviation and aeronautics domain, DT is employed in aerospace vehicle maintenance, flight model simulation, and fatigue life and aerothermal model prediction [33,34]. Francisco et al. [35] also deliberated on the application of DT in the energy sector and highlighted that DT is used for energy usage analysis, predictive maintenance, life cycle management, and fault diagnosis. Finally, in the meteorological domain, DT is used in weather prediction, geospatial asset management, and ageing infrastructure [36], whilst in the education sector, DT is applied in skills enhancement and effective delivery of knowledge using online platforms [37,38]. There is also a potential application of DT in medical training. These applications of DT in different domains show the potential of the technology to provide solutions to most of the global challenges and enhance productivity across industries.

3. Research Methodology

The study aimed at presenting a comprehensive review of the barriers affecting the holistic adoption of DT in the CI literature. This study, therefore, conducted a systematic review of the literature which is identified as a key component of any study [39]. Briner and Denyer [40] mentioned that this kind of review employs specific principles that involve transparency in delivery, replicability and updatability, and summarisation, as well as synthesisation of the specific aspects under consideration. The study utilised a similar methodology employed by [7,29,41,42] to systematically study the literature found within the scope of the research. The process comprises a preliminary searching of the literature using diverse databases, filtration of the retrieved literature, and a content analysis of the relevant literature. Consequently, a four-stage selection of academic publications, a brief review of titles and abstracts, a content review of related publications, and a systematic content analysis of the relevant publications were conducted. Figure 1 presents the research process utilised for the study.

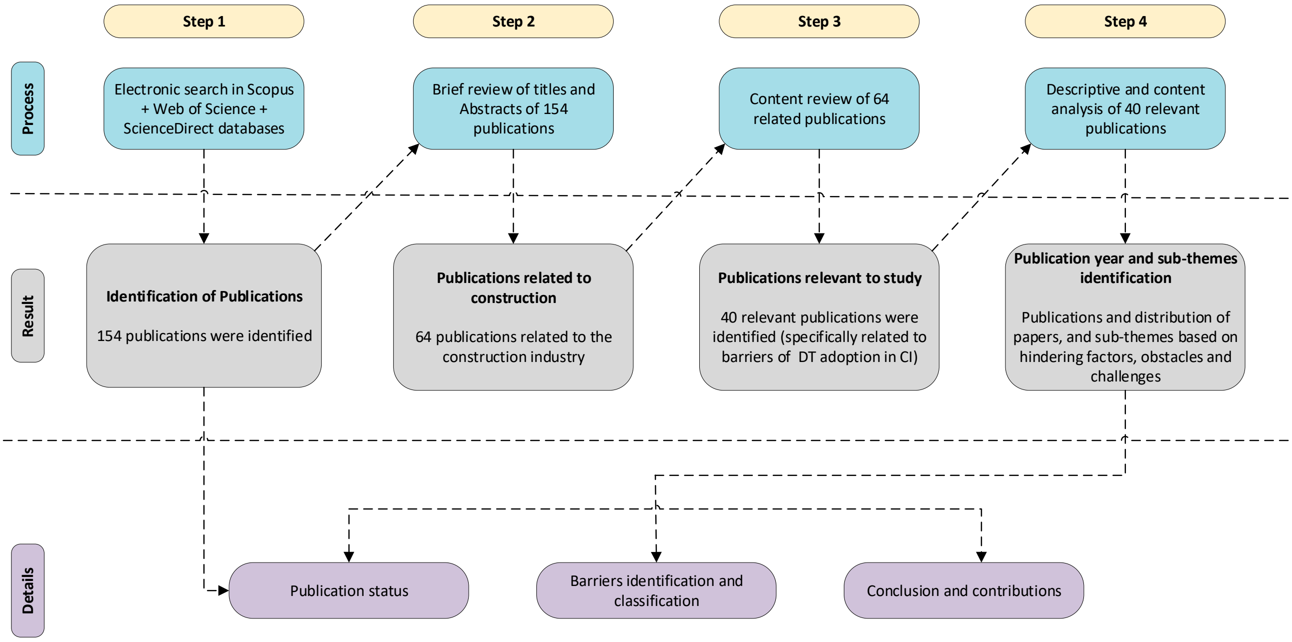

Figure 1. An overview of the literature review and research process adapted from Zhang and He [43].

3.1. Identification of Relevant Papers for the Study

The identification of the relevant publications for the study was carried out using three prominent databases: Scopus, ScienceDirect, and Clarivate Analytics' Web of Science databases. The initial search for the literature was carried out using Elsevier's Scopus database since it has wider coverage in terms of scientific publications [44,45]. Furthermore, Falagas et al. [46] mentioned that compared to Web of Science, Google Scholar, and PubMed, Scopus is a better performer when searching for literature. In comparison to other databases, Elsevier's Scopus database also has publications that are more recent and is much quicker in terms of indexing of papers. Thus, the Scopus database was initially utilised in searching for the literature. An extensive search for the literature was carried out utilising the keywords with suitable Boolean operators: ((“construction industry” OR “construction”) AND (“barriers” OR “obstacles” OR “challenges”) AND (“digital twin” OR “digital replica” OR “virtual twin” OR “virtual counterpart”)). Other terms such as avatar and digital shadow were not included in the keywords since they meant differently when focusing on DT in the CI. An avatar often refers to a person being digitally represented, whilst a digital twin refers to the digital representation of a physical asset. In the absence of a representation of a real person in the digital world, it is not logical to use the word “avatar” as a synonym to digital twin. Moreover, only specifically related keywords were included to ensure the most relevant papers were retrieved. There were no restrictions set in relation to the year of publications (search conducted on 10 August 2022). Notwithstanding, “article” or “review” was chosen for the document type because they deliver a more credible, reliable, and prominent sources of knowledge [47]. To ensure the credibility and authenticity of publications utilised in the study, only peer-reviewed journal articles as well as conference papers were included in the study. Moreover, it is worthy to note that although technology-related studies are reported significantly in non-academic or non-peer-reviewed domains such as reports, websites, forums, discussions, and the like, for the purposes of ensuring rigour in the systematic review, these were not included in the study. Furthermore, the language type was also limited to the English language to aid in achieving the aim and objectives of the study.

The primary search for the literature resulted in the identification of 55 publications using the search query. Due to the limited number of papers that were retrieved from Elsevier's Scopus database, further searches were conducted using Web of Science (WoS) and ScienceDirect databases. Further searches in WoS and ScienceDirect yielded 6 and 93 publications, respectively. This resulted in a total of 154 papers being retrieved from Scopus, ScienceDirect, and WoS databases. This presented an opportunity to retrieve and review an acceptable number of study outputs on barriers to adopting DT in the CI. All publications were then exported into the EndNote 20 bibliography management software. The authors read and analysed the titles and abstracts of the 154 papers and arrived at initial judgements regarding the appropriateness of the papers for inclusion in the study. The screening resulted in the removal of duplicates and irrelevant publications. Furthermore, this was to ensure that papers whose subject of interest contained some keywords in their "article title/abstract/keyword" fields but were not related to the CI were not included in the study. After going through this process of screening, a total of 64 related publications from 24 journals were retrieved. Following that, the researchers carried out a more critical and comprehensive review of the contents of the 64 related publications to determine the papers that were pertinent to the study topic under consideration. Moreover, this was done to ensure that referred journal publications only were included in the research to increase the chances of obtaining quality data [48]. The review of the 64 related papers resulted in the final identification of 40 relevant papers that were pertinent to this study for thorough analysis. The number of publications that were identified together with the final papers relevant to the research are presented in Table 2.

Table 2. Search outcomes of the pertinent papers for the research.

N/S	Name of Journal	No. of Chosen Publications	No. of Relevant Publications for Critical Analysis	References
1	*Applied Sciences (Switzerland)*	3	2	[49,50]
2	*Automation in Construction*	10	7	[1,51–56]
3	*Buildings*	6	5	[7,57–60]
4	*Computers in Industry*	5	3	[61–63]
5	*Construction Innovation*	2	1	[64]
6	*Developments in the Built Environment*	1	1	[65]
7	*Energies*	2	1	[66]
8	*Energy and Built Environment*	2	1	[67]
9	*Energy Reports*	1	1	[68]
10	*Environmental Technology & Innovation*	2	1	[69]
11	*IEEE Communications Magazine*	4	1	[70]
12	*IEEE Transactions on Industrial Informatics*	2	1	[71]
13	*International Journal of Safety and Security Engineering*	2	1	[72]
14	*Journal of Advanced Transportation*	1	1	[73]
15	*Journal of Building Engineering*	4	3	[2,74,75]
16	*Journal of Cleaner Production*	4	1	[76]
17	*Journal of Digital Landscape Architecture*	2	1	[77]
18	*Journal of Engineering, Design and Technology*	1	1	[78]
19	*Journal of Management in Engineering*	2	2	[79,80]
20	*Organization, Technology and Management in Construction*	1	1	[81]
21	*Remote Sensing*	2	1	[82]
22	*Sustainability (Switzerland)*	3	1	[83]
23	*Sustainable Cities and Society*	1	1	[84]
24	*Waste Management*	1	1	[85]
	Total	*64*	*40*	

Furthermore, the authors deemed it fit to consider the influence and impact of the selected papers for this particular study. The number of citations indicates how relevant and contributing an author's research is to the scientific community. Researchers in specific fields of study utilise cited works to expand their knowledge base and provide ground-breaking discoveries and inventions in specific domains of study [86]. Although the papers are largely from 2021 and 2022, some have very high citations, despite being published not long ago. This gives an idea of how the DT knowledge base is being expanded. There were also papers from 2019 and 2020. Thus, the number of citations received by the selected papers in Scopus and Google Scholar are presented in Table 3.

Table 3. Citation records of the papers identified for the research.

S/N	Reference	Type of Paper	No. of Citations in Scopus	No. of Citations in Google Scholar
1	Ali, Alhajlah, and Kassem [60]	Article	1	5
2	Antonino, Nicola, Claudio, Luciano, and Fulvio [72]	Article	12	20
3	Babalola, Musa, Akinlolu, and Haupt [78]	Article	10	14
4	Boje, Guerriero, Kubicki, and Rezgui [1]	Article	173	304
5	Bosch-Sijtsema, Claeson-Jonsson, Johansson, and Roupe [64]	Article	15	25
6	Coupry, Noblecourt, Richard, Baudry, and Bigaud [49]	Article	10	17
7	Demianenko and De Gaetani [66]	Article	5	8
8	Greif, Stein, and Flath [61]	Article	34	51
9	He, Li, Gan, and Ma [76]	Article	36	53
10	Hoeft and Trask [83]	Article	-	1
11	Hunhevicz, Motie, and Hall [51]	Article	-	16
12	Jiang, Li, Guo, Wu, Zhong, and Huang [62]	Article	4	6
13	Jiang, Liu, Kang, Wang, Zhong, and Huang [63]	Article	11	11
14	Kang, Besklubova, Dai, and Zhong [85]	Article	-	-
15	Li, Lu, Bai, Zhang, Tian, and Qin [52]	Article	3	5
16	Lu, Chen, Li, and Pitt [53]	Article	33	54
17	Lu, Parlikad, Woodall, Don Ranasinghe, Xie, Liang, Konstantinou, Heaton, and Schooling [79]	Article	71	127
18	Marocco and Garofolo [54]	Article	5	7
19	Meža, Mauko Pranjić, Vezočnik, Osmokrović and Lenart [73]	Article	9	16
20	Nguyen, Trestian, To, and Tatipamula [70]	Article	32	61
21	Opoku, Perera, Osei-Kyei, and Rashidi [2]	Article	36	61
22	Ozturk [74]	Article	11	24
23	Pregnolato, Gunner, Voyagaki, De Risi, Carhart, Gavriel, Tully, Tryfonas, Macdonald, and Taylor [55]	Article	-	-
24	Rafsanjani and Nabizadeh [67]	Article	2	5
25	Rao, Radanovic, Liu, Hu, Fang, Khoshelham, Palaniswami, and Ngo [56]	Article	3	2
26	Sacks, Girolami, and Brilakis [65]	Article	27	71
27	Shahzad, Shafiq, Douglas, and Kassem [57]	Article	5	10
28	Shilton [77]	Article	1	-
29	Teisserenc and Sepasgozar [58]	Article	7	9
30	Turk, Ma, and Klinc [81]	Article	-	-
31	Turner, Oyekan, Stergioulas, and Griffin [71]	Article	33	61
32	Ullah, Sepasgozar, Thaheem, and Al-Turjman [69]	Article	24	38
33	Villa, Naticchia, Bruno, Aliev, Piantanida, and Antonelli [50]	Article	6	14
34	Opoku, Perera, Osei-Kyei, Rashidi, Famakinwa, and Bamdad [7]	Article	-	-
35	Wei, Lei, and Altaf [59]	Article	-	2
36	Wu, Shang, and Xue [82]	Article	6	12
37	Xia, Liu, Efremochkina, Liu, and Lin [84]	Article	-	-
38	Xie, Qiu, Liang, Zhou, Liu, and Zhang [68]	Article	-	-
39	Zhang, Cheng, Chen, and Chen [80]	Article	6	7
40	Zhao, Feng, Chen, and Garcia de Soto [75]	Article	1	3

3.2. Content Analysis of the Papers Relevant to the Research

After the identification of the relevant publications, we conducted a descriptive and content analysis to ascertain the characteristics of the selected papers. We used frequency counts to provide an overview of year of publication as well as the distributions of the selected papers. The barriers were identified from the 40 publications that were relevant to the study. While some of the papers clearly specified some of the barriers in tables as well as charts, others needed thorough analysis of the contents to determine the barriers. The study followed the four-step approach to conducting content analysis as indicated by Zhang et al. [87]. Drisko and Maschi [88] mentioned that content analysis involves a systematic as well as structured method of combining several textual contents into smaller classifications related to the content on the basis of rules that are explicit to the coding system. This approach aided in the analysis of the barriers to the adoption of DT in the CI. Further, Assarroudi et al. [89] stated that content analysis involves three essential processes of data preparation, organisation, and reporting. The authors also mentioned notwithstanding the three processes, there are no rules regarding the methodology for analysing the data in a content analysis.

However, the four steps as indicated by Zhang, Oo, and Lim [87] include de-contextualisation, re-contextualisation, categorisation and compilation, and consistency assessment. The authors mentioned that de-contextualisation comprises the identification of the unit of analysis as well as inferring meanings from the data. In this scenario, the unit of analysis would be themes that are developed from the data instead of using word and sentences. The themes are then presented using codes that are developed from a set of criteria that had already been established. The study, therefore, developed a preliminary code that was standardised as the approach to de-contextualise the text. In addition, the authors stated that re-contextualisation involves coding openly through condensing the inferences from the unit of analysis of the themes. The homogeneity between the major themes determines the coding process. For instance, statements that relate to the data flow and management in digital twins are coded as technology-related barriers.

Subsequently, the next stage is the sub-themes categorisation and compilation. The process comprises abstracting as well as defining the themes on the basis of the content-characteristic words. In this phase, sub-themes that are related or unrelated are combined to form larger sub-themes. The final stage, which is the assessment of consistency, has to do with determining the credibility of the entire process. This can be done by comparing a number of judgements to ascertain the reliability of the process. This also ensures that subjective judgements together with the likelihoods of dissimilarities in judgements among several authors are eliminated. The codebook developed for this study included the identification of the year of publication of the paper, the authors of the paper, the title of the paper, and the conference proceedings or journal in which the study had been published. In addition, the country in which the study was conducted was also noted. Furthermore, the researchers identified the barriers to the adoption of DT in the CI, key findings, and the contributions that were explicitly stated in the papers. A further categorisation of the identified barriers was carried out and presented in Section 6.1.

4. Bibliometric Indicators of Publications

A number of data visualisation and analysis software and tools including VOSviewer, CitNetExplorer, Gephi, CiteSpace, VantagePoint, and BibExcel have been utilised in bibliometric analysis [2,84]. The VOSviewer software is identified as a very versatile bibliometric data analysis and visualisation tool. Further, Aria and Cuccurullo [90] stated that VOSviewer is capable of producing, visualising and using bibliometric networks. This study, therefore, utilised the VOSviewer software version 1.6.18 to provide an outlook on the co-occurrence network of keywords and collaboration networks among institutions and countries advancing the adoption of DTs in the CI research.

4.1. Co-Occurrence Network of Keywords of DT in Construction Industry Research

The theme for a specific research study is reflected by the keywords. The keywords aid in indexing the article for easy identification. According to Wuni et al. [91], all keywords are mapped to assist in providing a clearer understanding of the knowledge in a particular field of study. Zhao, Zuo, Wu, and Huang [44] also indicated that a network of keywords gives a positive representation of the knowledge area as well as the scholarly relationships that exist amongst them. In addition, the strength of the association between two keywords in a keyword co-occurrence network is dependent on the number of papers in which the keywords occur together [92]. The VOSviewer software tool was utilised in producing the keywords co-occurrence network. To be able to achieve an image of the keyword that is very readable during the generation of the keyword co-occurrence network, the author keywords were used as an alternative to all keywords input of the software.

Several science-mapping studies [93–95] have widely used this approach. However, it is worthy to mention that it has a limitation of being heavily dependent on the author's level of knowledge and experience in determining the relevant keywords. To address this limitation, this study tried using all keywords instead of author keyword input of the software, and this resulted in an unreadable and unrealistic network of keywords due to the large number of keywords. Further, fractional counting was used in the counting method, and this resulted in 561 keywords being extracted from the dataset. Van Eck and Waltman [92] mentioned that selecting fractional counting ensures that papers that were highly cited perform a less significant role in the development of the bibliographic coupling network as well as minimising the impact of publications that have several authors. To be able to arrive at a network that is optimum, the "minimum number of occurrences" of a keyword for it to be added in the network was set to 2. This resulted in 73 out of 561 keywords meeting the threshold. This criterion was achieved after several experimentations to produce an optimal, reproducible, and legible network. Other previous studies [91,93,96] have utilised the same criterion in developing the networks. A similar approach of experimentation was used for creating the remaining network diagrams in this study.

Further, terms that were identical, for example, digital twin, digital twin (dt), and digital twins; BIM, Building Information Modeling, and Building Information Modelling; Internet of Things and IoT; and cyber-physical system and cyber-physical systems were merged as digital twin, BIM, IoT, and cyber-physical systems, respectively. In addition, the study omitted generic keywords such as survey and case study. The resulting network comprised 65 nodes as well as 237 links. The resultant network is displayed in Figure 2. Furthermore, relying on the total occurrences together with the total strength of the links between the keywords, the top 20 keywords that are frequently used are presented in Table 4.

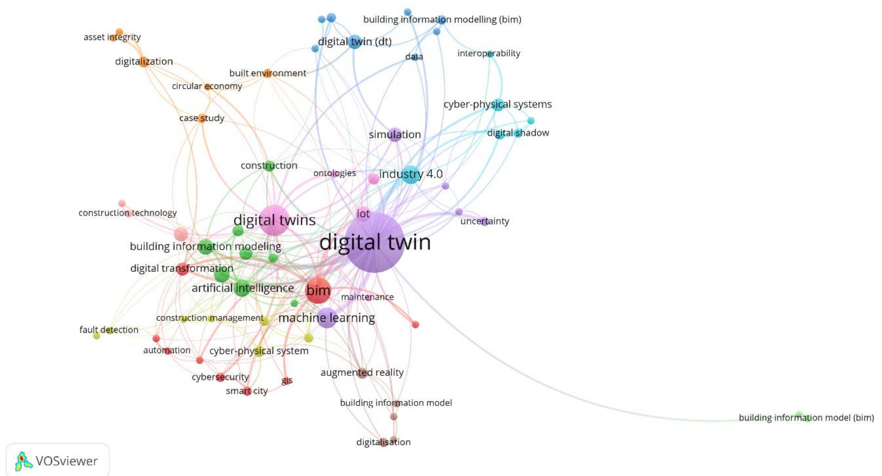

Figure 2. Keywords co-occurrence network of DTs in construction industry research.

Table 4. Most active keywords in digital twin research.

Keyword	Occurrences	Total Link Strength
Digital twin	89	67.00
BIM	35	28.00
Industry 4.0	9	9.00
Internet of Things	12	12.00
Artificial intelligence	8	7.00
Machine learning	11	7.00
Facility management	7	7.00
Cyber-physical systems	9	9.00
Digital transformation	5	5.00
Augmented reality	4	4.00
Digitalisation	4	4.00
Infrastructure	4	4.00
Simulation	6	4.00
Built environment	3	3.00
Construction	4	3.00
Digital shadow	3	3.00
Monitoring	3	3.00
Virtual reality	3	3.00
Fault detection	2	2.00
Construction 4.0	2	2.00

4.2. Scientific Collaboration Networks in DTs in Construction Industry Research

To be able to promote access to funding opportunities, expertise, and expansion of productivity, it is very vital to have an idea of the scientific collaborations among researchers within a specific domain. The scientific collaboration between researchers can always be determined using the co-authorship networks [97]. Further, Hosseini et al. [98] noted that the lack of collaboration among researchers results in lower research productivity across specific domains. On the basis of the aforementioned relevance of scientific collaborations, this current study presents the analysis of the co-authorship networks of institutions and countries in the following sub-sections.

4.2.1. Collaboration Network of Institutions

Collaboration among institutions with very high investment in research is very important in developing policies and partnerships [99]. Institutional collaborations become a critical factor once we are looking to embrace DT in the CI. In creating the network of collaborations between the institutions, "co-authorship" was selected for the analysis type, whilst "organisations" was chosen for the unit of analysis. In terms of the counting method, "fractional counting" was also chosen instead of full counting. The "minimum number of documents of an organisation" as well as the "minimum number of citations of an organisation" were set to 1 and 2, respectively, in order to aid in achieving an optimal, legible, and reproducible network. The resultant network comprised 171 out of 377 organisations identified met the threshold. These organisations were therefore used in generating the resultant network. However, the network had 6 nodes and 15 links between institutions collaborating on DT in the CI.

There is only a limited number of cross-institutional collaborations in DT research in the CI reported in literature from countries such as Australia, the UK, Algeria, and Greece (see Figure 3). Nevertheless, the majority of these collaborative relationships presently possess minimal strength as visualised in the thickness of the lines that connect the various institutions. There is a need to build stronger institutional networks to foster higher standards of scholarships and deliberation on the adoption of DT in the CI [94]. It is noteworthy to mention the addition of Australia's national research agency, CSIRO's Data61, and Cyber security CRC in the network since they represent a classical illustration of purely research-based institutes and agencies contributing to the advancement of the adoption of DT in the CI.

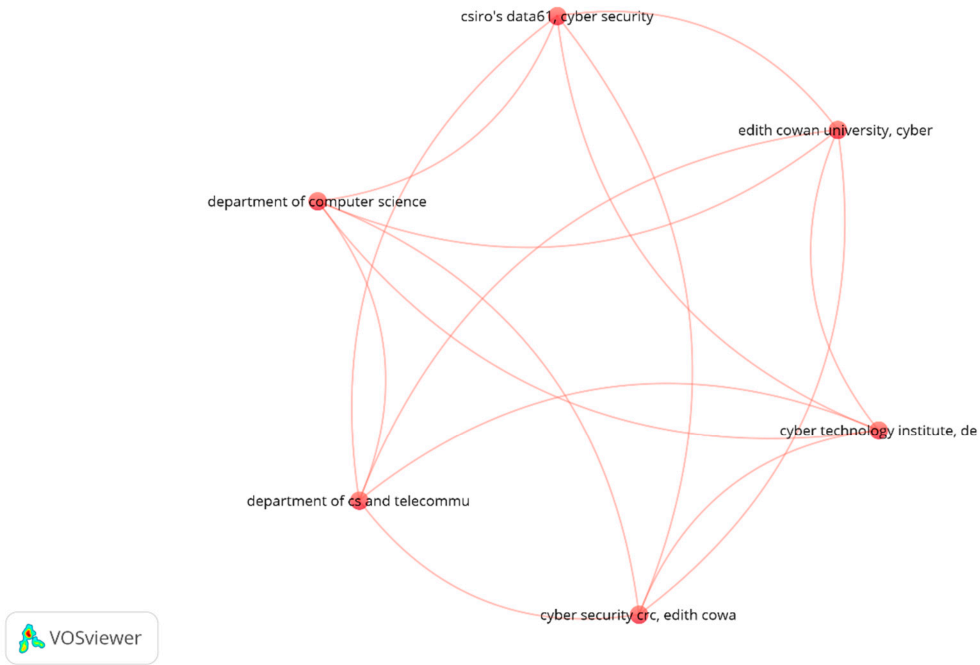

Figure 3. Cross-institutional collaborations in DT research in the CI.

4.2.2. Collaboration Networks of Countries

The scientific collaboration network of countries aids in ascertaining the countries which are advancing research in a particular field [2,93]. It must be noted that some countries contribute to a specific research area more than others due to several existing factors. Notwithstanding, the knowledge of countries who are actively embracing DT in the CI research has the potential of fostering collaboration, promoting technology transfer, and enhancing joint research funding programmes. Figure 4 indicates international collaborations in DT research in the CI between various countries. In the figure generation process, the "co-authorship" was selected for the analysis type, "countries" was selected for the unit of analysis, and "fractional counting" was selected for the counting method. The "minimum number of documents of a country" and the "minimum number of citations of a country" were both set to 3 to ensure the generation of an optimal, legible, and reproducible [93]. Fifteen out of the fifty countries that were determined met the threshold. These 15 countries were then added to the resulting network. The size of a node (country) in the figure depicts the contribution of a country to the DT adoption in the CI research discourse. For instance, bigger nodes represent the United Kingdom, United States, China, and Germany. In addition, the study identified seven clusters of the most active countries in DT adoption in the construction industry. The United Kingdom, the United States, the United Arab Emirates, and France belong to one cluster and are represented by the red colour. Green, blue, yellow, and purple colours represent the remaining clusters. It must be noted that the adoption of DT in the CI is highly seen among developed countries. This is not surprising since most developing countries are now embracing contemporary and advanced technologies in various parts of their economies such as in the construction industry. The variation in publications among the active countries in DTs in construction industry research is presented in Table 5.

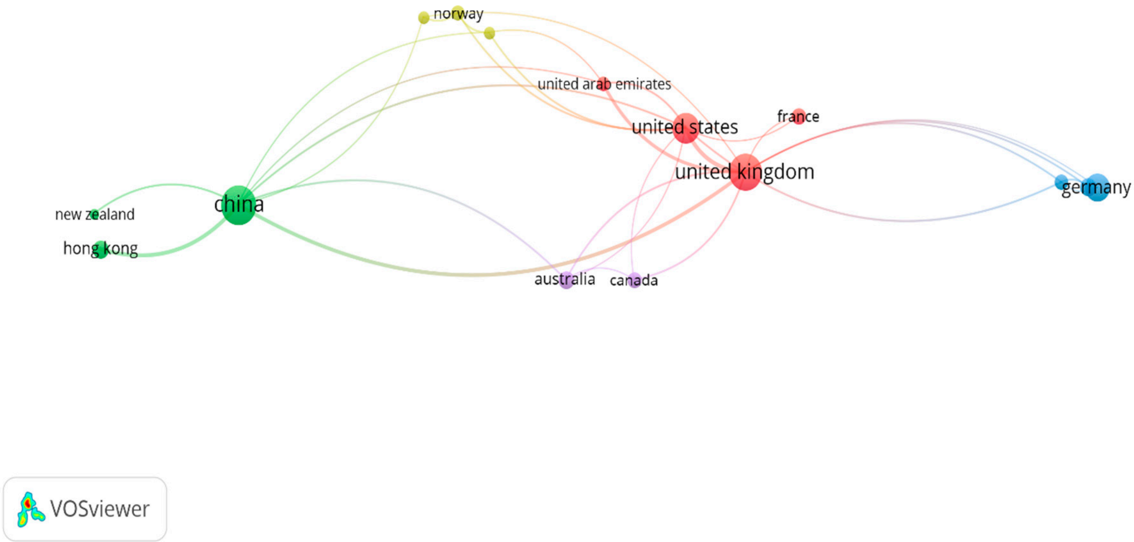

Figure 4. International collaborations in DT research in the CI.

Table 5. Variation in publications among active countries in DTs in construction industry research.

Country	Papers	Citations	Total Link Strength
United Kingdom	33	453	16.00
China	39	269	12.00
United States	23	402	11.00
United Arab Emirates	5	9	5.00
Hong Kong	8	77	4.00
Denmark	6	13	3.00
Australia	8	130	3.00
Norway	6	298	3.00
Portugal	4	7	3.00
Canada	7	36	2.00
Sweden	4	28	2.00
Italy	8	36	2.00
France	7	27	1.00
Germany	19	40	1.00
New Zealand	3	18	1.00

5. Systematic Review of Barriers to the Adoption of DT in the CI

Status of Publications Relevant to Barriers to the Adoption of DTs in the CI

The yearly publications within a specific research field indicate the degree of attention from both researchers and industry practitioners gained in that field. From Figure 5, the first relevant paper geared toward assessing the hindering factors on the adoption of digital twins in the CI was in 2019. As earlier indicated by Opoku, Perera, Osei-Kyei, and Rashidi [2] that the actual utilisation of DT within the CI was slow until 2018, it is not surprising that a relevant study focusing on the barriers to the adoption of DT in the CI was in a later year, as revealed in this study. Further, it is also reasonable since the DT concept in industries that are more technologically inclined, for instance, the manufacturing industry, had the technology in its development stage, and it was slowly being conceptualised in other industries such as the CI [25]. Since then, there was a gradual increase in the number of studies that were relevant from one paper in 2019 to five papers in 2020. This finding supports the results of Opoku, Perera, Osei-Kyei, and Rashidi [2] that revealed that, in 2020, researchers had started exploring the real utilisation of the DT concept in the CI, which move it from the conceptualisation to an infancy stage. Notwithstanding the COVID-19 global pandemic that disrupted the activities in both research and industry, the number of relevant annual publications increased progressively, resulting in 19 papers published in

2021. The year (2021) is also seen as the peak year for publications that were relevant to the barriers affecting the adoption of DT in the CI (see Figure 5). The increased attention in the application of DT in the CI is noticeable in this study, where 15 papers have already been published as of August 2022. The incredible upsurge in the number of pertinent papers has shown that researchers together with industry practitioners have acknowledged the abilities of DT in providing solutions to majority of the challenges encountered in the CI [65].

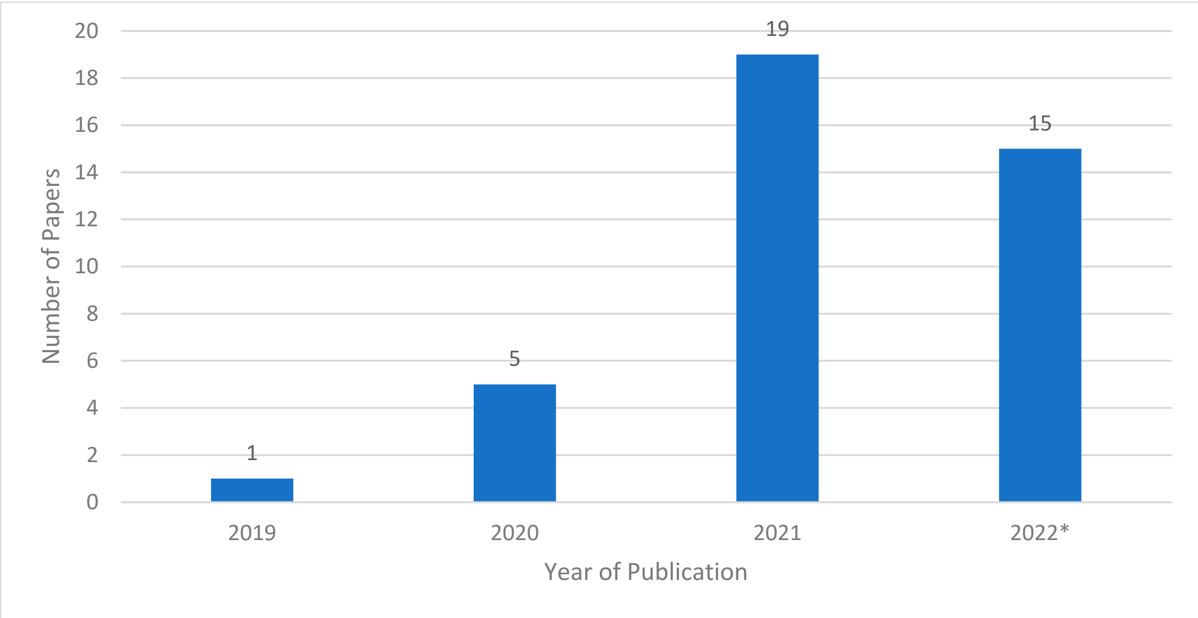

Figure 5. Annual trend of relevant papers published from 2019 to 2022. * On-going publications.

Further, the authors deemed it necessary to consider the impact factors of the journals whose papers were used in the study. The impact factor of a journal assesses the relative importance of the journal within a specific field of study and measures the frequency with which the journal's "average article" has been cited in a particular time period. Thus, the authors resorted to the Journal Impact Factor (JIF) Quartile ranking for each journal as presented by Clarivate Analytics' Web of Science database. Figure 6 establishes the distributions of the 40 papers according to their journal rank by JIF quartile. It also presents the number of journals and papers belonging to each JIF quartile. From Figure 6, it can be seen that the majority of the journals (10 journals) whose papers were used in this review are ranked Q1. It is also important to mention that more than half (52.5%) of the papers used in this review are Q1 journal papers. This result enhances the credibility of this study since most of the papers used in the study are from journals that are highly valued due to their wide scope of recognition and great impact on the construction industry.

Finally, this study also classified the papers on the basis of the project and building types for which DTs have been used in the CI. Figure 7 reveals that a larger number of the applications of DT in the CI have been conducted in building projects with a few in civil infrastructure projects. Further, in terms of building type, industrial buildings have seen the majority of DT applications with minimal applications in educational buildings. However, university campuses and schools have highly dynamic environments and present excellent opportunities for the active participation of researchers in developing digital technologies such as DTs, IoT, and the like [100,101]. Notwithstanding, smart campus deployment of some of these technologies has been mainly conducted in lab-based environments with limited real-life user engagement [102].

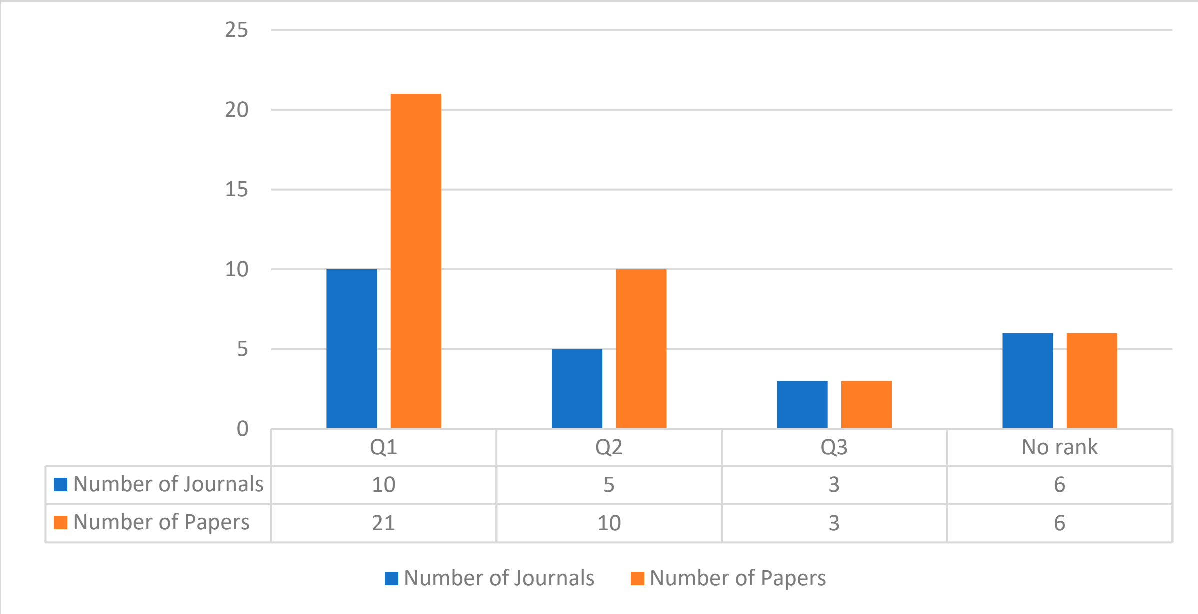

Figure 6. Categorisation of papers using ranking by Journal Impact Factor (JIF) Quartile.

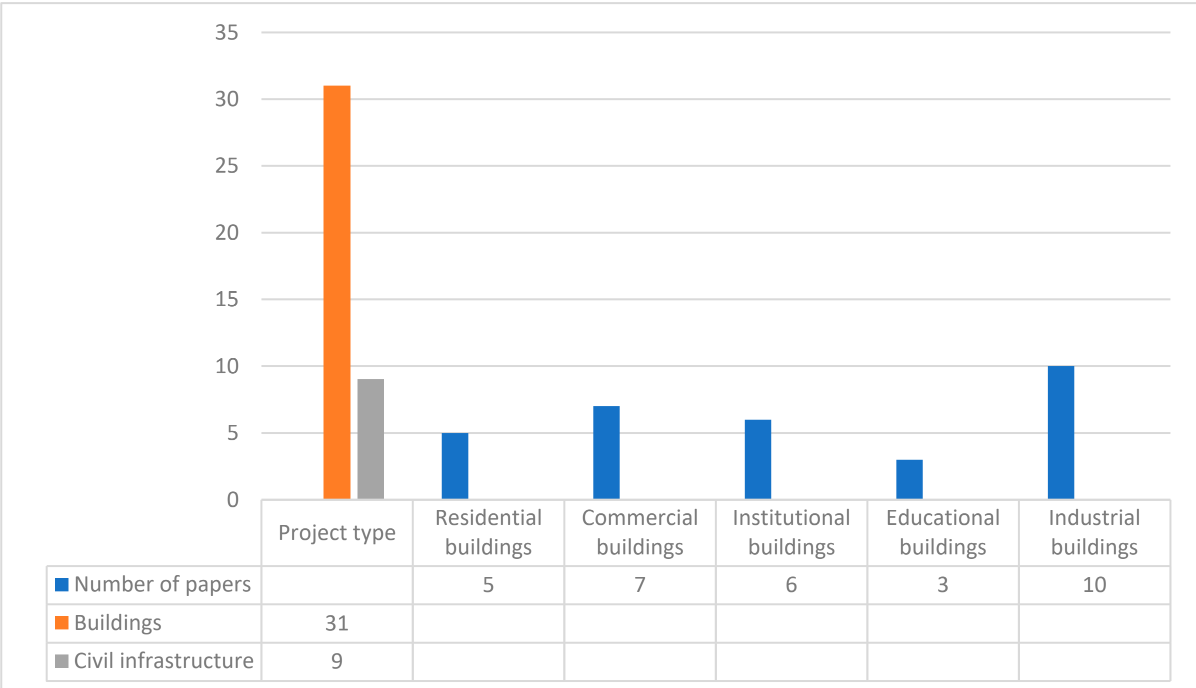

Figure 7. Categorisation of papers according to project and building types.

6. Barriers to the Adoption of DT in the CI

After carrying out the four-stage methodology, a total of 30 barriers to the adoption of DT in the CI were discovered (see Table 6). These 30 barriers are therefore presented and ranked according to the number of times a barrier is mentioned in the analysed papers. Though this number seems to be the same for the majority of the barriers to the adoption of DT in the CI that were mentioned, a few outstanding exemptions were determined. More explicitly, other researchers within the construction industry have mentioned a significant number of times the challenges of low levels of knowledge, low levels of technology acceptance, lack of clear DT value propositions, project complexities, and the static nature of building data. Further, Table 6 also shows the aggregated papers that relate to the various sub-themes. All the recognised barriers to the adoption of DT in the CI are presented in detail in this study. It is worth mentioning that a few of the identified barriers are based on practical evidence, whilst most of these barriers are the expectations of researchers in their studies.

Table 6. Barriers to the adoption of DT in the CI.

Code	Barriers	References	Sum	Rank
b1	Low level of knowledge	[2,7,55,56,61,67,70,71,77,79]	10	1st
b2	Low level of technology acceptance	[2,49,53,54,61,69,74]	7	2nd
b3	Lack of clear DT value propositions	[2,7,55,61,62,67,85]	7	2nd
b4	Project complexities	[50,53,59–61,67,76]	7	2nd
b5	Static nature of building data	[1,2,49,72,78,83]	6	3rd
b6	Lack of competence	[54,55,57,61,67]	5	4th
b7	Investment difficulties	[2,51,61,64,67]	5	4th
b8	Fragmented empirical DT evidence	[2,54,62,75]	4	5th
b9	Lack of trust in data security	[54,57,58,66]	4	5th
b10	Several applicable designs	[65,68,76,81]	4	5th
b11	Diversity in source systems and interoperability	[1,57,65,76]	4	5th
b12	Need for constant internet connectivity	[2,7,61,67]	4	5th
b13	Scalability issues	[61,67,82]	3	6th
b14	Lack of government incentives	[61,67,69]	3	6th
b15	Fragmented composition of workforce data	[58,84]	2	7th
b16	Large numbers of building codes	[65,68]	2	7th
b17	Difficulties in systems integration	[54,67]	2	7th
b18	Uncertainties with data quality and reliability	[63,85]	2	7th
b19	Fragmentation in data management	[58,67]	2	7th
b20	Limited enabling technologies	[2,62]	2	7th
b21	Lack of standard tools and methodologies	[57,68]	2	7th
b22	Difficulties in data storage, processing, and analysis	[62,67]	2	7th
b23	Professional disconnection	[67,84]	2	7th
b24	Inconsistencies in project data	[65,67]	2	7th
b25	Legal and ethical issues	[83]	1	8th
b26	Software selection difficulties	[62]	1	8th
b27	Difficulties in setting realistic expectations	[61]	1	8th
b28	System instability and sudden failure	[52]	1	8th
b29	Issues of maintainability	[73]	1	8th
b30	Multicultural project challenges	[67]	1	8th

6.1. Classification of the Barriers to DT Adoption in the CI

Table 7 shows the 30 barriers to the adoption of DT in the CI. These barriers are organised into four different categories, namely, stakeholder-oriented barriers, industry-related barriers, construction-enterprise-related barriers, and technology-related barriers. The categorisation of the identified barriers was to improve the understanding of, clarify, and simplify the barriers established in the literature. The research followed a similar categorisation technique as used by Ghobadi [103] and Chan et al. [104]. The categorisation is grounded in four robust codified logic. For instance, Chan, Tetteh, and Nani [104] adopted this technique to establish a conceptual framework to guiding, determining, and assessing international construction joint ventures' success. Ghobadi [103] also utilised the same technique for developing a framework for categorising the drivers for sharing software teams' knowledge using the organisation's viewpoint of change. Opoku, Perera, Osei-Kyei, Rashidi, Famakinwa, and Bamdad [7] also adopted this classification technique to identify the drivers for utilising DT in the CI. The interrelationships as well as the correlations between the identified factors are identified through a logical coding and comparison between the outcomes to ensure consistency within the classification factors. Further, a connection is then established between categorisations of the current outcomes and previous studies. Finally, the classifications of the factors are validated through focus group discussions. This research used six academics who possess comprehensive insights into the implementation of DT technology in the CI to complete the classification of the barriers. This activity further enhanced the credibility of the categorisation process. The four main categories together with their associated barriers are therefore presented in Table 7. For instance, a low level of technology acceptance, project complexities, and the static nature of building data form the industry-related barriers to the adoption of DT in the CI. The categories of barriers are therefore presented and discussed in detail in the subsequent sections. Further, a conceptual framework for the categorisation of the barriers to the adoption of DT in the CI has been presented in Figure 8.

Table 7. Classification of DT adoption in the CI barriers.

Category	Barriers
Stakeholder-oriented barriers	Low level of knowledge Lack of clear DT value propositions Lack of competence Professional disconnection Difficulties in setting realistic expectations Issues of maintainability
Industry-related barriers	Low level technology acceptance Project complexities Static nature of building data
Construction-enterprise-related barriers	Investment difficulties Lack of government incentives Legal and ethical issues
Technology-related barriers	Lack of trust in data security Diversity in source systems and interoperability Need for constant internet connectivity Scalability issues Difficulties in systems integration Uncertainties with data quality and reliability Fragmentation in data management Limited enabling technologies Lack of standard tools and methodologies Difficulties in data storage, processing, and analysis Software selection difficulties System instability and sudden failure

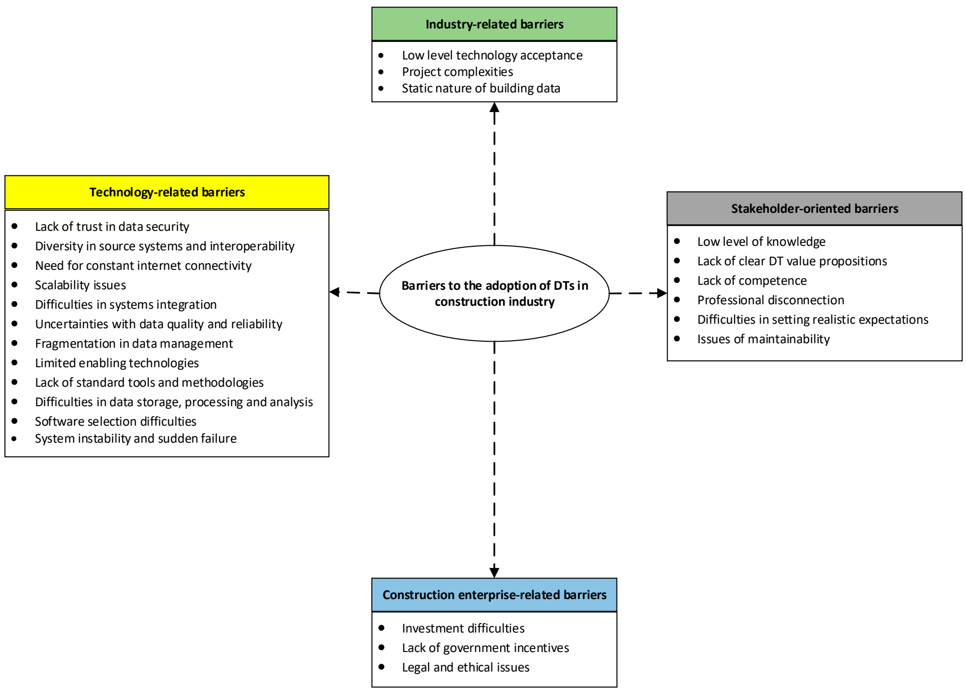

Figure 8. A conceptual framework for the categorisation of the key barriers to the adoption of DT in the CI.

6.1.1. Stakeholder-Oriented Barriers

The effectiveness of the adoption and application of any technology within the CI is highly reliant on the stakeholders of the industry. Thus, the stakeholders of the industry must fully accept the industrial implementation of DT. For this to be possible, there must be an unambiguous understanding of the digital twin concept by stakeholders to enhance its implementation. This ambiguity with the digital twin concept has been recognised by several researchers [2–4] within the CI. There are also divergent views among stakeholders and industry professionals regarding the prowess of DT in the design and construction of buildings as well as infrastructure projects [3].

From the stakeholders' perspective, a low level of knowledge, a lack of clear DT value propositions, a lack of competence, professional disconnection, difficulties in setting realistic expectations, and issues of maintainability of contemporary technologies affect the adoption of DT in the CI [55,56,61,73]. One key reason for this category of barriers is the affectation of some construction stakeholders regarding the concept of digital twins. There is so much discussion on digital twins without a clear-cut understanding of DT technology and its potential within the construction industry. For instance, most industry practitioners and researchers have misconceptions regarding digital twins, whilst others liken it to BIM due to their similarities [4]. There is therefore no consensus built regarding the abilities of digital twins within the industry. Some researchers merely integrate IoT data with BIM models to represent a DT without a bidirectional communication between the physical and the virtual entities. This confirms the low level of knowledge concerning the DT concept within the CI. Furthermore, several individuals and stakeholders have delusions about the potential of advanced technologies such as digital twins, BIM, blockchain, and the like in addressing problems of the CI, and this has caused their neglect and lack of knowledge, together with the understanding of these technologies [105,106]. Thus, these idiosyncrasies of construction stakeholders significantly affect the industry's competencies regarding the application of digital technologies such as digital twins and the like. In addition, due to the novelty of the DT concept and technology within the construction industry, there are issues regarding the value propositions of the technology [7,62,85]. Additionally, the professional disconnection and fragmentation also prevent the smooth adoption of emerging digital technologies such as digital twins in the construction industry.

6.1.2. Industry-Related Barriers

This category of barriers is related to the construction industry itself. A clearer understanding of the concept and technology of DT can drive its implementation in the CI. However, a lack of knowledge as well as understanding of emerging technology has the potential to provide resistance to its acceptance and adoption [53,69,74]. This is a significant reason why the CI is viewed and identified among the industries that were least digitalised as well as sluggish to innovation, specifically in the utilisation of digital technologies [107,108]. The nature of the CI regarding the complexities of projects significantly affects the adoption of some of these emerging technologies. The industry is composed of several fragmented trades and components, which oppose the delivery of a holistic approach to data integration necessary for the implementation of digital technologies such as digital twins.

In addition, the fragmentation in supply chains is another challenge that is worth mentioning. These complexities of projects and fragmentation of the industry present a significant challenge to the smooth adoption of DT in the CI. Further, the static nature of building data also serves as a key challenge to implementing digital twins. Unlike BIM, which works with static data and provides a representation of the design of the structure or building to be built with the aim of understanding together with the communication of the design, DT require real-time data to present the status as well as the character of the building or structure it reflects [7]. As demonstrated by Antonino, Nicola, Claudio, Luciano, and Fulvio [72], it is imperative to have real-time dynamic data for the creation of a digital twin. This can significantly improve and optimise maintenance during the facilities management phase of a building project. In addition, the authors indicated the need to automate the updating process of their digital model. This is an important feature once there is a consideration for a digital twin. Further, they established the value of accessing real-time data for creating digital twins for enhancing value for building management. The construction industry needs a dramatic change to enable the utilisation of complex real-time data sensing as well as analysis to enhance the smooth implementation of digital twins [67].

6.1.3. Construction-Enterprise-Related Barriers

The third set of barriers under consideration arises from the construction enterprise itself. Individual organisations are confronted with several challenges that prevent the smooth adoption of digital twins in their operations. Further, these organisations' adoption of digital twins would inevitably impose higher financial obligations. As indicated by West and Blackburn [109], considerations regarding cost are key when deciding to implement DT to dissimilar construction project types. Thus, organisations would need to be mindful since digital twins require higher initial investments when utilised in a project [110]. This study identified that investment difficulties, lack of government initiatives, and legal and ethical issues may hinder the smooth adoption of digital twins by construction enterprises [51,61,67,69,83]. For instance, Greif, Stein, and Flath [61] pointed out the hard economic difficulties that arise from the utilisation of DT and the need for construction enterprises to align infrastructure investments towards their application.

Notwithstanding, an issue may arise where individual enterprises may not be sure of the specific aspects or stages of their projects that receive more investments to harness the maximum potential of digital twins. There is also a lack of governmental support for DT utilisation in the CI. To promote the adoption of DT in the CI, various governments could provide initiatives and policies to propel their adoption due to the numerous potential benefits that come with the applications of the technology. It is worth noting that only a few governments have integrated DT technology into their construction industries. For example, the UK is implementing the National Digital Twin Programme (NDTp) through the Centre for Digital Built Britain (CDBB) to ascertain high-quality and data security to enhance the building, management, operation, and decommissioning of infrastructure projects [111]. Moreover, in Australia, a combined centralised source of data for enhancing the operation and maintenance of the Sydney Opera House was designed by the restoration team using some digital twin concepts [112]. In addition, as stated earlier regarding data in digital twins, legal and ethical issues relating to data breaches in organisations hinder the smooth adoption of digital twins and other technologies such as BIM in the construction industry [105].

6.1.4. Technology-Related Barriers

The final category of barriers to the adoption of DT in the CI is technology-related barriers. This category includes difficulties in systems integration; lack of trust in data security; diversity in source systems and interoperability; scalability issues; fragmentation in data management; software selection difficulties; lack of standard tools and methodologies; uncertainties with data quality and reliability; difficulties in data storage, processing, and analysis; need for constant internet connectivity; limited enabling technologies; and system instability and sudden failure [54,61,65]. As indicated in earlier studies [107,108], the construction industry is engulfed in several challenges regarding its use of technology. The challenges prevent the smooth implementation of DT in the industry. One key challenge with the adoption of technologies such as DT in the CI is the difficulties with systems integration. This relates to the transition from an outdated and old legacy system and equipment as well as technology to a new state-of-the-art technology, e.g., from BIM to digital twins. This challenge also includes integrating different technologies. In addition, issues regarding data security in the application of digital twins are a great challenge. These include risks associated with data acquisition, storage, processing, exchange, and protection of intellectual property. Since digital twins operate by connecting the physical and the digital model using large volumes of data, data become a significant component in a digital twin [113]. For this reason, industry practitioners and players are highly concerned about the security and trustworthiness of data in digital twins.

Furthermore, there are also issues with scalability and the fact that there has to be constant internet connectivity for the operation of digital twins [67,82]. This presents a significant challenge to their utilisation in the CI. There are also limitations in the hardware and software that ensures effective bidirectional data transfer and communication between the physical and digital entities. This hinders the possibility of achieving the full potential of DT technology within the CI. A unique characteristic of DT is its capability of mirroring and presenting the status and character of the physical entity, which is the existing building or structure in real time. However, ensuring efficient and proactive streaming of data from the physical entity to the digital twin has always been a challenge [84]. Furthermore, the processing of the massive data generated in real-time communication also presents a significant challenge in adopting digital twins [114]. Another important issue that is worth mentioning is the access to quality data to validate the authenticity, accuracy, and reliability of the digital twin and this affects its implementation [63,85].

7. Conclusions

DT presents the opportunity to develop digital models, which can be continually updated using several data sources to predict the current and future states of physical assets. It is providing a vital role in addressing the challenges confronting several industries including construction. Thus, in recent times, DT has received enormous recognition among researchers and industry practitioners to aid in addressing the problems confronting the CI. This research identified the key barriers to the adoption of DT in the CI by systematically reviewing 40 journals as well as conference papers. The paper also presented a scientometric analysis assessing the state of the art of studies on DT in the CI. The results indicate researchers are increasingly becoming interested in applying DT in the CI. It was also revealed that the United Kingdom, the United States, China, and Germany have the utmost number of scholars advancing studies into the adoption of DT in the CI. The findings also indicate that only a limited number of institutions from Australia, the United Kingdom, Algeria, and Greece have developed collaborative relationships in DT in the CI research. Further, the extensive content analysis led to the determination of 30 barriers to adopting DT in the CI. The top five barriers discovered include low level of knowledge, low level of technology acceptance, lack of clear DT value propositions, project complexities, and the static nature of building data. The 30 barriers were also extracted, classified, and integrated into a framework of four key categories. The categories were stakeholder-oriented barriers, industry-related barriers, construction-enterprise-related barriers, and technology-related barriers. A comprehensive analysis of these classifications was included in this paper.

7.1. Suggestions for Practice and Further Research

Practically, this study provides a readily available point of reference that presents the state of the art of investigation on DT adoption in the CI. Further, the developed framework can also serve as an industry-specific lens for identifying the barriers that prevent the smooth adoption of DT in the CI. Thus, the outcomes from this study can aid stakeholders to adequately strategise to overcome these barriers. In addition, this study will broaden the knowledge base on the application of DT and its associated barriers, which is essential for the successful utilisation of DT in the CI. In facilitating the unrelenting investigation into the inventive capabilities of DT in addressing the challenges of the CI, the findings suggest fertile grounds for carrying out further empirical investigations into the benefits of DT to the CI. This would inform decision making concerning the industrial implementation of DT. In addition, future research is recommended to be carried out using case studies to empirically test the identified barriers since most of them are grounded in the views of the researchers whose studies have been used in this research.

7.2. Research Limitations including Ways of Addressing Them in Future Studies

Although this research has significant contributions, there are some limitations that are worth mentioning. The researchers acknowledge that only three databases, namely, ScienceDirect, Scopus, and Web of Science were used for the search and, thus, other pertinent studies concerning the barriers to adoption of DT in the CI could have been missing. Therefore, the outcomes might not completely mirror the whole available literature on barriers to the adoption of DT in the CI. Although the relevant literature was carefully selected, not all keywords may have been taken care of in the search for literature. Notwithstanding, there is enough justification since it is not practically possible to reflect all studies associated with the barriers to the implementation of DT in the CI in a single review paper.

Finally, we also admit that the selection of pertinent publications as well as the discovering and classification of the barriers might have been influenced by subjective judgements. The aforementioned shortfalls, therefore, present possible avenues for future studies and should be taken into consideration when making an inference to the research outcomes. Notwithstanding, this research is revolutionary as it is the first to identify and present a categorised set of barriers to the adoption of DT in the CI.

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