Review

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# Exploring Digital Twins Applications for Asset Management in the AEC/FM Industry

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*Review*

# Exploring Digital Twins Applications for Asset Management in the AEC/FM Industry

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**Abstract:** The emergence of digital twins (DTs) represents a recent advancement in technological processes that support the planning, construction, and oversight of constructed assets. A DT is essentially a digital model that facilitates simulations and two-way information exchange with its real-world counterpart (a physical twin), creating opportunities for data-driven decision-making. Despite the promising prospects of DTs, both the technology and the methodologies for developing them, as well as their potential applications, remain not fully understood in both academic and industrial contexts. This research explores the applications of DTs for the management of existing assets within the AEC/FM industry. The study presents the results of a comprehensive literature review that explores existing knowledge in this domain. The findings reveal that procedures for creating DTs are still in their early stages, emphasizing potential applications in asset management throughout their lifespan, facilitating sustainability upgrades, and supporting the maintenance and restoration of heritage assets. The review concludes by providing recommendations for future research in this evolving field.

**Keywords:** architecture; engineering and construction (AEC); asset management; digital twin; facility management; review

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## 1. Introduction

Over the past decade, the rapid pace of technological evolution alongside digitalization has led to a tremendous shift in several sectors such as healthcare, education, and construction [1–3]. Digitalization can be defined as the adoption of advanced information technologies to enable automated, efficient, and effective business practices [4]. Evolving technologies such as artificial intelligence (AI), the "Internet of Things" (IoT), blockchain, and data analytics have facilitated the transition towards digitalization.

The construction and architectural industries are also sectors that have benefited from digitalization [5]. The technological revolution allows architects to showcase distinctive architectural forms while achieving sustainability, reducing energy, water, and raw material consumption [6], and providing a better use experience [7]. As a result, many technologies and terms have emerged, such as Building Information Modelling (BIM), cloud computing, big data, smart cities, machine learning, artificial intelligence, block-chain technology, and industry 4.0, which are contributing towards digitalization of the AEC/FM industry. The latest technology added to this list is the "digital twin" (DT) which is gaining research and industry attention, for its claimed potential in managing construction as well as the operational phase of built assets.

A DT is essentially a digital model that conducts simulations and facilitates bi-directional information exchange with a tangible counterpart in the physical world (referred to as a physical twin). This linkage presents opportunities for decision-making centered around data. DTs find diverse applications within the asset management realm, particularly in architecture, engineering, and construction/facilities management (AEC/FM). For instance, a twin of a constructed asset can be designed to illustrate the functioning of its systems, establishing a corresponding data connection to capture operational data and mirror real-time information in the digital world. Despite the potential advantages, both the technology and the processes involved in creating digital twins, along with their potential applications, remain incompletely understood within academia and industries. This paper

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aims to analyze current trends in the use of DTs and in particular focus on DT applications in the asset management of built environment projects.

A systematic literature review of DT applications in the AEC/FM industry is provided. A bibliometric analysis of the retrieved articles highlights this area's interest and research trends. In addition, we categorize articles into five different categories based on their focus areas, including DTs in general, creation of DTs, application of DTs for heritage restoration, DTs for asset management, and DTs for sustainability.

The rest of this paper is organized as follows. Section 2 presents a background and overview of the DT concept. The methodology adopted in this review is described in Section 3. The bibliometric analysis of the extracted studies is presented in Section 4, and Section 5 details our categorization of DT applications in the AEC/FM industry. In Section 6, we discuss some open challenges hindering the implementation of DT in the AEC/FM industry. Finally, the paper concludes with a discussion of future research directions in Section 7.

## 2. Background

The AEC industry has witnessed a continuous drive towards digitalization since the early 1980s, starting with the emergence of computer-aided design (CAD) and electronic digital communication with the introduction of the Internet and email [8]. These developments reshaped the industry's workflow by providing novel tools and methods that facilitate the exchange of information.

As illustrated in Figure 1, the digital revolution that was initiated in the late eighties and furthered in the nineties, brought about a shift from manual to CAD-based drawing production. This transition resulted in enhanced speed and accuracy in engineering drawing processes and opened up opportunities for improved collaboration [9]. Consequently, computing and automation began incorporating design within virtual environments. Subsequent advancements in the new millennium enabled the progression from two-dimensional (2D) to three-dimensional (3D) CAD representations, accompanied by the introduction of building information modeling [10], IoT [11], and, more recently, the DT concept [12]. These developments permitted the digital representation of buildings and the establishment of databases and digital warehouses.

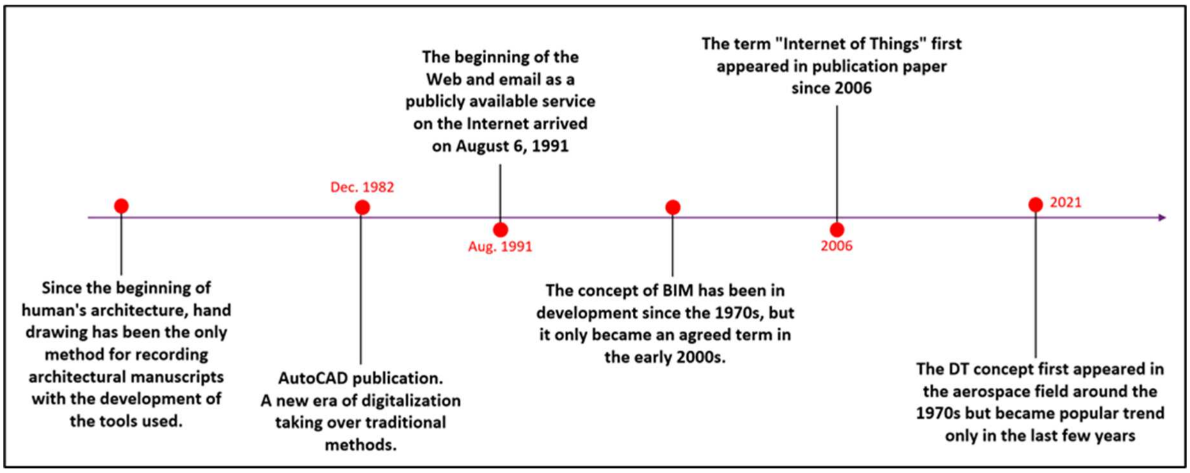


**Figure 1.** Evolution of digital twins.

### *2.1. Digital Twins – An Overview*

The term "digital twin" was first coined in 2011 by Tuegel et al. describing a method to predict an aircraft's lifecycle by simulating its behavior with a digital model [13]. Later, the National Aeronautical Space Administration (NASA) defined a DT as: "A Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [14]. Some authors define a DT as a digital representation of a physical production

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system file that uses integrated simulation data and integration services containing information from multiple sources throughout the product lifecycle [15–17]. In 2019, Madni et al. [18] defined a DT as a virtual instance of a physical (dual) system that continually updates performance, maintenance, and health data throughout the physical system's life cycle.

Expressed as simply as possible, a DT is just a highly complex virtual model that is the counterpart (or twin) of a physical object connected with a bi-directional data link supported by sensors [12]. Sensors connected to physical assets collect data mapped to virtual models [18]. Anyone working with DTs can obtain important information about how physical things work in the real world. A DT is a system that consists of three main subsystems: physical products in real space, virtual products in virtual space, and connections between the virtual and real products' data and information [19]. This illustrates the DT's importance as a tool for helping engineers and operators understand a product's current and future performance. The analysis of data from connected sensors, combined with other sources of information, allows predictions to be made [20]. With such information, organizations can learn more and faster while also breaking old boundaries surrounding management assessment and complex life cycles [20]. DTs give an unprecedented view of how a building performs from different perspectives. A DT can help identify potential errors in the construction and management phase and troubleshoot problems from afar [21]. The data can help decide when to replace products or parts causing malfunctions, saving time and money [12].

With the emergence of the IoT, the implementation of DTs has become more cost-effective, leading to wide acceptance across industries [18]. The global market value of DTs reached USD 5.30 billion in 2020 and is expected to expand at a compound annual growth rate of 39.9% from 2021 to 2028 [22]. Therefore, the AEC industry needs to explore and evaluate the potential applications of DTs which is the motivation for this study.

## 3. Methodology

This study is based on a systematic literature review, conducted in three steps by using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, as shown in Figure 2. Step 1 involves extracting relevant studies from databases such as the Association for Computing Machinery (ACM), EBSCO, Scopus, and Web of Science (WoS), Scopus. In step 2, a comprehensive set of analyses is conducted, incorporating Google Trends data derived from the web, image, and news searches. The syntheses of the searched documents indicate the global focus and interest of the public and researchers in the current study's keywords and terms [23]. Methods used include keyword analysis, annual publication trends observations, scientific keyword mapping, co-author analysis, affiliated organizations, country of export origin, and citation analysis. Finally, step 3 categorizes the identified papers based on the focus areas, presenting conclusions and future research directions.

**Figure 2.** The methodology employed in this systematic review.

### *3.1. Literature Retrieval*

Scopus, WoS, EBSCO, ScienceDirect, and ACM databases were searched to retrieve the relevant articles. Search strings using keywords such as "digital twin," "building," and "asset management" were developed in step 1 of the methodology. These strings are utilized to retrieve the articles from the databases, as stated in Table 1. These searches resulted in 881 articles, including Scopus, WoS, EBSCO, ScienceDirect, and ACM. The articles retrieved are limited to the English language. However, no time bounds were applied during article retrieval.

**Table 1.** Search string and numbers of retrieved articles for the considered databases.

| Database | Search string | Results |
|---|---|---|
| Scopus | TITLE-ABS-KEY ("Digital twin" AND building)<br>TITLE-ABS-KEY ("Digital twin" AND "asset management") | 484 |
| WoS | ((TI=("digital twin" AND (building OR "asset management"))) OR AB=("digital twin" AND (building OR "asset management"))) OR AK=("digital twin" AND (building OR "asset management")) | 326 |
| EBSCO | KW ("digital twin" AND building) OR KW ("digital twin" AND "asset") OR TI ("digital twin" AND building) OR TI ( "digital twin" AND "asset") OR AB ("digital twin" AND building) OR AB ("digital twin" AND "asset") | 76 |
| ScienceDirect | Title, abstract, keywords: "digital twin" AND (building OR "asset management") | 77 |
| ACM | [[Publication Title: "digital twin"] AND [[Publication Title: building] OR [Publication Title: "asset management"]]] OR [[Abstract: "digital twin"] AND [[Abstract: building] OR [Abstract: "asset management"]]] OR [[Keywords: "digital twin"] AND [[Keywords: building] OR [Keywords: "asset management"]]] | 109 |

The article types are restricted to original research articles, reviews, conference papers, short papers, and book chapters. This practice is in line with the claim made by Akram et al. that these article types are of high quality and reliable [24]. An initial investigation based on the articles' titles revealed 245 duplicate studies indexed in the considered databases. Consequently, a total of 636 articles were considered for screening. Figure 3 shows the adopted PRISMA systematic flow diagram. The following seven points from the PRISMA guidelines are considered for the systematic review process:

1. Eligibility criteria include articles with the selected keywords in their title, summary, or keywords.
2. The information sources are Google Trends, Scopus, WoS, ScienceDirect, ACM, and EBSCO databases.
3. The search strings used to retrieve the articles from the databases are presented in Table 1.
4. The research selection process includes searching and screening keywords, eliminating duplications, and conducting qualitative analysis in the form of reading abstracts and keywords.
5. Using the VOSviewer tool [25], articles retrieved from the databases were analyzed, and read in detail, and keywords were combined.
6. Data items include keywords, classification, publication trends, article types, primary sources, scientometric mapping, co-authors, organizational affiliation, and source country.
7. The summary measures include DTs and their application in different categories.

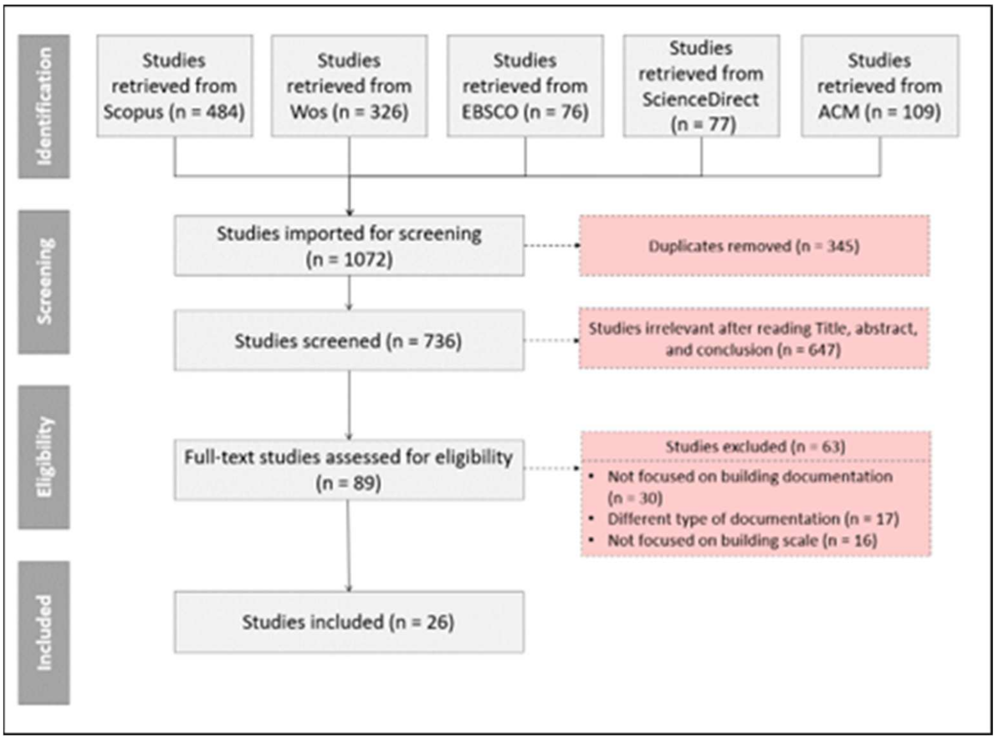


**Figure 3.** PRISMA systematic review flow diagram.

## 4. Results

### *4.1. Google Trend Analysis*

A Google trend analysis is conducted to highlight the global interest in the keywords and themes used in this study and to investigate the attention toward DTs for documentation and asset management (Figures 4–6). Three keywords are compared: "digital twin," "sustainable buildings," and "digital documentation," and the search trends are plotted over 5 years, i.e., 5 June 2016 to 4 June 2021. Analysis is conducted on three distinct types of searches: general web search, image search, and news search.

Figure 4 shows the trends for the web searches, indicating that the term "digital twin" is the most searched. The terms "sustainable buildings" and "digital documentation" have almost the same trend. Moreover, searches for "digital twins" have increased over time. Figure 5 shows the image-based search trends for the three keywords. A trend similar to the web search is observed with "digital twin" having the most searches. However, there are fewer image searches for "digital documentation". Figure 6 shows the news searches for the keywords. The term "digital twin" has more searches compared to the "sustainable buildings" and "digital documentation" searches. However, compared to the overall web and image searches, the news-based trends are fewer for all the keywords.

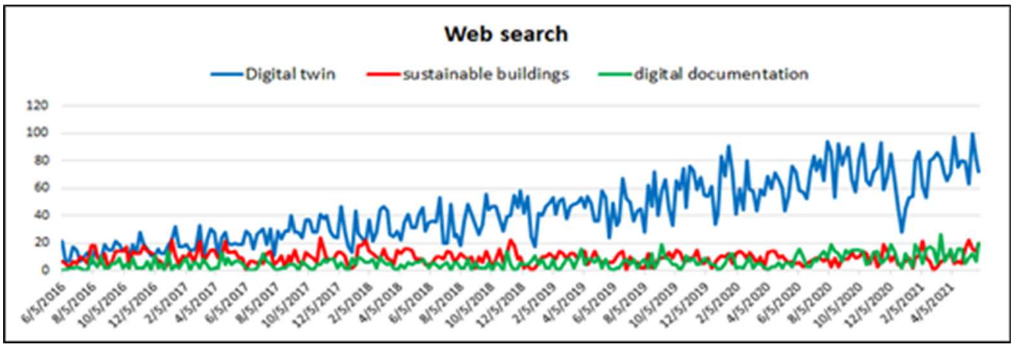


**Figure 4.** Google web search trend for the current study keywords.

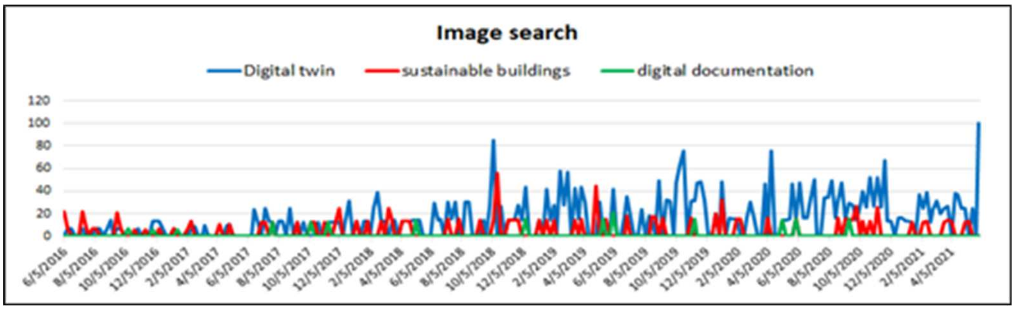


**Figure 5.** Google image search trend for the current study keywords.

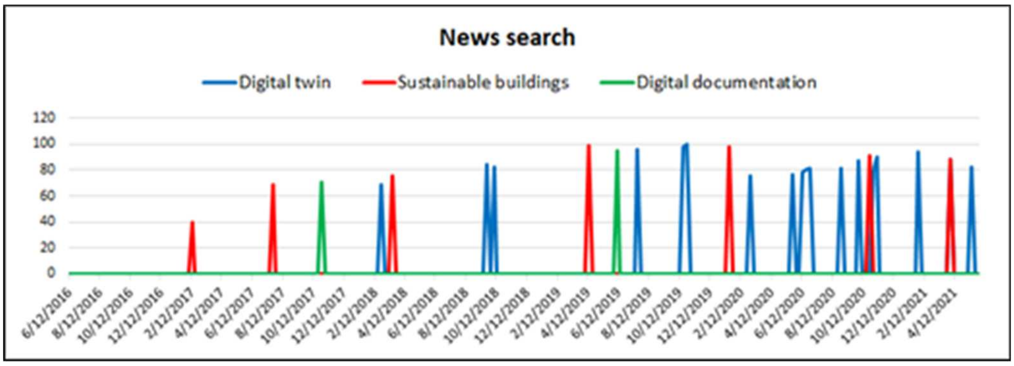


**Figure 6.** Google news search trend for the current study keywords.

## 4.2. Yearly Publication Trends for the Retrieved Articles

Figure 7 presents the yearly publication trends for articles retrieved from the Scopus, WoS, EBSCO, ScienceDirect, and ACM databases. It shows that publications on the topic under study began to appear after 2016, increasing after that. The figure shows that more than 87% of the articles were published in the last 4 years, and 71% of those studies were published after 2019, highlighting the increased focus on DTs for asset management. Furthermore, no articles were retrieved before 2016, indicating the field's recent emergence.

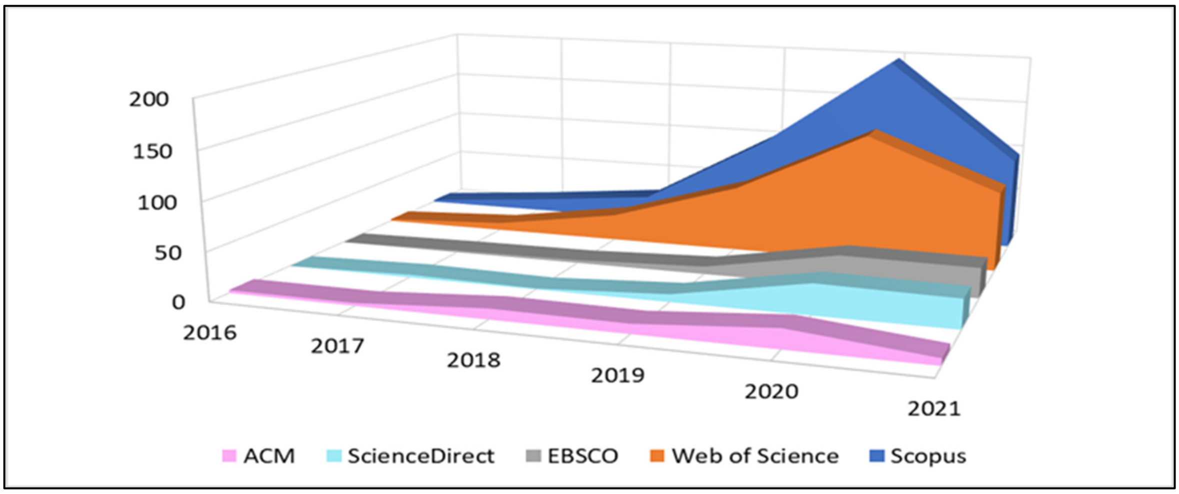


**Figure 7.** Yearly distribution of the retrieved articles from the considered databases.

## 4.3. Classification of Retrieval Articles based on Focus Area

Based on the information extracted from the databases, Figure 8 highlights the top 10 research areas related to DT, with more than 35% of the total (46.8% ScienceDirect, 34% Scopus, 34.6% WoS, and 27.3% EBSCO) retrieved articles belonging to the "Engineering" category. This illustrates the

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high acceptance rate of DTs by investors and engineers, their understanding of DT benefits, and the savings that can be achieved because DTs help make better financial decisions, improve team collaboration and predictive maintenance, and accelerate risk assessment. The "Engineering" category is followed by "Computer Science," containing more than 18% of the retrieved articles, also a technology-focused field. It is remarkable how many fields may benefit from DTs, as it includes many other areas, including business management, energy, decision science, telecommunications, and others.

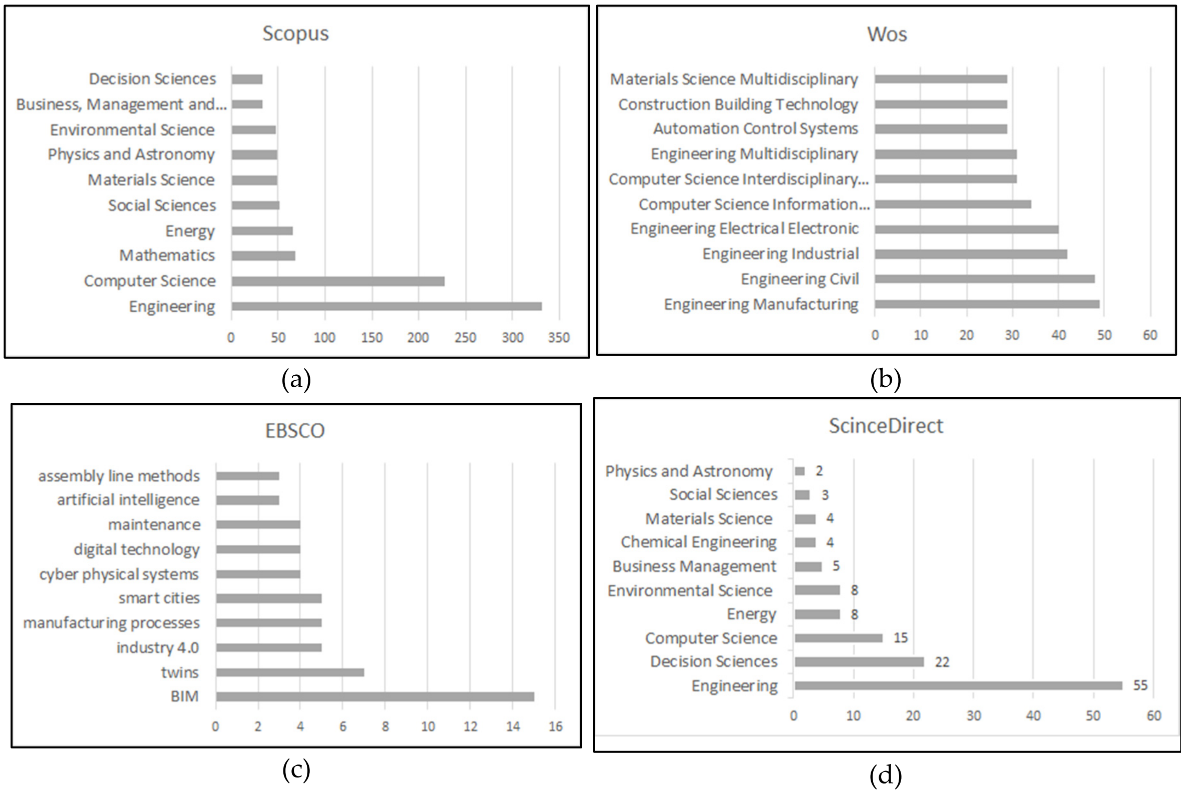



**Figure 8.** Articles categorization: (a) Scopus, (b)Web of Science, (c) EBSCO, and (d) ScienceDirect.

### *4.4. Types of Retrieved Documents*

After analyzing yearly trends and areas of research, the types of retrieved documents are investigated. The documents are restricted to 11 types: journal articles, proceedings papers, review articles, early access, book chapters, editorial materials, news items, notes, books, trade publications, and magazine articles. Since the original journal articles (original research and review), conference articles, and book chapters generally report on research findings and new developments than other publications, these three document types were prioritized during the extraction stage. Accordingly, 47.6% of the database's retrieved articles are classified as original research, followed by proceedings papers (42%) and book chapters (3.7%). Table 2 illustrates the numbers and types of documents found in the five databases, showing the high tendency for Scopus to index conference papers compared to the other databases.

**Table 2.** Types of retrieved documents.

| Document type | Databases | | | | |
|---|---|---|---|---|---|
| | WoS | Scopus | EBSCO | ACM | ScienceDirect |
| Journal articles | 192 | 208 | 55 | 1 | 68 |
| Proceedings papers | 111 | 249 | 0 | 102 | 0 |
| Review articles | 18 | 19 | 0 | 0 | 0 |
| Early access | 9 | 0 | 0 | 0 | 0 |
| Book chapters | 3 | 21 | 10 | 0 | 7 |

| | | | | | |
|---|---|---|---|---|---|
| Editorial materials | 2 | 3 | 0 | 0 | 1 |
| News items | 2 | 0 | 0 | 2 | 0 |
| Notes | 1 | 2 | 0 | 0 | 0 |
| Books | 0 | 2 | 0 | 0 | 0 |
| Trade publications | 0 | 0 | 5 | 0 | 0 |
| Magazine articles | 0 | 0 | 3 | 4 | 0 |

### *4.5. Keyword Mapping*

Keywords are the core element of research detection. The keyword analysis of articles aids in understanding the important aspects of the research along with trends and evolution. VOSviewer uses natural language processing algorithms and text mining methods to build a keyword network and uses grouping methods to explore their relationships and organize knowledge. In addition to author-generated keywords, some databases use "index keywords" as topic titles to include relevant keywords that the author missed. This study uses both authors' and index keywords to perform scientific quantitative analysis. A keyword co-occurrence analysis in VOSviewer was performed using the full counting method with a minimum inclusion criterion to limit the number of keywords. A minimum keyword co-occurrence criterion is set to 10 for the Scopus database, 5 for the WoS database, and 3 for ScienceDirect.

Table 3 shows the keyword co-occurrence analysis results for the Scopus and WoS databases. After setting the minimum inclusion criteria, 56 of the 3534 keywords retrieved from Scopus were selected for analysis. For WoS, 1439 keywords were retrieved, and 59 were selected for final analysis. A total of 327 keywords were retrieved from ScienceDirect, of which 14 were selected.

**Table 3.** Keyword co-occurrence analysis.

| Assessment | Consideration | Scopus results | WoS results | ScienceDirect |
|---|---|---|---|---|
| Type of analysis | Co-authorship | | | |
| Counting method | Full counting | 3534 | 1439 | 327 |
| Unit of analysis | All keywords | 56 | 59 | 14 |
| Minimum occurrence | | 10 | 5 | 3 |

Table 4 shows the frequency, total number of links, and total link strength for the top 10 of the 56 selected keywords from Scopus. The number of links represents the co-occurrence connection between the two keywords, and the total link strength is a positive number indicating the number of articles in which the two keywords co-occurred. The results show that the most frequently used keyword is "digital twin," with 314 occurrences, representing 40% of the top keywords. The second most frequent keyword is "BIM," with 113 occurrences and approximately a 14.4% share. All other top keywords have a share of less than 10% each.

Regarding the links (Table 4), the largest number occurred for "digital twin," followed by "BIM," "architectural designs," and "IoT," indicating that the investigation is focused on DT-enabled lifecycle analysis and asset management in the AEC industry. The keyword that has the highest total link strength is "BIM," followed by "IoT" and "digital twin".

**Table 4.** Top 10 keywords, their number of links, and total link strength for Scopus.

| Keyword | Frequency | Number of links | Total link strength |
|---|---|---|---|
| Digital Twin | 314 | 933 | 94 |
| BIM | 113 | 613 | 170 |
| IoT | 75 | 357 | 109 |
| Architectural designs | 64 | 368 | 47 |
| Lifecycle | 56 | 266 | 51 |
| Information management | 38 | 224 | 48 |
| Industry 4.0 | 33 | 126 | 42 |

| | | | |
|---|---|---|---|
| Manufacture | 31 | 106 | 37 |
| AI | 30 | 130 | 44 |
| Embedded systems | 30 | 130 | 38 |

Figure 9 shows the network visualization of the 56 selected keywords from the Scopus database that co-occurred at least 10 times. The network visualization represents the keyword co-occurrences, with the circle sizes indicating the weights of the keywords. The figure shows that the keywords are grouped into five clusters colored red, green, blue, orange, and yellow. The five clusters indicate that DT research for asset management and lifecycle analysis is focused on five related topics: 1) Industry 4.0 and smart manufacturing (red cluster); 2) BIM and the AEC industry (green cluster); 3) IoT (blue cluster); 4) life cycle management (orange cluster); and 5) smart and sustainable cities (yellow cluster). The figure shows a very close linkage between four clusters (red, green, blue, and orange), whereas the one cluster (yellow) appears more disconnected because this investigation is not primarily focused on DT-enabled sustainable architecture.

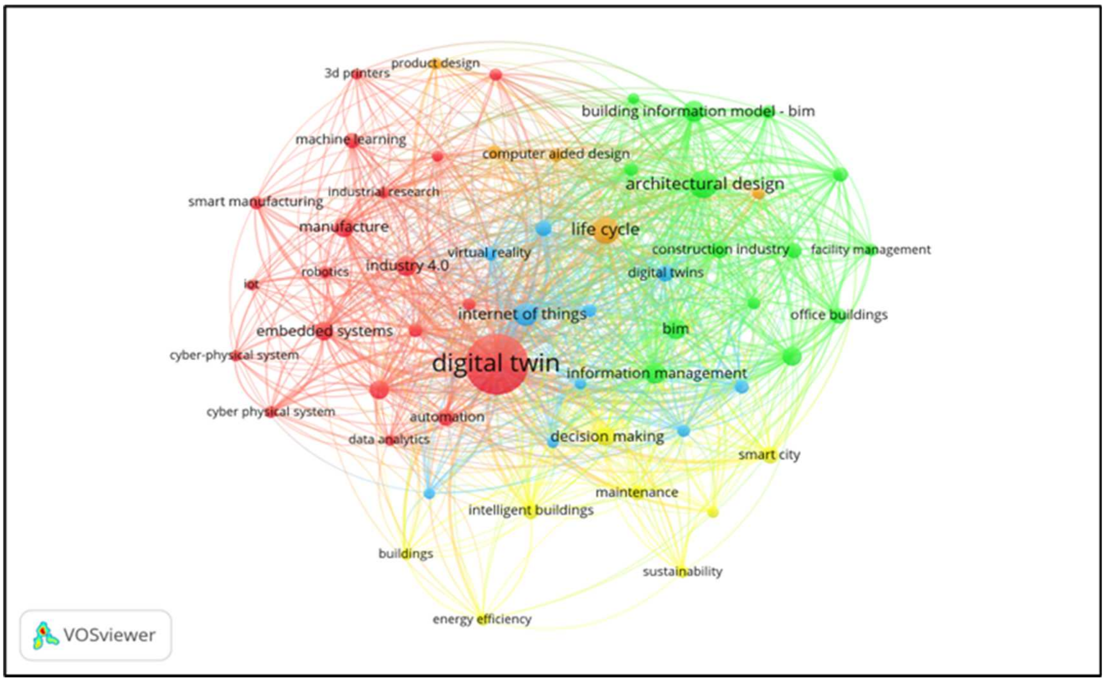



**Figure 9.** Scopus keywords mapping.

Table 5 shows the frequency, total number of links, and total link strength for the top 10 of the 59 selected WoS keywords. The most frequently used keyword is "digital twin," with 175 occurrences, representing around 40% of the top keywords. The second most frequent keyword is "BIM," with 51 occurrences and a share of around 11.59%. All other top keywords have a share of less than 10% each. Regarding the links (Table 5), the largest number occurred for "digital twin," followed by "BIM," "IoT," and "System." The keyword having the highest total link strength is "BIM," followed by "IoT" and "digital twin".

**Table 5.** Top 10 keywords, their number of links, and total link strength for WoS.

| Keyword | Frequency | Number of links | Total link strength |
|---|---|---|---|
| Digital twin | 175 | 415 | 85 |
| BIM | 51 | 202 | 99 |
| System | 38 | 134 | 73 |
| Design | 32 | 113 | 44 |
| IoT | 32 | 152 | 88 |

| | | | |
|---|---|---|---|
| Model | 27 | 87 | 53 |
| Industry 4.0 | 26 | 98 | 54 |
| Simulation | 26 | 71 | 35 |
| Management | 17 | 79 | 34 |
| Framework | 16 | 89 | 43 |

Figure 10 shows the network visualization of the 59 selected keywords from the WoS database that co-occurred at least five times. The keywords in the figure are grouped into five clusters colored red, green, yellow, blue, and orange. The five clusters indicate that DT research for asset management and lifecycle analysis is focused on five related topics: 1) modeling of smart manufacturing systems (red cluster); 2) BIM-enabled asset management (green cluster); 3) Industry 4.0 (yellow cluster); 4) BIM framework and challenges (blue cluster); and 5) DT system (orange cluster). The figure shows very close linkages between all five clusters.

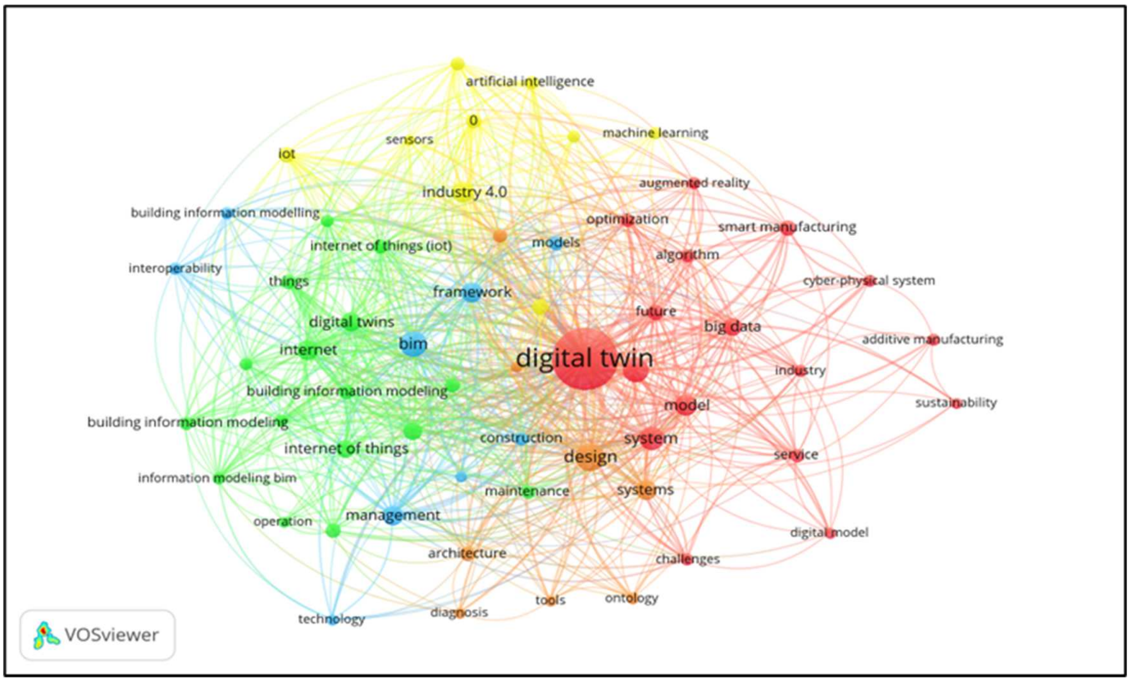



**Figure 10.** Web of Science keywords mapping.

Table 6 shows the frequency, total number of links, and total link strength for the top 10 of the 14 selected ScienceDirect keywords. The most frequently used keyword is "digital twin," with 47 occurrences, representing around 54.65% of the top keywords. The second most frequent keyword is "BIM," with 10 occurrences and a share of around 11.62%. All other top keywords each have a share of less than 10%. Regarding the links (Table 6), the largest number occurred for "digital twin," followed by "BIM." The keyword having the highest total link strength is "digital twin".

**Table 6.** Top 10 keywords, their number of links, and total link strength for ScienceDirect.

| Keyword | Frequency | Number of links | Total link strength |
|---|---|---|---|
| Digital twin | 47 | 31 | 14 |
| BIM | 10 | 12 | 6 |
| Industry 4.0 | 5 | 5 | 3 |
| Machine learning | 5 | 3 | 2 |
| Smart cities | 4 | 6 | 4 |
| Additive manufacturing | 3 | 1 | 1 |
| Artificial intelligence | 3 | 3 | 3 |

| | | | |
|---|---|---|---|
| Asset management | 3 | 4 | 2 |
| Cyber-physical systems | 3 | 4 | 3 |
| Industry foundation classes | 3 | 4 | 3 |

Figure 11 shows the network visualization of the 14 selected keywords from the ScienceDirect database that co-occurred at least three times. The keywords are grouped into five clusters colored green, red, blue, yellow, and orange. The five clusters indicate that DT research for asset management and lifecycle analysis is focused on five related topics: 1) DT in manufacturing (green cluster); 2) AI and Industry 4.0 (red cluster); 3) BIM and IoT (blue cluster); 4) asset management (yellow cluster); and 5) smart cities (orange cluster). The figure shows that the clusters are disconnected, possibly because of the small number of studies retrieved from the database. The focus of these studies is scattered around DTs.

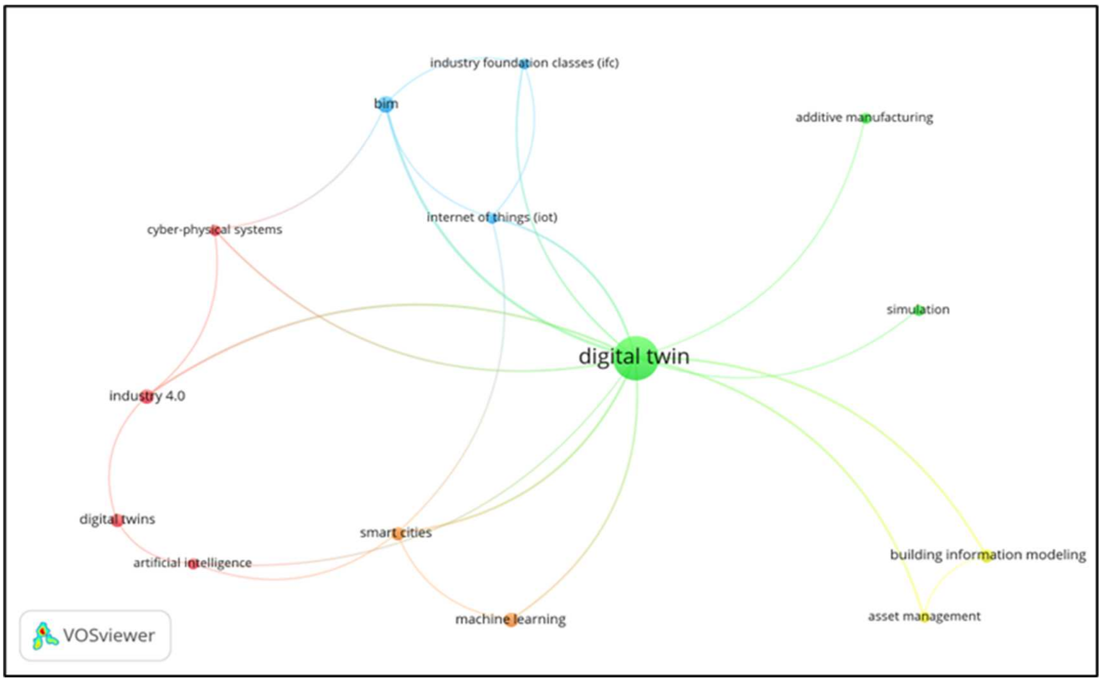



**Figure 11.** ScienceDirect keywords mapping.

*4.6. Co-authorship Analysis*

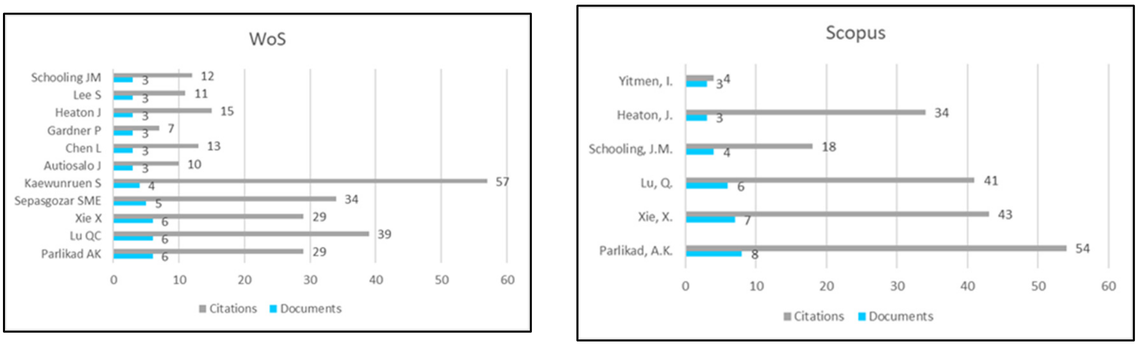
The names of all authors were recorded, and the citations to pertinent documents were counted using the VOSviewer co-authorship filter. A minimum contribution of three research articles by an author is set for Scopus and WoS. The number of authors recorded for WoS articles was 1179. There were 169 authors recorded for Scopus and 19 for ACM. After the minimum inclusion criteria, 11 authors emerged as top contributors to WoS and six to Scopus, as shown in Table 7.

**Table 7.** Co-authorship analysis.

| Assessment | Consideration | Scopus results | WoS results |
|---|---|---|---|
| Type of analysis | Co-authorship | | |
| Counting method | Full counting | 169 | 1179 |
| Units of analysis | Authors | 6 | 11 |
| Minimum Occurrence | | 3 | 3 |

Figure 12 represents the top authors who have contributed to the two types of research repositories and their citations to searched articles. For articles retrieved from WoS, A.K. Parlikad, Q.C. Lu, and X. Xie contributed the most. However, regarding citations, the four articles authored by

S. Kaewunruen lead with 57 citations. Figure 12 also shows the results of all shortlisted authors retrieved by Scopus for articles with three or more contributions. A.K. Parlikad leads with eight contributions and 54 citations, followed by X. Xie with seven contributions and 43 citations. Figure 13 illustrates the number of citations compared to the number of documents for the top 10 contributing authors based on the information extracted from Scopus, WoS, and ACM.




(a) (b)

**Figure 12.** Authors – citations analysis: (a) Web of Science and (b) Scopus.

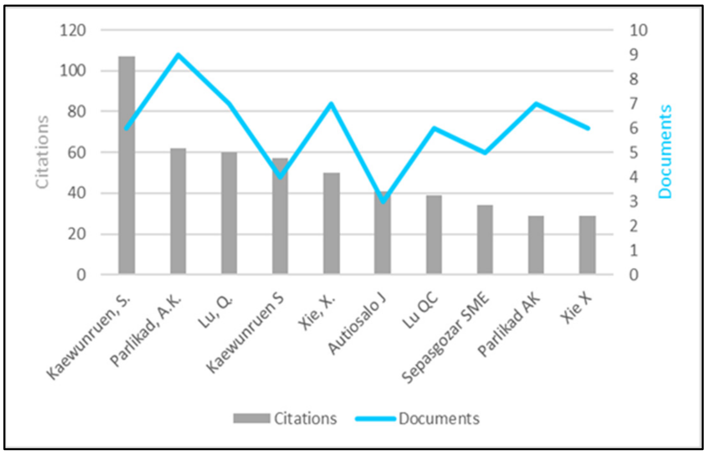



**Figure 13.** Top contributing authors based on citations.

4.6.1. Co-authorship analysis based on organizational affiliations

Minimum inclusion criteria were established for two articles per organization to analyze authors' organizational affiliations. A total of 469 organizations are associated with articles retrieved from WoS and 107 from Scopus. Therefore, 27 organizations were shortlisted for WoS with a minimum contribution of three and 107 for Scopus with no minimum contribution, as shown in Table 8.

**Table 8.** Co-authorship analysis based on organizational affiliations.

| Assessment | Consideration | Scopus results | WoS results |
|---|---|---|---|
| Type of analysis | Co-authorship | | |
| Counting methods | Full counting | 107 | 469 |
| Units | Organizations | 107 | 27 |
| Minimum occurrence | | 1 | 3 |

Based on the number of articles retrieved, a list of top organizations contributing to the Scopus and WoS databases is provided in Table 9. The University of Cambridge leads with 22 documents and 99 citations, followed by Polytechnic di Milano with 13 documents and 102 citations, and the

University of Sheffield is third with seven documents and 17 citations. One special operations organization is the Beijing Institute of Technology, whose four documents drew 114 citations.

**Table 9.** Top contributing organizations.

| Organization | Indexing | Documents | Citations |
|---|---|---|---|
| University of Cambridge | WoS, Scopus | 22 | 99 |
| Polytechnic di Milano | WoS, Scopus | 13 | 102 |
| University Of Sheffield | WoS, Scopus | 7 | 17 |
| Aalto University | WoS, Scopus | 6 | 39 |
| University of California, Irvine | WoS, Scopus | 6 | 37 |
| University of Birmingham | WoS, Scopus | 5 | 62 |
| Norwegian University of Science and Technology | WoS, Scopus | 5 | 5 |
| Delft University of Technology | WoS, Scopus | 4 | 59 |
| Chalmers University of Technology | WoS, Scopus | 4 | 19 |
| Beijing Institute of Technology | WoS, Scopus | 4 | 114 |

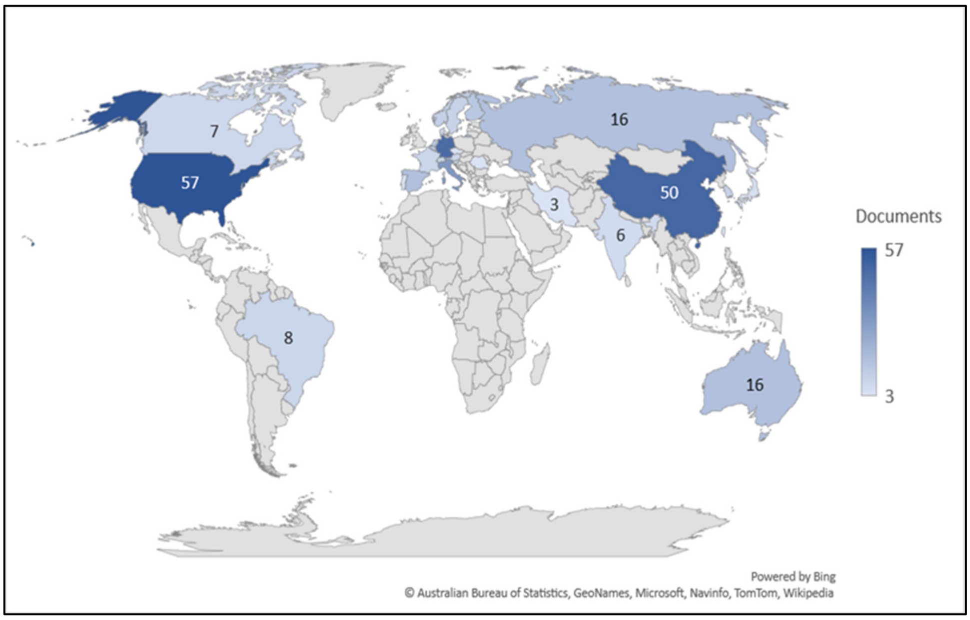
4.6.2. Co-authorship analysis based on country of origin

The countries contributing the most to the documents of the two repositories were also determined. A country analysis was performed with a minimum inclusion criterion of three documents per country for Scopus and WoS. Forty-eight countries have contributed to the WoS repository and 26 to Scopus. After applying restrictions, 31 countries were pre-selected via WoS-retrieved items and nine countries via Scopus after applying restrictions, as shown in Table 10.

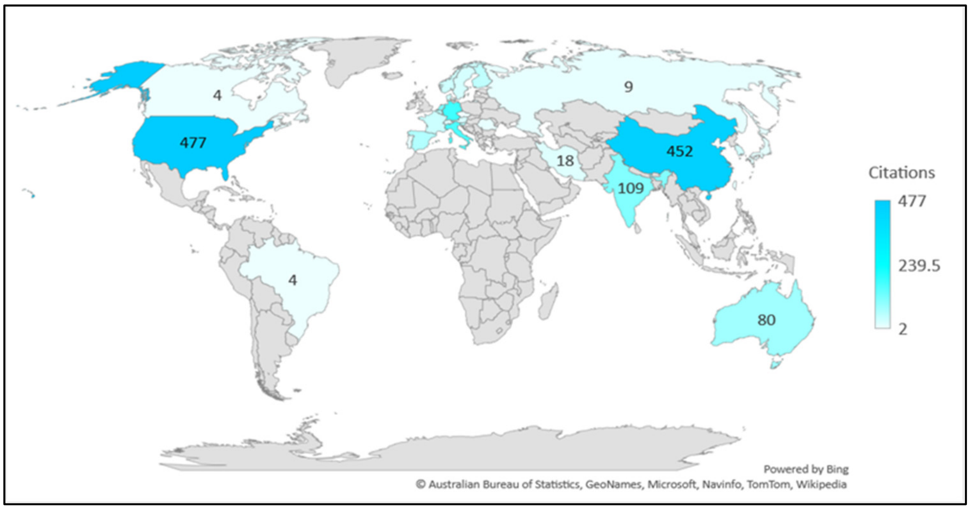
**Table 10.** Co-authorship analysis based on country of origin.

| Assessment | Consideration | Scopus results | WoS results |
|---|---|---|---|
| Type of analysis | Co-authorship | | |
| Counting methods | Full counting | 26 | 48 |
| Units | Countries | 9 | 31 |
| Minimum occurrence | | 3 | 3 |

Figure 14 illustrates a world map of the leading countries contributing to the WoS and Scopus archives by the number of documents and citations. The USA contributed the most documents (57), representing around 13% of the retrieved articles, followed by the United Kingdom (51) corresponding to 11.5% representation, and China (50) with over 11.2% representation. Regarding citations, the USA leads with 477 citations, then China (452) and the United Kingdom (221). Other highly cited countries include Germany, India, and the Netherlands.




(a)




(b)

**Figure 14.** Country of origin analysis: (a) Web of Science and (b) Scopus.

## 5. Categorization of the Included Articles

In this segment, the articles considered in the study are organized according to their respective focus areas. The 26 included articles are grouped into five categories, as illustrated in Figure 15. The subsequent sections provide explanations for each category and highlight the contributions of the respective articles.

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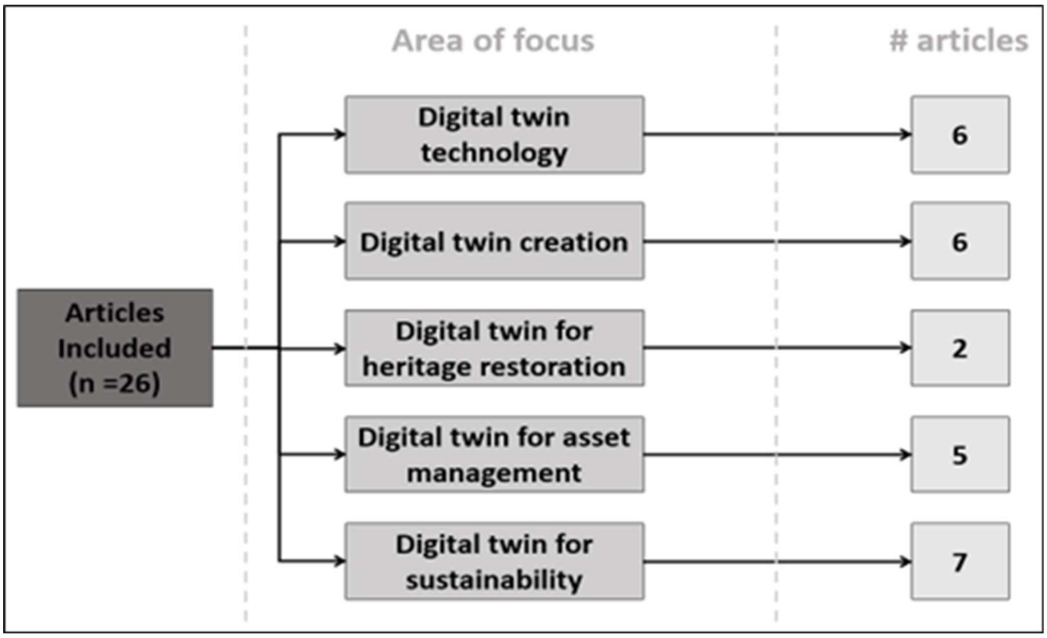


**Figure 15.** Categorization of the included articles in the systematic review.

*5.1. Digital Twin Technology*

This section delves into the examination of articles focusing on the extraction of DT definitions, applications, and implementation challenges across various industries. The articles within this category center on concepts, characteristics, applications, and challenges related to DT technology.

Barricelli et al. [26] scrutinized 75 articles to dissect existing DT definitions. They presented key DT characteristics and outlined diverse application domains in which the technology has been employed, categorizing them into manufacturing, aviation, and healthcare. The authors described two DT lifecycles, one involving the creation of a twin for a non-existing physical object and another where the object already exists but lacks a twin. The analysis revealed that the design process varies accordingly, simultaneously encompassing both the physical object and its twin or focusing on connecting the existing object to its twin. The study also brought attention to digital implementation issues, including ethical considerations, data security, privacy, deployment costs, governmental regulations, and technical limitations. While the healthcare, aviation, and manufacturing industries extensively explored DT applications, the need for further research in other sectors was emphasized.

Camposano et al. [27] conducted a qualitative study examining the comprehension of DTs among Finnish AEC/FM practitioners. Through semi-structured interviews with 28 professionals in 2018 and 2019, the authors found that respondents, rather than grasping precise DT details, were more inclined to be familiar with the technology's vision and implementation in organizations. DTs were distinguished from digital models, by the respondents, based on attributes such as dynamic time, virtual representation, higher dimensional abstraction, bidirectional data flow between the physical object and its twin, technological components, and high actor interdependency. The study concluded that AEC/FM practitioners lack a unanimous definition of DTs and often rely on simplistic metaphors, advocating for a cohesive understanding of the technology for better inter-organizational acceptance.

Delgado and Oyedele [28] analyzed 54 articles to scrutinize structural and functional descriptions of DTs in the built environment. The authors identified three types of models: conceptual models, system architectures, and data models as part of the structural model, and process and communication models in the functional model. Conceptual models were further categorized into prototypical, model-based, interface-oriented, and service-based, while process models included DT creation, synchronization, asset monitoring, prognosis and simulations, optimal operations, and optimized designs. Notably, the study found that prognosis and simulation models were predominantly applicable to the AEC industry implementations.

Ozturk [29] conducted a bibliometric review analyzing the applicability and challenges of DT in the AEC/FM industry. Based on the review of 151 articles, the author found that DT implementation in the AEC/FM industry is focused on five areas: 1) building lifecycle management; 2) virtual-based information utilization; 3) virtual–physical building integration; 4) information-based predictive management; and 5) information integrated production. Another bibliometric and systematic review was conducted by Agnusdei et al. to analyze existing DT applications supporting safety management [30]. The authors found that integrated DT and safety management research is focused on six areas: 1) decision-making and offshore applications; 2) IoT and lifecycle approaches; 3) industry 4.0; 4) machine learning for DT and safety support; 5) safety engineering; and 6) hazards and risk management.

In summary, DT technology is promising for the AEC/FM industry, but there are several challenges, such as technical limitations, data ownership, etc, which still exist and should be addressed for wider implementation in real scenarios.

### *5.2. Digital Twin Creation*

Digital twins refer to virtual representations of physical objects, processes, and systems with bidirectional data exchange capabilities between the physical entity and its digital replica. The first and foremost step in creating a twin using the discrete-event simulation technique is to identify the different elements involved in the physical system and their inter-relationships. The second step is to represent the physical system in a digital space, which involves representing the identified elements, production operations, and inter-relationships. The third step in creating a DT involves the interconnection and interaction between the physical system and its digital representation models. A data interaction technique should be implemented in this step that aggregates the middleware, a memory database, and a relational database to implement the physical–digital interaction [31].

Jiang et al. [31] implemented the discrete event simulation modeling technique to rapidly create a shop floor's DT. However, the authors focused only on proactive simulations without considering predictive simulations. Khajavi et al. [32] implemented a simulation approach to create a DT of an office building at the Aalto University in Finland. This was accomplished by collecting and analyzing 25,000 sensor readings. The data were collected using a wireless sensor network installed on the building's façade. The experiments revealed that most of the technical DT creation issues were related to data collection through sensors due to frequent discharging of the sensors' batteries, disruption of data transmission channels, and the number and positioning of the sensors.

Furthermore, a DT can be created using either a data-based or system-based DT [33]. In the data-based approach, the data from the physical system is structured according to criteria such as functionality, enabling users to quickly gain an overview of the system's performance. The data-based method can be efficient if the users are only exposed to the data and not the physical system's technical information. By contrast, a system-based approach creates and combines several virtual models of the physical system to obtain a nearly exact representation of reality. System-based creation can provide more comprehensive insight into the physical system's performance than a data-based system. However, creating a system-based DT requires full knowledge of the technical details of the system and the components involved. To enhance the predictive performance based on data-based models and improve the efficiency of the current performance analysis, a hybrid data- and system-based model was recommended [33].

Lu et al. [15–17] introduced a framework for generating DTs at both the building and city levels, with a particular focus on the operational and maintenance phases within the building development lifecycle. To illustrate the viability of the proposed framework, the authors applied it to create a DT for the West Cambridge site at the University of Cambridge in the UK. The implemented scenario seamlessly integrated diverse data sources, demonstrating effective and efficient data query, analysis, and decision-making during the operation and maintenance phase. Additionally, the authors underscored the practical challenges encountered in DT creation, including issues related to heterogeneous data sources, automated integration of data from these sources, data synchronization, and ensuring data quality.

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However, simply creating a building DT does not benefit or create value for the AEC/FM industry. It is crucial to understand how to use the developed DT to create value. The benefits of DT and the costs and risks involved should be determined through the benefits management process [36]. This process involves identifying and structuring benefits, planning benefits realization, executing the benefits realization plan, evaluating and reviewing results, and discovering the potential of future benefits. Based on an empirical study of nine projects, Love and Matthews [36] proposed a business dependency network to analyze the post-creation benefits of a DT.

In summary, a simulation-based approach is suitable for creating a DT [31]. An integrated data- and system-based model should be considered to enhance the simulated virtual model's reactive, proactive, and predictive performance [33]. However, attention is required while collecting sensor data for virtual model creation because most errors are introduced at this stage [32]. The current state of DTs in the AEC/FM industry is mainly focused on how to create a DT [36]. More studies focusing on how to realize the benefits of a DT after its creation are required.

### *5.3. Digital Twins for Heritage Restoration*

Heritage monuments and buildings are valuable assets that convey a historical legacy to later generations. These buildings degrade over time, and restoring them is crucial to preserve their aesthetic value and fulfill their original purpose [37]. The documentation of heritage buildings is the most crucial process during restoration because a lack of documents can lead to inefficient project management, high maintenance costs, and lost time [38]. Documentation for heritage buildings often involves a heterogeneous range of qualitative and quantitative data gathered and analyzed by different stakeholders in isolation. A lack of communication and coordination among stakeholders can lead to duplicated efforts and incomplete documentation [39]. Recent technological advances can address data fragmentation issues and the lack of governability in heritage buildings' documentation and restoration processes.

After examining various documentation aspects associated with the restoration of heritage buildings, data can be classified into four distinct types: 1) archaeological/historical data, which pertains to the historical context of the building; 2) geometry data, which relates to the building's shape and distinctive features; 3) pathology data, concerning the decay or damage to the building; and 4) performance data, encompassing the building's performance metrics in areas such as energy efficiency, thermal characteristics, comfort, safety, and security [39]. In this context, historic building information modeling (HBIM) can aid in the integration and management of graphical and textual data from multiple sources without manual intervention and facilitate communication and coordination between stakeholders. Moreover, DTs enable modeling interrelationships between sensor-collected data and the historic building site, mitigating threats related to the initial design, occupancy, and spatial configuration [40]. An integrated HBIM-DT approach enables the creation of a preventive restoration mechanism for heritage buildings. HBIM models with real-time IoT data and DT technology enhance the relationship between the physical on-site building and the digital model, allowing the non-specialist stakeholder to contribute to the decision-making process [40].

To summarize, DT technology has shown promising potential for heritage building restoration and damage prediction. However, the digitalization of heritage restorations using DTs requires a deep understanding of the heritage site, and the structuring of this information in digital data models is a complex process [41].

### *5.4. Digital Twin for Asset Management*

The publications within this category primarily center around the implementation of DTs for effective asset management throughout the entire lifecycle of an asset. Decision-making related to assets holds significant importance in asset management [42], emphasizing the necessity for well-informed decision-making facilitated by proficient data and information management [42].

The integration of digitization into asset management proves beneficial. For example, the utilization of sensors aids in data collection, while advanced digital controls contribute to minimizing unplanned downtime through cost-effective management of assets. Illustrating the imperative role

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of decision support in asset lifecycle management and showcasing the potential of DTs in this context, Marco et al. [43] explored the significance of DTs in asset management, particularly emphasizing their role in the decision-making process related to assets in a conceptual article. This decision-making process involves four principles and two aspects.

Principles:

- Emphasis on the lifecycle (decisions should align with long-term objectives).
- Focus on the system (consideration of the decision's impact on the entire system, not just individual components).
- Prioritization of risk (implementation of decision-making followed by risk management strategies).
- Centricity on assets (emphasis on data and information pertaining to assets).

Considerations within the decision-making process (the subsequent factors should be taken into account when making decisions related to assets) encompass:

- Asset lifecycle: the enduring impact of the decision on the asset.
- Asset hierarchical control level: the level at which the decision is made (strategic/tactical/operative), ensuring alignment with other levels.

The decision-making process necessitates effective data/information management [43]. Currently, there is not a complete integration of data/information management with the lifecycle management of assets, but this gap can be addressed through the implementation of DTs. Macchi et.al, [44] have emphasized the significance of DTs in asset-related decision-making by examining use cases derived from the authors' past projects. These use cases are categorized based on their asset control levels (i.e., strategic, tactical, and operational) and asset lifecycle phases (i.e., beginning of life, middle of life, and end of life). The data obtained from a DT can be utilized for tasks such as asset configuration, reconfiguration, planning, commissioning, condition monitoring, and health assessment [44].

James and Ajith [45] detailed the creation and construction of DTs through a BIM-based methodology, devising an Asset Information Model (AIM) conducive to DT generation. The AIM encapsulates the necessary data and information linking assets to a level essential for the optimal operation of an asset management system. The authors illustrated this concept through a case study conducted on the West Cambridge campus. The process of developing the AIM to facilitate DT creation involved the following steps:

- Categorization of assets (according to their functions, such as heating, ventilation, power, and lighting) within a BIM model. Document the classification system through Unified Modeling Language (UML) diagrams.
- Creation of an AIM relational database based on UML diagrams depicting the established classification system.
- Integration of BIM models with the database within a unified model (commonly referred to as a federated model).

The considered case study in [45] consists of four BIM models representing four individual buildings on the West Cambridge campus. Three of the buildings were fully constructed, and one was under construction. A point cloud dataset was obtained using a Light Detecting and Ranging (LiDAR) scanner mounted on a car, and the utilities such as water, sewer, power, and communications were modeled as 3D geometry. In the first step in developing the AIM, the assets of two BIM models (i.e., two buildings) were classified, consisting of 6881 assets. In the second step, 41 UML diagrams and 149 relational database tables were created. The third step federates the 3D geometry, BIM models, and point cloud LiDAR data. The classified assets within the BIM models were then exported to the AIM, and the AIM relational database and federated 3D model were linked. In total, 6881 assets and associated data were exported from the BIM models.

Dolgov et al. [46] discussed the challenges and aspects of developing DTs for production system management. The DT consisted of an information model and an evaluation system. The information model was based on the collected data for management and consisted of three blocks: 1) initial data,

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which is conditionally constant; 2) a production schedule, which changes periodically; and 3) status and statistics, which change constantly. After data collection within the information model, the enterprise (production system) was simulated using the collected data. The simulation permitted the assessment and management of production capacity in different scenarios, the justification of necessary equipment or composition, the validation of a plan or schedule, and the development of recommendations for increasing the efficiency of the enterprise.

Lu et al. [47] analyzed literature and industry-defined standards influencing BIM and asset management during the operation and maintenance phase. The authors proposed a DT-enabled framework for intelligent asset management, comprising three layers: 1) smart assets, representing the digital counterparts of physical systems; 2) smart asset integration, concentrating on the incorporation of asset data and big data analytics technology; and 3) smart DT-enabled asset management, illustrating the interaction between human operators and the DT. DT-based asset management facilitates the creation of dynamic digital models that autonomously learn and update the status of their physical counterparts. However, the study did not delve into the interaction between smart assets and various stakeholders involved in the asset management process. Bolshakov et al. [48] outlined approaches for organizing the lifecycle management of technical systems, assets, and infrastructures using DTs. Furthermore, they underscored the necessity for formal definitions and standardization to implement DTs effectively in practice.

To summarize, DTs can enable interconnections between data and asset management to enable efficient asset-related decision-making [44]. In addition, AI-based decision-making improves the intelligence and integration of the overall asset management system [47]. Effective and efficient DT-based communication and cooperation enable a close connection between the stakeholders and the asset management process [47]. However, the deployment of DTs for asset management is still hindered by a lack of definition and formalization of the information required to create and update the asset management model [48].

### *5.5. Digital Twin for Asset Management*

The articles in this category concentrate on the application of DTs for assessing the sustainability of structures. Kaewunruen and Xu [49] scrutinized the design, construction, and maintenance processes of a railway station in London, utilizing BIM and a DT to guide construction participants in environmentally conscious planning, design, and project operation. The authors converted the 3D model of the structure into a 6D BIM model, encompassing time and cost schedules along with carbon emission calculations. They demonstrated the utility of BIM in predicting the sustainability of the structure during emergency situations. Additionally, the authors simulated three building renovation options using a DT in the event of a fire emergency to assess the most cost-efficient and environmentally friendly option. However, it is important to note that the implemented models in the study may not guarantee optimal accuracy due to a lack of design data for the considered building and its surrounding area.

Kaewunruen et al. [50] introduced a DT-enabled lifecycle assessment for evaluating the sustainability and vulnerability of a subway station in China. The authors utilized a DT to benchmark estimated costs and carbon emissions at each stage of the project lifecycle. Simulation results indicated that the construction stage incurs the highest cost, while carbon emissions costs are highest during the operation and maintenance phases. The authors also assessed different materials and simulated various renovation options to evaluate their cost and carbon emissions efficiency. However, it's worth noting that the proposed model was static and not self-re-updatable, which may prove ineffective in managing dynamic risks throughout the project lifecycle.

Tagliabue et al. [51] proposed a framework to transition from manual static sustainability assessments to a DT and IoT-enabled approach. The effectiveness of the proposed framework was demonstrated in a real-world scenario involving an educational building at the University of Brescia. The authors showcased how the DT enhances decision-making related to sustainability. Oroz-co-Messana et al. [52] concentrated on devising a method for creating a resource-efficient DT model of a neighborhood to conduct lifecycle analysis and sustainability assessments.

Francisco et al. [53] utilized data from smart meters to establish daily energy benchmarks for buildings, categorized by specific periods such as occupied and unoccupied periods during the school year, occupied and unoccupied periods during the summer, and the peak summer period. Simulation results revealed that energy scores for each building, when analyzed periodically, were significantly different from scores during the overall period. The authors recommended incorporating these periodically segregated efficiency metrics into DT-enabled energy management platforms.

Wang et al. [54] proposed a DT-based framework for a green building maintenance system. The proposed framework enables the stakeholders involved in the operation phase to solve the problem of insufficient information and automated management of green building maintenance. The feasibility of the proposed framework was verified by developing a prototype based on Bentley Systems software. The simulation results revealed that the framework could reflect green buildings' accurate and real-time status and improve green building maintenance efficiency using automated management. However, the proposed framework involves complex cross-application communication without considering heterogeneity among different data islands. Jakobi et al. [55] demonstrated the application of a BIM use case to minimize the performance gap that arises from inconsistencies between individual planning phases in a project's lifecycle. However, the authors evaluated the proposed model theoretically without performing an empirical analysis.

To summarize, the applicability of DTs for sustainability can lead to inconsistent and inaccurate models due to a lack of standard protocols. Moreover, under existing copyright law, it is challenging to preserve the privacy of critical and sensitive data [49]. In addition, DTs can optimize construction efficiency, cost, carbon emission, and buildability to improve building resilience and sustainability [50]. To further improve the energy efficiency of buildings, it is advisable to integrate temporally segmented daily energy metrics into a digital twin [53].

## 6. Discussion

DTs enable integration and communication between physical systems/entities and their virtual instances. They have been used extensively in the AEC/FM industry at the planning, design, construction, and operating levels. The application of DTs in the AEC/FM industry can be categorized mainly in the heritage restoration [15–17], asset management [44–48], and sustainability [49–55] domains. Although digital twin applications have improved performance in the AEC/FM industry [56], several challenges should be addressed for large-scale, efficient technology implementation. These challenges are as follows:

- Data acquisition: Creating a DT requires large amounts of data from different sources. Collecting these data is challenging, especially if the data are owned by private entities [57]. Moreover, transferring the data to a centralized location requires high network overhead, energy consumption, and cost [58]. One potential solution is using distributed technologies such as federated learning to create DTs that can eliminate the transfer of big data to a centralized location [59].
- Data heterogeneity: DTs involve data from different sources in different formats. The integration and interoperability of these heterogeneous spatial-temporal data pose a challenge in DT realization [60]. Conventional databases are insufficient to store and manage the heterogeneous and increasing volume of data with different semantics and syntaxes needed for DTs [61].
- Data privacy and security: The vast amounts of DT data are under constant privacy and security threats because of the inclusion of sensitive and important information [12]. Consequently, it becomes crucial that DT implementation follows current practices and policies in security and privacy regulations [62]. Recent trends have shown the use of blockchain [63] to improve transparency and trust in the DT process [64].
- Lack of standards: Efficient implementation of DTs requires common standards and interoperability [65]. Current deployment is hindered by a lack of consensus on the different standards, protocols, and procedures [66].

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- High implementation cost: The implementation of DTs requires many sensors to sense and collect data. This increases the hardware deployment, connectivity, and data transfer costs [67]. Moreover, DTs' effective and efficient deployment and operation require a well-connected IT infrastructure enabling IoT and data analytics [62].

These challenges should be addressed to efficiently and effectively realize DT technology in the AEC/FM industry.

## 7. Conclusions

The concept of DTs in the AEC/FM industry represents a relatively new area of investigation. While practical applications of DTs are prevalent in the aviation and manufacturing sectors, examples within the AEC/FM industry are limited. This study identifies literature reviews and a few proofs-of-concept for DT implementation in the AEC/FM industry, particularly in the early stages of researching how DTs can be applied in asset management.

Furthermore, this systematic literature review highlights potential applications of DTs targeting the asset management domain within AEC/FM, offering a comprehensive discussion. The identified areas encompass asset management throughout the lifecycles of existing facilities and infrastructures, evaluation and retrofitting of existing facilities for sustainability, and the restoration and efficient management of heritage buildings.

To further explore the true potential of DTs in the asset management domain, future research endeavors should focus on presenting practical frameworks, techniques, methodologies, and case studies from real-life projects. Such efforts would enhance understanding of the AEC/FM industry and pave the way for additional research and technological developments, ultimately revolutionizing the asset/facility management domain.

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