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Digital twin for product versus project lifecycles' development in manufacturing and construction industries

F. H. Abanda[1] · N. Jian[2] · S. Adukpo[3] · V. V. Tuhaise[1] · M. B. Manjia[4]

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Abstract

Digital twin, as an important enabling tool for digital transformation, has received increasing attention from researchers and practitioners since its definition was formalised. Especially in the global context and exacerbated by Covid-19, the applications of the digital twin have offered opportunities for many industries. While the digital twin has already been widely used in many sectors such as manufacturing and the construction industry—one of the key engines of economic development, is still lagging behind many other sectors. This study uses the systematic literature review to assess the applications of digital twin in manufacturing and construction respectively, the benefits it brings, and the impediments to its application. Based on this, a comparison is made of digital twin applications in the manufacturing and construction industries to draw lessons. This study concluded that although the use of digital twin in manufacturing is better than construction overall, it is still not reaching its full potential. Despite many benefits brought by the digital twin to construction during the project lifecycle, the construction sector faces even greater challenges than manufacturing in digital twin adoption. By comparison, this study drew five lessons to drive better adoption of the digital twin. The construction industry needs to accelerate the deployment of relevant hardware, promote the standard unification of digital twin, explore the whole lifecycle application of the digital twin, enhance data protection, and embrace changes. This study was limited in the scope of data collection. Future research could focus on gathering information from specific case studies, to produce more comprehensive perspectives.

Keywords Construction sector · Digital Twin · Digital transformation · Manufacturing sector · Lifecycle performance assessment

Introduction and background

Digitalisation is emerging as a key driver of technological innovation, and gradually directing the development and transformation of many industries (Botkina et al., 2018). A major element of the digitisation drive and transformation is the concept of digital twins. In this digital transformation era, digital twins, are making a radical impact on a wide range of industries (Tao & Qi, 2019). This became even more prominent in the recent Covid-19 pandemic, where digital twin-enabled remote commissioning and information interaction offered new solutions for enterprises in blocked or inaccessible areas (Leng et al., 2021). Through data transmission and updating via sensors, digital twin can be argued to reflect almost every aspect of a product or process (Qi et al., 2021). Therefore, the emergence and application of the digital twin have created great opportunities for the interaction of the physical and virtual world (Opoku et al., 2021).

The concept of the digital twin has been evolving since its first formal definition and application prospects were introduced by NASA in 2012 (Glaessgen & Stargel, 2012). A sector where digital twin has progressively been used and become dominant is the manufacturing industry. Digital twin

✉ F. H. Abanda
fabanda@brookes.ac.uk

1 School of the Built Environment, Oxford Brookes University, Oxford OX3 0BP, UK

2 Department of Mechanical, Aerospace and Civil Engineering, The University of Manchester, Manchester, UK

3 The Bartlett School of Sustainable Construction University College, 1-19 Torrington Place, WC1E 7HB London, UK

4 Department of Civil Engineering, National Advanced School of Engineering, The University of Yaoundé I, PO Box. 8390, Yaoundé, Cameroon

has served as a crucial hub for the delivery of manufacturing products in the context of smart manufacturing (Lu et al., 2020b). Digital twin applications have contributed to improving productivity, reducing product delivery risk, managing the product lifecycle effectively, and bringing a broad range of benefits to manufacturing product delivery (Pires et al., 2019). The diverse application of digital twins in manufacturing and the associated improvements in manufacturing processes and products has attracted the attention of adjacent industries like the construction industry. The construction industry is one of the key engines for economic growth and employment in most countries. For example, the value of the worldwide construction industry exceeded US$10 trillion, contributing an average of around 8% of Gross Domestic Product (GDP) to national economies since 2017 (Opoku et al., 2021). However, despite the enormous size of the construction industry, the efficiency of project delivery and the adoption digital strategies and tools are still concerning. The construction industry has long been regarded as one of the least innovative and digitalised sectors, and the lack of innovative technology use has made low project delivery efficiency in construction one of the most recognised problems (Li et al., 2017; Perera et al., 2020). This is despite the promotion of digitisation by policy makers, and the perceived benefits of digitisation. In the UK for instance, the government through its Construction Strategy policy has mandated the adoption of digital strategies such as BIM Level 2 (now BIM Stage 2 as per ISO 19650-1 & 2) on all government procured projects from 2016. The emergence of various smart technologies and the need to digitise the physical world to improve construction processes and assets has positioned digital twins as a potential solution to some of the industry's challenges (Ozturk, 2021). Notwithstanding the identified benefits of digitalisation, and in particular, digital twins for the construction industry, there is a low adoption rate of these tools. As it stands, construction has a low adoption rate of digital twin and lags behind other industrial sectors like manufacturing (Madubuike et al., 2022). Some recent studies have sought to investigate reasons for such low adoption, and what could be done by the construction industry to increase its uptake. Whilst this emerging research provides some good insights, the construction industry as a whole can learn from adjacent industries such as manufacturing on how they have adopted digital technology, what it is been used for, how they have implemented it at scale, and the benefits that can be derived from the use of BIM. However, there is currently little research in the literature comparing the use of digital twin in manufacturing and construction, and few articles have focused on drawing lessons by comparing the digital twin adoption in these two industries. Thus, the aim of this study is to compare the use of digital twin in project delivery in the manufacturing and construction industries, and to draw out insights on how the construction industry can promote the use of digital twin application. The paper uses a systematic review methodology to undertake this comparison.

The following research questions will be pursued in order to achieve the research objectives:

Q1. What is the state of digital twin adoption in the manufacturing product lifecycle? What are the digital twins' applications and what are the associated barriers to its application?
Q2. What is the state of digital twin adoption in the construction project lifecycle? What are the digital twins' applications and what are the associated barriers to its application?
Q3. What are the differences in digital twin applications in the project (product) lifecycle in manufacturing and construction?
Q4. What lessons can be drawn from the comparison between manufacturing and construction in using digital twin?

The remainder of the paper is structured as follows: "Literature review" section addresses the origin and definition of the digital twin as well as the project lifecycle approaches in manufacturing and construction. "Research Methodology" section presents the methodology adopted for the study. "Findings from the systematic review" section presents the findings of the systematic review to provide the status of digital twin application in manufacturing and construction. This is followed by the discussions in "Discussions" section. Finally, the paper concludes with a summary of the study, limitations and suggestions for further research in "Conclusions" section.

Literature review

This section reviews the origin of the digital twin concept and its definition so as to provide a more comprehensive understanding of digital twin.

The origin of the digital twin concept

Grieves (2014) introduced the idea of the "digital twin" for the first time in an industry presentation on product lifecycle management in 2002. At the time, the term "digital twin" was used to refer to a digital information structure called a "mirrored space model" that was created independently as a descriptive structure only and maintained links to the physical system throughout its lifecycle (Grieves & Vickers, 2017). In 2005, three elements of the mirrored spaces model, namely real spaces, virtual spaces and a linking mechanism, were defined by Grieves (2005). There was no formal adoption of the concept by any industry at the time. It was not until 2012 that the term 'digital twin' was first adopted in the public domain by NASA, and in consequence a specific definition of

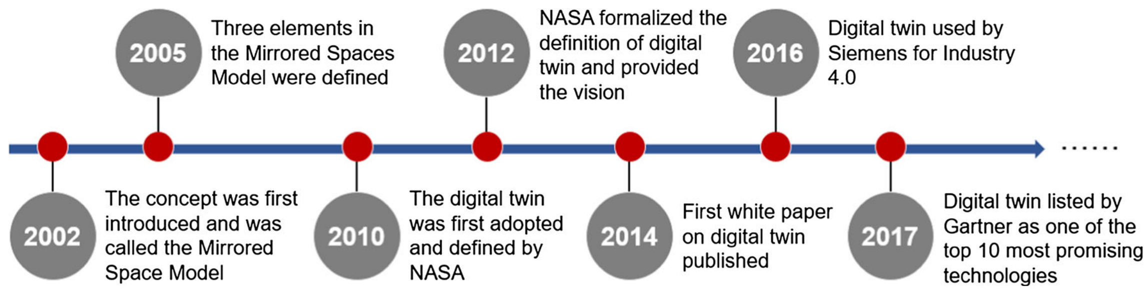

Fig. 1 The development of digital twin concept. Adapted from Qi et al. (2021)

the technology was formulated for the first time (Shafto et al., 2012). By 2014, the first white paper on the digital twin was published, reflecting the digital twin evolution from a concept to a number of practical applications (Grieves, 2014). Since then, digital twins have received increasing attention from researchers, and publications related to digital twin have shown rapid growth (Tao et al., 2019b). Relatedly, an increasing number of organisations and institutions such as Siemens, Gartner, etc. have discussed and investigated the applications and prospects of digital twin and considered it as one of the most promising technologies (Qi et al., 2021; Tao et al., 2019b). Figure 1 provides an overview of the development of the digital twin concept.

The definition of digital twin

Digital twin has been defined in diverse ways over the years. Table 1 provides a summary of some of the several definitions of digital twin proposed by researchers.

In the early days of the emergence of digital twin, the definition and understanding of the digital twin were not yet mature due to technical limitations. As the technology for capturing, collecting and computing data gradually developed, the definition of the digital twin has gradually developed and refined. Core to the recent definitions is emphasis on digital twin's core features to include dynamic bilateral data exchange between the physical and digital worlds and between physical objects and virtual models (Grieves, 2014). Moreover, according to Kritzinger et al. (2018), differing in the level of integration of physical and digital counterparts, digital twin has been classified into three types, i.e., digital model, digital shadow and digital twin. Digital models are the lowest level of integration between physical and virtual models of the three types. They are merely digital representations of physical objects without any automatic information exchange between their physical and digital objects (Kritzinger et al., 2018). Regarding digital shadow, the automatic data exchange between physical and digital objects is only one-way, i.e., changes to the physical object's state affect its digital counterpart, but changes to the digital entity's state cannot change the physical object's state (Kritzinger et al., 2018). Digital twin is the most integrated physical and digital object, as the automatic data flow allows for a bidirectional automatic exchange (Borth et al., 2019).

According to Shafto et al. (2012), when NASA first defined the digital twin, the definition of the digital twin was given as a multi-physics, multi-scale system that reacted to the state of the real twin through updates and historical data. The merit of this definition is its emphasis on the multifaceted, multiscale nature of the digital twin. However, it only shows that the digital twin is the digital reflection of real object and does not reflect the impact of the virtual model on the physical entity. Compared to the definitions given by other researchers, Bajaj et al. (2016) define and discuss the application areas of the digital twins in the mechanical, electrical and software fields, but failed to describe the two-way, real-time interaction of data. Similarly, according Grieves and Vickers (2017), they defined the digital twin as an information structure that comprehensively describes physical objects from the microscopic atomic level to the macroscopic geometric level, providing a detailed description of the digital twin model level, but also did not emphasise the bidirectional interaction of data between physical and virtual objects. The research on digital twin by Bolton et al. (2018) focused on the intersection of digital and social disciplines, and therefore the definition given by them places more emphasis on the simulation function brought by the digital twin and the help it brings to learning. The definition by Tao et al. (2019b) will be adopted as the definition of the digital twin in this study because it captures the essential components of the digital twin.

Digital Twins, IoT, Intelligent manufacturing, digital manufacturing, and smart manufacturing are all terms used to describe modern manufacturing approaches that leverage advanced technologies to improve productivity, efficiency, and flexibility. While there is some overlap between these concepts, they have distinct characteristics. Digital twins and IoT play critical roles in all three manufacturing concepts. The IoT refers to the network of interconnected physical devices and sensors that collect and exchange data. By connecting physical assets to digital twins through IoT, manufacturers can monitor and control operations in real-time,

Table 1 Definitions of the digital twin by different researchers. *Source*: by author

No	References	Definition
1	Shafto et al. (2012)	A digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin
2	Rosen et al. (2015)	Access to very realistic models of the current state of the process and their own behaviour in interaction with their environment in the real world
3	Bajaj et al. (2016)	A unified system model that can coordinate architecture, mechanical, electrical, software, verification, and other discipline-specific models across the system lifecycle
4	Grieves and Vickers (2017)	The Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level
5	Bolton et al. (2018)	a dynamic virtual representation of a physical object or system across its lifecycle, using real-time data to enable understanding, learning and reasoning
6	Tao et al. (2019b)	Digital twin is a real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them
7	AIAA and AIA (2020)	A set of virtual information constructs that mimics the structure, context and behaviour of an individual / unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realize value
8	Semeraro et al. (2021)	A set of adaptive models that emulate the behaviour of a physical system in a virtual system getting real time data to update itself along its life cycle. The digital twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system
9	ISO 23247-1:2021 (2021)	It is a digital representation of an observable manufacturing element with synchronisation between the element and its digital representation
10	BSI Flex 260: v1.0 2022-01 (2022)	A digital twin is a digital representation of an observable element with a means to enable a relationship between the two elements, when added to controlling and human components to fulfil a function, they form a cyber-physical system. The digital twin receives and transmits information to the cyber-physical system, linking the digital representation of an element and its performance in the real environment

analyze data for insights, and optimize performance and efficiency. Intelligent manufacturing, digital manufacturing, and smart manufacturing are interconnected concepts that leverage advanced technologies. While intelligent manufacturing emphasizes the use of intelligent systems, digital manufacturing focuses on the integration of digital technologies, and smart manufacturing encompasses both concepts while aiming for a connected and responsive manufacturing ecosystem. Digital twins and IoT are essential enablers of these manufacturing approaches, providing real-time data, simulation capabilities, and connectivity for monitoring, analysis, and optimization.

The underpinning drive of the aforementioned concepts are the need to develop products and projects in the manufacturing and construction sectors respectively. In order to ensure an effective and high-quality products and projects concepts such as product development, project development, Product Lifecycle Management (PLM) and Building Information Modeling (BIM) have been used. A brief explanation about these concepts will be examined in the ensuing section.

Product and project development lifecycle approaches in manufacturing and construction

Product development refers to the process of creating and bringing a new product or service to the market or improving an existing one. Project development refers to the process of transforming a construction project idea into a fully planned and organized endeavour and goes through sequential stages or phases that a construction project goes through, from its initial conception to its completion and handover. PLM is a comprehensive approach to managing a product's lifecycle, from its conceptualization to design, manufacturing, distribution, use, and eventual retirement. BIM, on the other hand, is a methodology widely used in the architecture, engineering, and construction (AEC) industry. It involves the creation and management of digital representations of a building or infrastructure project throughout its lifecycle, from design to construction and operation. Given the context of this study, this study will focus on product and project development for the manufacturing and construction sectors respectively.

When examining a product's lifecycle from the manufacturer's perspective, the entire process including concept generation, design, procurement, manufacturing, and recycling needs to be considered (Cao & Folan, 2012). Liu et al. (2021) used a four-phase model to describe the lifecycle of project delivery, i.e., "design", "manufacturing", "service", and "retire". Similarly, a closed-loop lifecycle model framework with "design", "manufacturing", "product use", "maintenance, repair and overhaul" (MRO) has been used to analyse the usage of the digital twin in manufacturing by Tao et al. (2018). Son et al. (2021) adopted an eight-phase lifecycle of "concept generation", "design", "manufacturing", "transportation", "sales", "utilization", "after-sales service", "recycle and disposal". It can be seen that the project delivery lifecycle of manufacturing projects can vary slightly due to the different products produced. The manufacturing industry is large and has a wide variety of products. The model used by Son et al. (2021) provides the most comprehensive overview of the product delivery lifecycle in manufacturing as it contains many phases. In comparison, the lifecycle model used by Liu et al. (2021) is more concise and contains some of the phases covered in Son et al. (2021). Drawing from the complementary nature of the lifecycle models by Liu et al. (2021), Tao et al. (2018) and Son et al. (2021), a more encompassing lifecycle model of manufacturing with seven phases will be used in this study. The lifecycle includes concept generating, design, manufacturing, transportation, sales, utilization and after-sales service, recycling and disposal phases.

In the construction industry, the Association for Project Management Body of Knowledge, presents six phases of a project lifecycle to include: concept, definition, deployment, transition, operation and termination (Murray-Webster & Dalcher, 2019). Eight phases of the project lifecycle are identified by the Chartered Institute of Building (CIOB) as follows: inception, feasibility, strategy, pre-construction, construction, testing and commissioning, completion, handover and operation, post-completion review and in use (CIOB, 2014). This classification is similar to the Royal Institute of British Architects' (RIBA) definition of the project lifecycle, which is strategic definition, preparation and briefing, concept design, spatial coordination, technical design, manufacturing and construction, handover and use (RIBA, 2020). Opoku et al. (2021) categorised the project lifecycle into the "design and engineering", "construction", "operation and maintenance", "demolition and recovery" phases. Similarly, Yitmen et al. (2021) introduced a construction lifecycle management model that included "design", "construction", "operation", "maintenance", and "end-of-life". Ozturk (2021) used a construction lifecycle model with five phases of "initiation", "design", "execution", "operation and maintenance", and "demolition" to investigate the role played by the digital twin. Wilking et al. (2021) proposed a generic definition of a Digital Twin that can be applied throughout different sectors. Three main phases have been considered in the Wilking et al. (2021) definition, which include: Beginning of Life (BoL), Middle of Life (MoL) and End of Life (EoL).

Overall, these lifecycle models are essentially based on the design, construction, operation and demolition phases of the project delivery lifecycle in the construction industry, but they differ in the level of detail on different phase. Although the three main phases, BoL, MoL and EoL have been used in for assessing the applications of digital twin (Wilking et al., 2021), the phases are so wide with very blurred boundaries. This led to two or more digital twin applications to easily be allocated to a certain phase, which could have been allocated to separate phases should a lifecycle with so many phases had been chosen. Hence, in this study, four phases of the project lifecycle that include "design and engineering", "construction", "operation and maintenance" and "demolition and recovery" phases (Opoku et al., 2021) is adopted for the construction sector. In the manufacturing sector, the concept generating, design, manufacturing, transportation, sales, utilisation and after-sales service, recycle and disposal phases have been adopted.

Research methodology

This study adopts a systematic literature review approach. It is a method whereby the literature is critically screened and evaluated using rigorous criteria and then used the outcome to draw research conclusions (Davis et al., 2014; Gough et al., 2016). As such, the systematic review is suitable for assessing the state of knowledge on a particular topic (Snyder, 2019). Considering the aim of this study, this research needs to gather collective evidence on digital twin usage, providing an overview of the benefits and barriers that exist in their application. This requires the study to cover as many relevant articles as possible rather than a more creative data collection (Snyder, 2019). This section will describe the steps of the systematic literature review of this study including the sources, methods and time frame of literature selection, the criteria used to evaluate and select the literature, and the methods used to synthesise and analyse the findings.

Research questions formulation

Identifying the questions to be studied is the first step in the data collection and analysis process. The research questions that guide this study have been formulated and outlined in "Introduction and background" section of this paper.

Literature selection criteria definition

After defining the questions to be studied, some inclusion criteria for the relevant literature need to be established to regulate the scope of literature selection. Clear criteria would help to reduce the potential for bias in the literature selection process (Xiao & Watson, 2019). The literature selection criteria developed for this study were as:

- The content of the literature is an analysis and discussion about digital twin applications in manufacturing or construction project lifecycles.
- The benefits of digital twin applications for the manufacturing or construction industry or the barriers to its applications are analysed or discussed by the article.
- The article contributes to the promotion the digital twin implementation in manufacturing or construction project lifecycles.

Literature identification

The reliability and validity of secondary data (literature) depend to a large extent on its source. The selection of reliable and authoritative sources guarantees a high-quality collection of literature and it is a key factor in ensuring the validity of research findings. In this study, the articles collected were all from academic journals. The Web of Science database is used for undertaking the search. It is one of the most commonly used databases in the natural sciences and engineering, providing an authoritative and reliable source of literature. The most efficient way to find the list of literature in the search process is by keyword searching using the database engine. Advanced search options available in Web of Science database were used to improve the efficiency of literature searches by combining keywords through Boolean operations. In this study, keywords related to digital twin, manufacturing and construction were combined and used to search and identify the literature. These keywords and combinations include 'Digital Twin' AND 'Manufacturing'; 'Digital Twin' AND 'Production'; 'Digital Twin' AND 'Application in manufacturing'; 'Digital Twin' AND 'manufacturing' AND 'Benefit'; 'Digital Twin' AND 'Production' AND 'Benefit'; 'Digital Twin' AND 'Manufacturing' AND 'Advantages'; 'Digital Twin' AND 'Production' AND 'Advantages'; 'Digital Twin' AND 'manufacturing' AND 'Barrier'; 'Digital Twin' AND 'Production' AND 'Barrier'; 'Digital Twin' AND 'Manufacturing' AND 'Challenges'; 'Digital Twin' AND 'Production' AND 'Challenges'; 'Digital Twin' AND 'Construction'; 'Digital Twin' AND 'Building'; 'Digital Twin' AND 'Application in construction'; 'Digital Twin' AND 'construction' AND 'Benefit'; 'Digital Twin' AND 'Building' AND 'Benefit'; 'Digital Twin' AND 'Construction' AND 'Advantages'; 'Digital Twin' AND 'Building' AND 'Advantages'; 'Digital Twin' AND 'construction' AND 'Barrier'; 'Digital Twin' AND 'Building' AND 'Barrier'; 'Digital Twin' AND 'Construction' AND 'Challenges'; 'Digital Twin' AND 'Building' AND 'Challenges'; 'Digital Twin' AND 'Project Delivery'. The period for the search was set to the literature published within the last 10 years, i.e., journal articles published since the beginning of 2012. The year 2012 was chosen as the starting point because that was the year the digital twin concept started gaining popularity (Shafto et al., 2012).

Evaluation of the literature

The assessment of the quality of the literature consists of two steps: an initial screening and a detailed reading review. Firstly, the initial screening included retaining only academic journal articles, skimming and assessing the titles, abstracts, keywords and conclusions, and removing duplicates. The initial screening helped to refine the literature list, excluded articles that did not match the content of this study, and gave a general idea of the content of the articles. After the initial screening, the remaining articles were read in full to assess the validity of the content. This step ensured that the quality of the literature is optimised in terms of the best use of the article collection.

Analysis and summary of the literature

After the screening and quality assessment process, the literature needs to be consolidated, categorised, analysed and summarised according to its content. To ensure a scientific and structured approach, the systematic literature review was used to analyse and summarise the literature with the help of VOSviewer software. The systematic literature review method was carried out based on the bibliometric analysis. Bibliometrics is a rigorous method used to analyse large amounts of scientific data, interpret the evolution of specific fields as well as shed light on emerging areas (Donthu et al., 2021). Bibliometrics takes a scientific development perspective and visualises the status of information connections and research in the field by analysing and integrating multiple information within the literature, such as co-authorship analysis and co-citation analysis. The method connects important concepts and information between the literature, allowing for a more structured and systematic analysis (Zabin et al., 2022). In addition, VOSviewer software was used for visualizating the analysis of results of the bibliometric network (van Eck & Waltman, 2017). VOSviewer can generate images of co-authorship, keyword co-occurrence, bibliographic coupling, etc. based on node distance and size, with better visualisation than other bibliometric analysis software, therefore it was chosen for this study (Han & Gong, 2021). The observation and investigation of the images drawn in VOSviewer can help in the subsequent review. To make the process of data analysis clearer and more intuitive, the process is illustrated in Fig. 2.

Findings from the systematic review

This section is a review of the bibliometric analysis results. Firstly, the process and results of literature gathering and screening are presented. Then the results of the bibliometric analysis of the literature related to manufacturing and construction are explained separately. Finally, the results of the manufacturing and construction sectors are compared with each other.

Literature collection and screening results

The results of the search by keyword are shown in Table 2 and 3. The first column on the left-hand side of the table represents the search terms used, with the second column showing the number of articles obtained within a specified time frame. The third column shows the output recorded based on screening by journal publications. Subsequently, by scanning the title, abstract, keywords as well as conclusions, the fourth column of the table shows the journal publications that remain. After combining results and removing duplicates, as well as reading the literature in full for detailed filtering, the number of remaining articles is shown in the fifth column of the table. Articles were included in this study if they met one of the three criteria stated in "Literature selection criteria definition" section. After the screening process, there were 166 and 61 articles relevant to the digital twin applications in the manufacturing project lifecycle and construction project lifecycle respectively.

Bibliometric results on the manufacturing sector's digital twin profile

Figure 3 shows a summary of the articles by timelines published in the manufacturing sector. It shows that from 2017 to 2016 there were very few publications on digital twin application cases in the manufacturing project lifecycle. However, from 2017 onwards, the number of publications grown significantly year on year, and the number of publications in this area is expected to continue to rise. The average annual growth rate (excluding 2022) being 46.9%. It should be noted that due to the time of this study, the data on the number of relevant publications in 2022 is still incomplete and thus does not form part of the annual growth rate.

The articles were subsequently imported into VOSviewer to generate a visual overview and also to obtain an idea of the scientific landscape. The generated word clouds about the sources and countries in which the articles were published are shown in Figs. 4 and 5.

Figure 4 shows that most articles are published in high-impact journals. The International Journal of Advanced Manufacturing Technology, Journal of Applied Sciences, Journal of Manufacturing Systems, Robotics and Computer-Integrated Manufacturing are the most prominent journals.

The study also sought to identify countries where the publications are made. The data shows that developed countries are the major sources of articles regarding digital twin in manufacturing project delivery. Much of the research come from developed countries such as Germany, the USA, Singapore, England, Italy, South Korea, Australia and France. This is not surprising given the nature of their industries and how technology is used in such countries. It is also worth noting that a number of developing economies, such as China, South Africa and Brazil, have also carried out some research about the digital twin implementation in manufacturing project lifecycle, with China making a notable contribution.

Bibliometric results on the construction sector's digital twin profile

In the construction sector, the distribution of research literature about digital twin implementation cases in project lifecycle over the years is shown in Fig. 6. It shows that

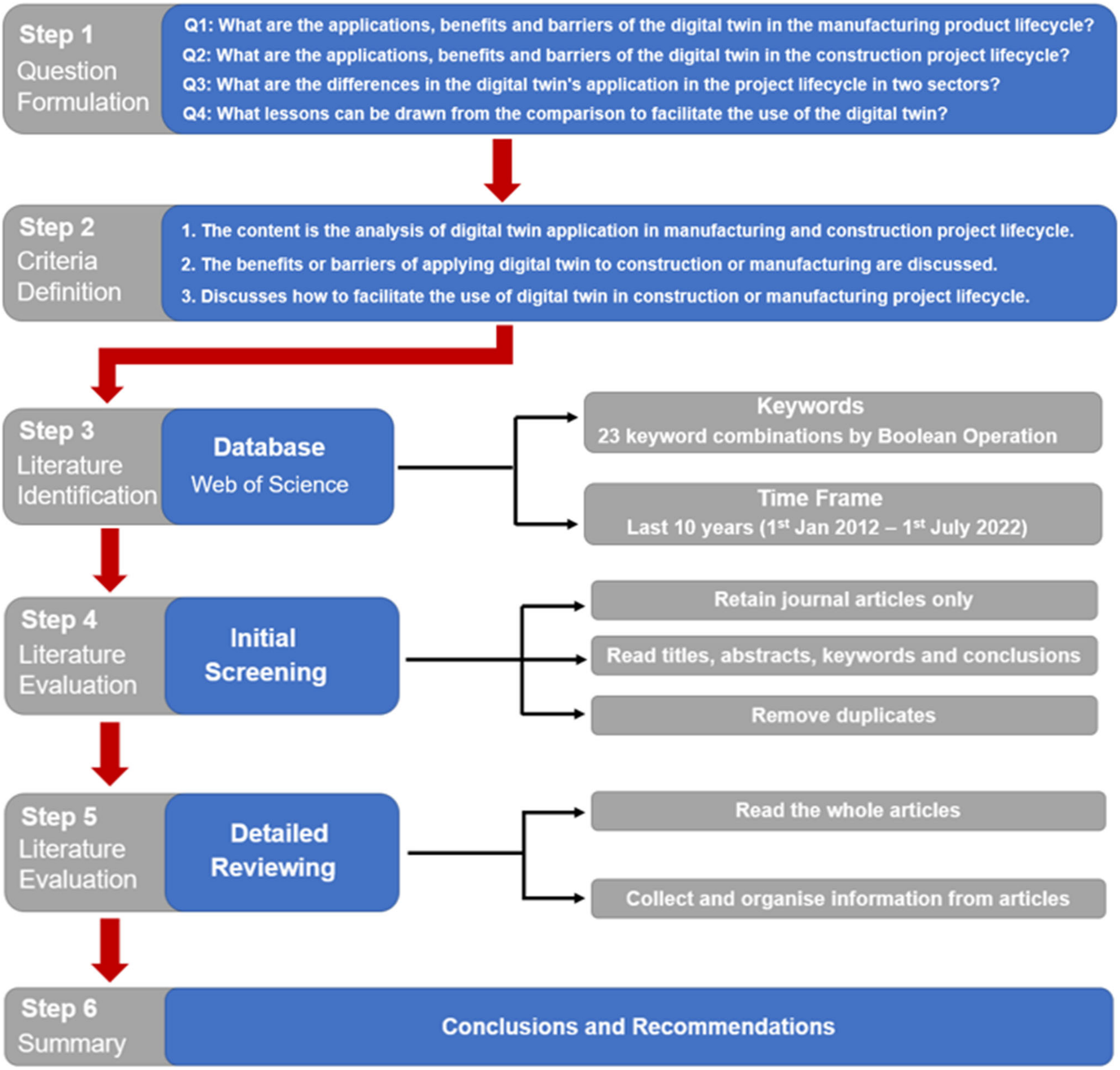

Fig. 2 Data analysis process. *Source* by authors

Table 2 Literature screening for digital twin in manufacturing. *Source* by authors

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Manufacturing'	1824	1117	160	166
'Digital Twin' AND 'Production'	1321	762	102	
'Digital Twin' AND 'Product delivery'	31	20	3	

Table 3 Literature screening for digital twin in construction. *Source* by authors

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Construction'	502	350	42	61
'Digital Twin' AND 'Building'	1078	710	52	
'Digital Twin' AND 'Project delivery'	50	28	2	

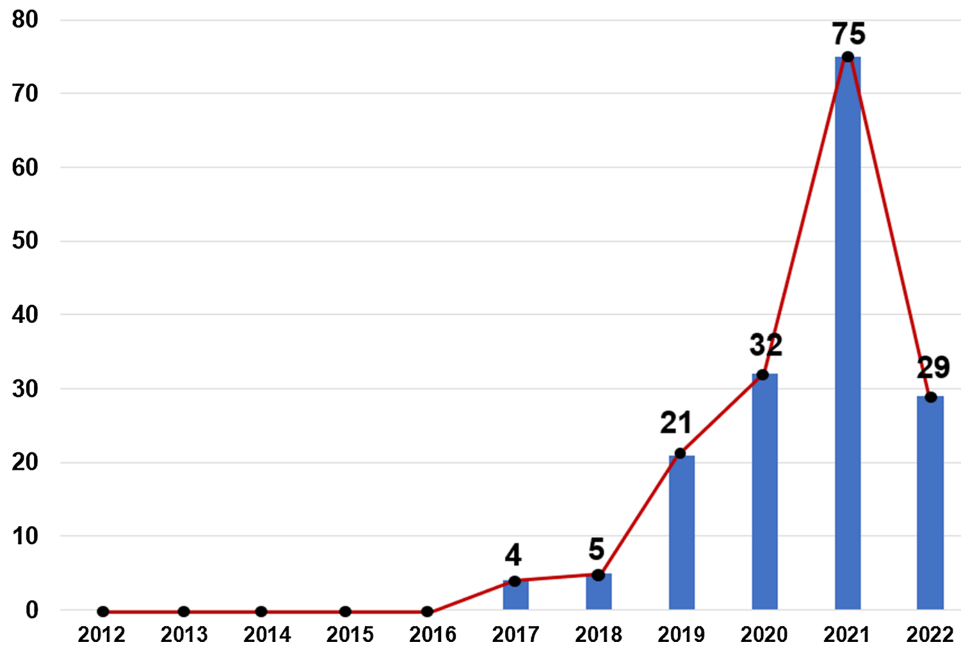

Fig. 3 Number of publications about the digital twin usage in manufacturing. *Source* by authors

around 2017, research publications on digital twin in the construction sector began to emerge from around 2018, and have gradually increased over time. Although the statistics on the number of relevant publications in 2022 are still incomplete due to the time of this study, the increasing trend in the number of publications is still evident. Publications has on the average increased by about 63% annually from 2019 to 2021.

Figures 7 and 8 shows the word cloud information by journals and countries.

Figure 7 shows that the majority of studies relating to digital twin deployment in construction project delivery came from journals such as Buildings, Sustainability, Applied Sciences, Automation in Construction and Advances in Civil Engineering. A large proportion of the articles are published in journals related to construction, civil engineering or construction and energy.

The publications are spread amongst 21 countries. The main source countries for publications were found to be China, the UK and the Germany, with 23, 14 and 11 publications respectively. As can be seen in Fig. 8, although developed countries such as the UK, Germany, Australia, Italy and Singapore still account for the majority of research sources, many developing countries such as China, Romania, Saudi Arabia and Qatar have also contributed to investigations into the adoption by construction sector of digital twin in the project lifecycle.

Comparison of the bibliometric results in manufacturing and construction

To capture the similarities and differences, the bibliometric analysis results of the implementation of digital twin in manufacturing and construction ware compared holistically. Firstly, the amount of literature published on the digital twin application in both industries over the years is shown in Fig. 9.

Comparing the number of publications, the manufacturing industry has been leading with more publications since 2012. The publication gap tends to widen rapidly over the years (except 2022 where the data is still incomplete). The bibliometric analysis also show that there were fewer studies on digital twin applications around 2012. The rapid development of other relevant fields, such as big data, the Internet of Things (IoT), has boosted digital twin advances and research on its industrial applications in recent years (Tao et al., 2019b). Hence, in both industries, the volume of literature on the digital twin application has shown rapid growth.

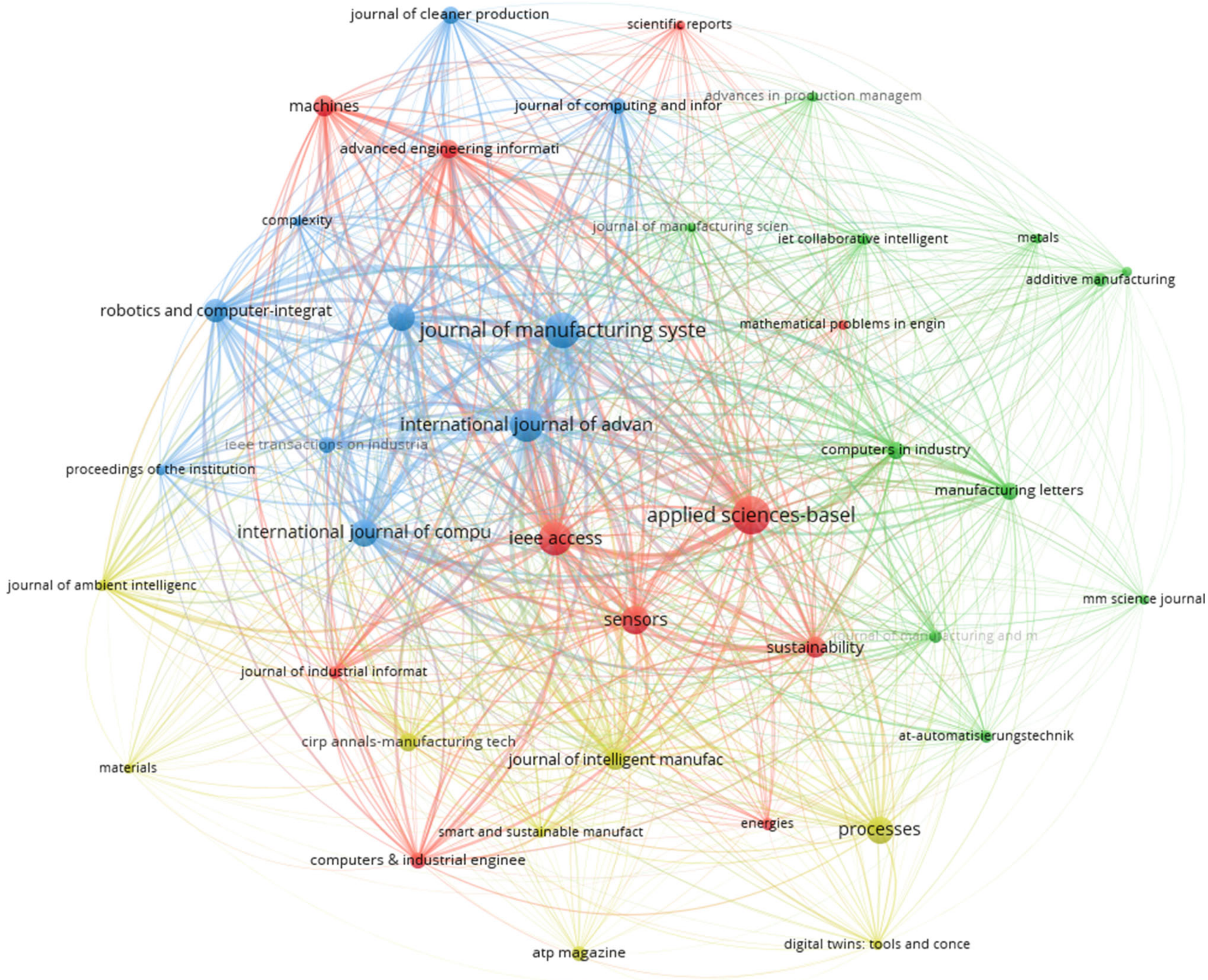

Fig. 4 Word cloud of literature sources on digital twin in manufacturing. *Source* by authors

Secondly, a comparison of the publication sources of the literature reveals that there are 61 and 34 publication sources for studies relating to the digital twin use in manufacturing and construction respectively. The sources of journals on the digital twin utilisation cases in the manufacturing project delivery process are more diverse and the research areas are more widely distributed. In manufacturing, journals in fields related to smart manufacturing, advanced manufacturing, robotics and computing are the main sources, while in construction, the main sources of literature are journals related to the fields of buildings, constructions, civil engineering, sustainability and energy.

A comparison of the countries in which the literature was published revealed that studies relating to the digital twin deployment in manufacturing came from 33 different countries, whereas the number of countries of publication in terms of the construction sector is only 21. This suggests that research on digital twin in manufacturing is more widely distributed around the world than in construction. Despite the differences in the number of countries sourced, the similarity between the two is that the developed countries are still the main source of literature. Overall, the research about the digital twin utilisation in construction project lifecycle lags behind that of the manufacturing industry.

Digital twin applications in the manufacturing sector

The search terms that are used for the application of digital twin in manufacturing are listed in Table 4. Moreover, Fig. 10 shows the word cloud regarding the digital twin's applications in manufacturing.

As can be seen in Fig. 10, digital twin has been used in various domains such as computer science, smart manufacturing,

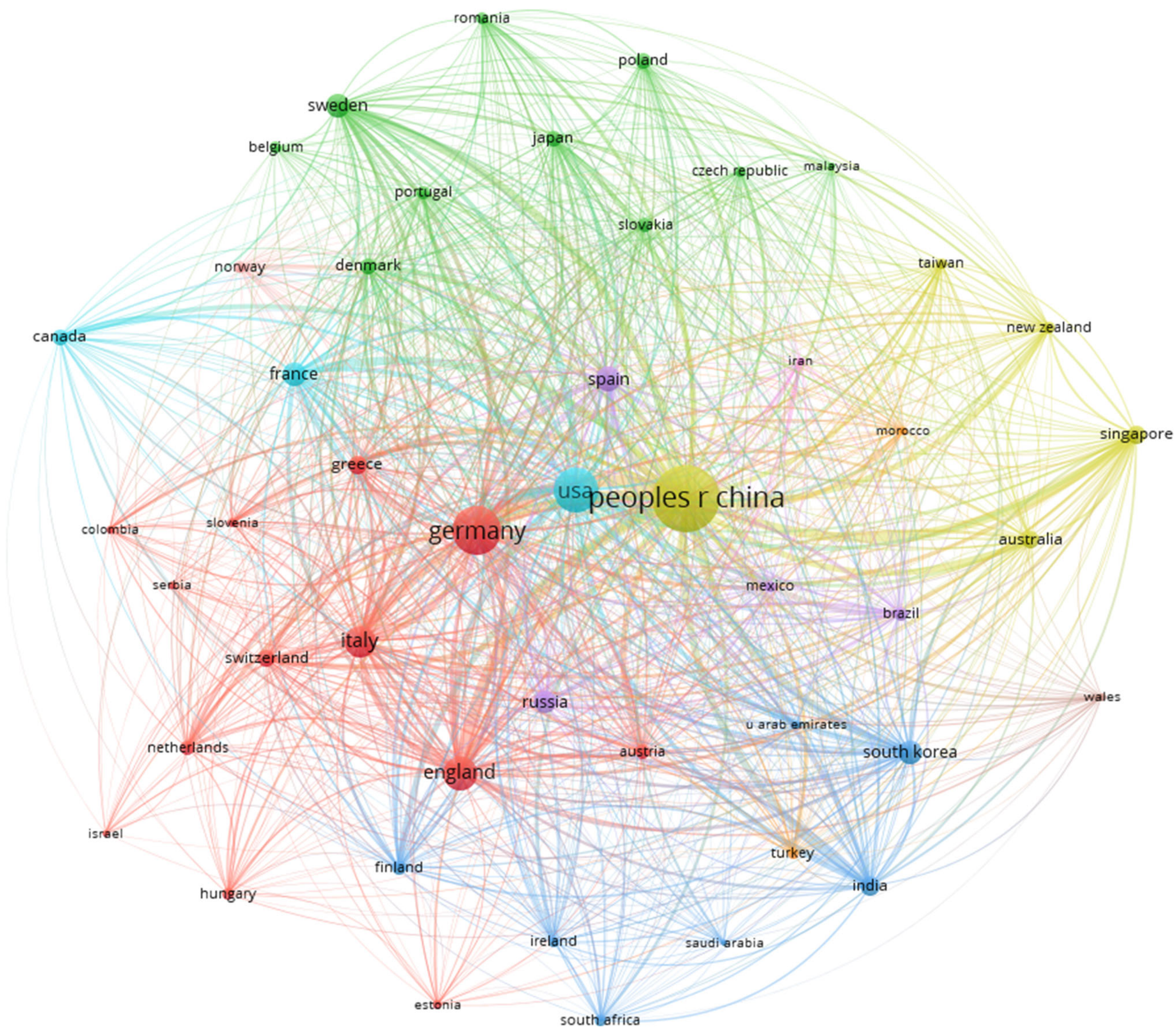

Fig. 5 Word cloud of publication countries for digital twin in manufacturing. *Source* by authors

materials science, robotics, human–robot collaboration and logistics in manufacturing. In these domains, digital twin has been useful in product design, simulation, production forecasting, fault diagnosis, decision support, predictive maintenance, scheduling, monitoring, etc. In addition to the preceding applications, through integration with technologies such as augmented reality, the Internet of Things, big data as well as artificial intelligence and deep learning, etc., digital twin has many functions in manufacturing products. Broadly, digital twin applications in manufacturing from a product lifecycle perspective are described under seven phases. These are concept generating, design, manufacturing, transportation, sales, utilisation and after-sales service, recycling and disposal.

Concept generating phase

Concept generating is the process that defines the design and key features of a product based on customer requirements and information about the product (Son et al., 2022). Digital twins have been investigated for exploring and discovering market needs guiding designers in developing functions based on customer requirements and quick confirmation of design solutions are areas. Ma et al. (2020) combined association analysis and cluster mining with the digital twin, which enabled designers to use the digital twin to better access market needs and explore hidden design requirements. Moreover, by combining big data, the digital twin was able to fully explore customer needs and identify new areas to improve customer satisfaction (Wang et al., 2021a, 2021b, 2021c).

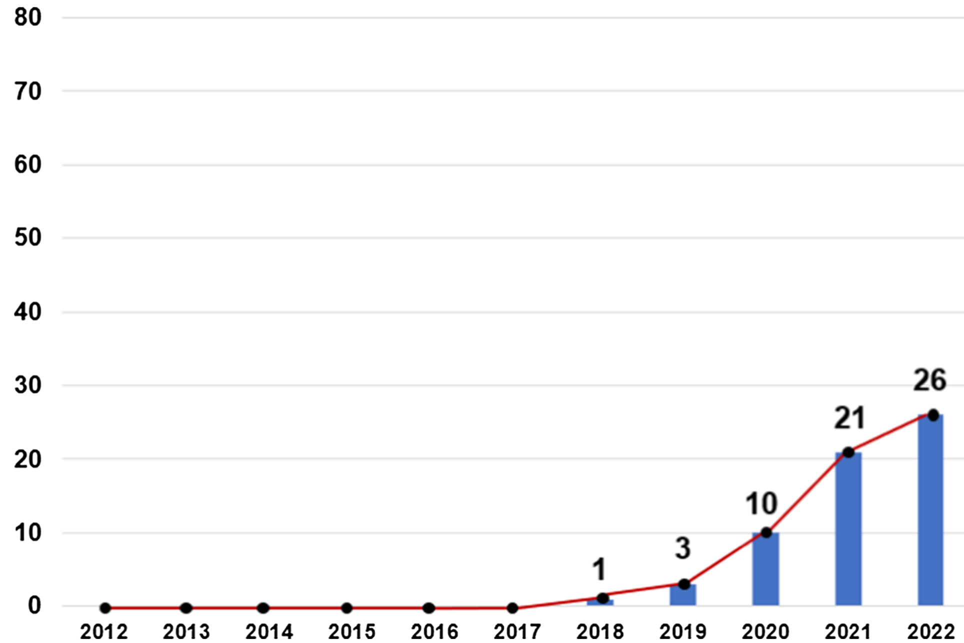

Fig. 6 Number of publications about the digital twin usage in construction. *Source* by authors

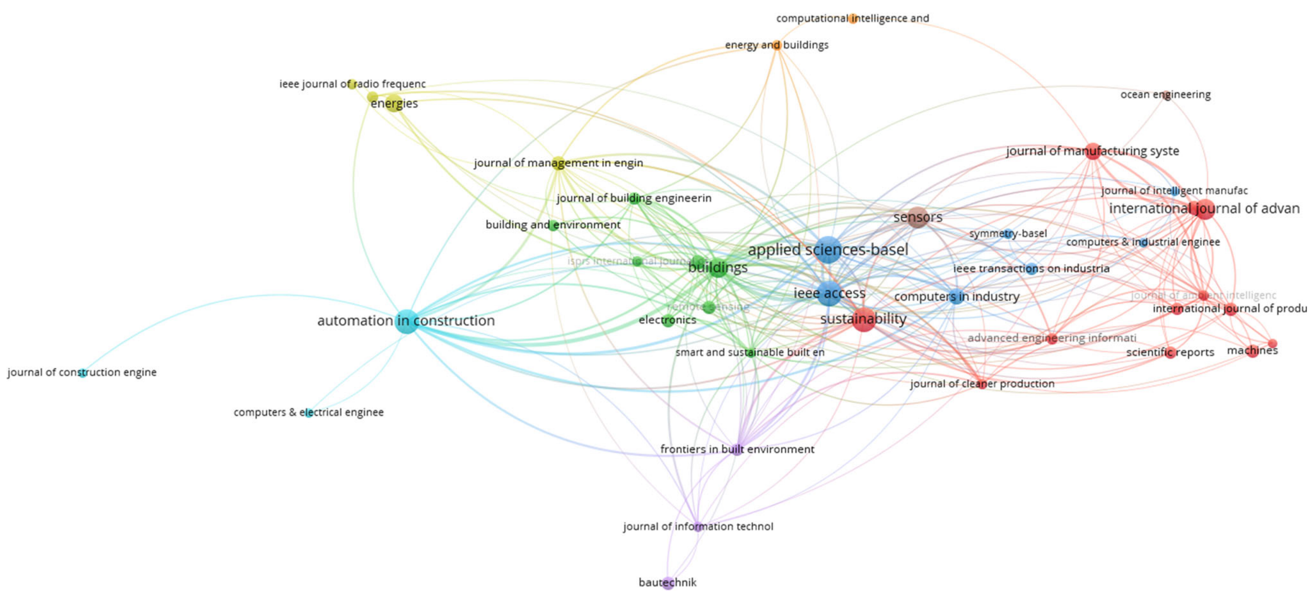

Fig. 7 Word cloud of literature sources on digital twin in construction. *Source* by authors

Cheng et al. (2020) applied a digital twin enhanced industrial internet system that contained product lifecycle history data to this phase to better assist designers in selecting better conceptual design options. Moreover, with the help of digital twin, it is possible to deepen the designer's understanding of the target customer's needs. By integrating the feature recommendation system into the digital twin, customer feedback could be analysed to recommend new features for the target product and guide designers to develop functions sensibly (Tao et al., 2019a).

Design phase

Product design for manufacturing comprises three sub-stages: product design specification, conceptual design and detailed design, representing the process of gathering product information and defining it precisely, finding solutions that meet the design specification and determining the specification of components and materials according to the manufacturing function (Son et al., 2022). The digital twin's utilisation in the product design phase is exemplified in rapid design and customised production, virtual and remote testing, as well as product design optimising. A study by Yan

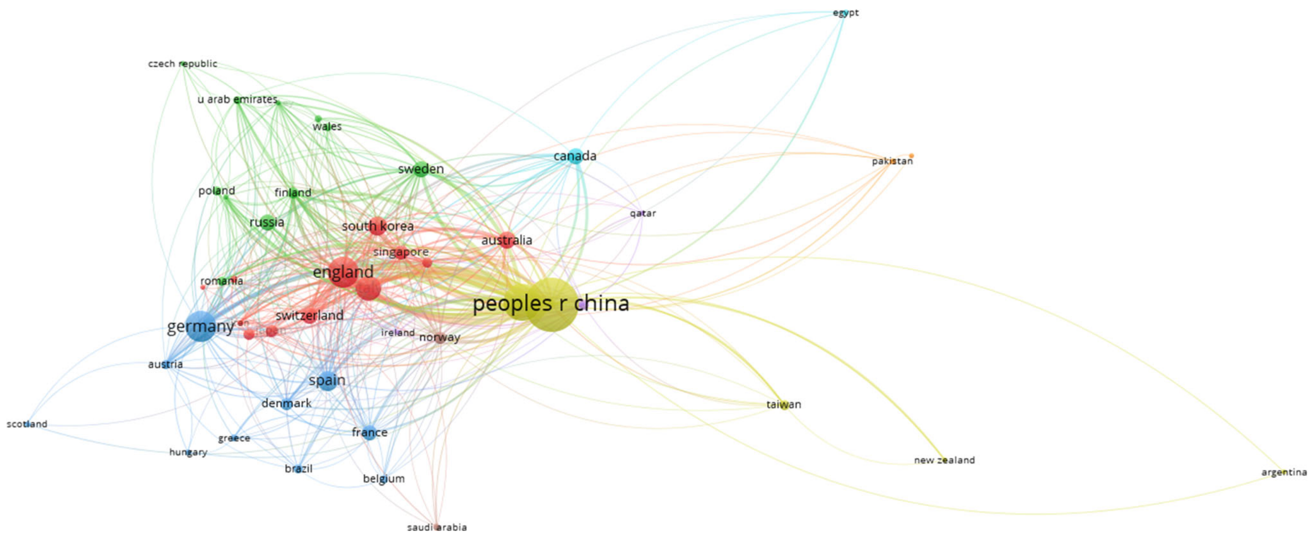

Fig. 8 Word cloud of publication countries for digital twin in construction. *Source* by authors

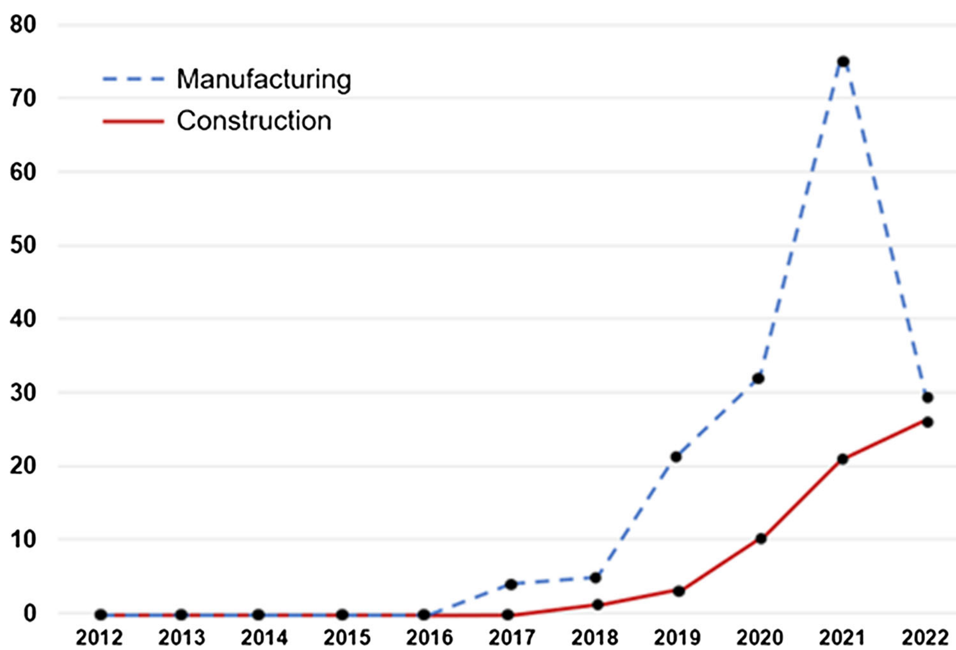

Fig. 9 Comparison of the number of articles [Total number of articles, Manufacturing (166); Construction (61)]. *Source* by authors

Table 4 Literature on digital twin applications in manufacturing. *Source*: by author

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Manufacturing'	1824	1117	158	197
'Digital Twin' AND 'Production'	1321	762	102	
'Digital Twin Application' AND 'Manufacturing'	618	373	85	

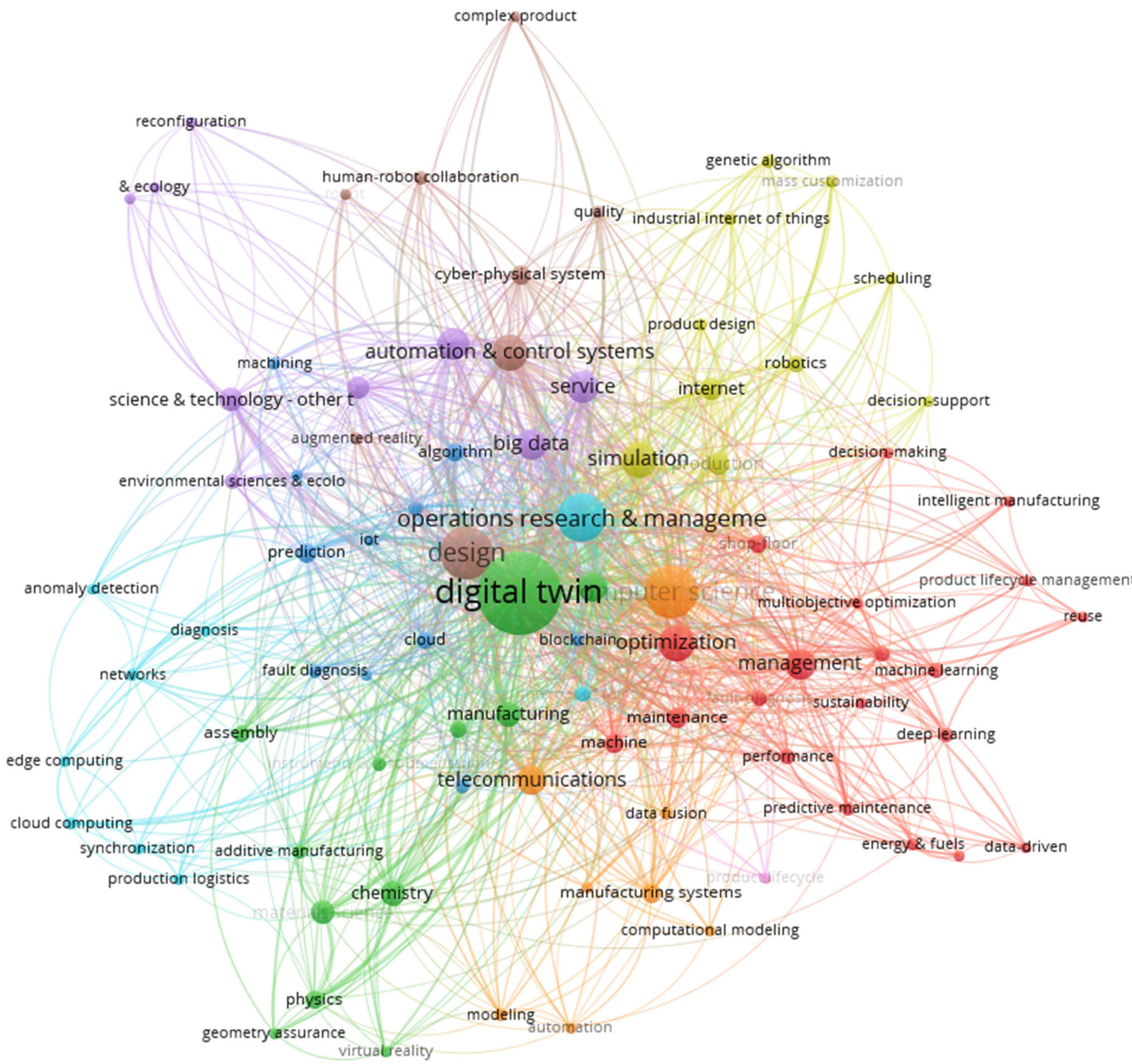

Fig. 10 Word cloud of digital twin applications in manufacturing

et al. (2021) developed a new digital twin design platform for furniture production, which shorten the design cycle. By applying stored digital twin models of typical equipment, Wu et al. (2021) were able to rapidly realise layout design, equipment configuration and virtual machining of marine pipeline production lines, enabling rapid production customisation. Ultra-high fidelity digital prototypes enabled by the digital twin platform have been used for digital verification, replacing the traditional costly and inefficient physical verification, achieving rapid confirmation of design solutions before physical manufacturing and facilitating rapid product development (Huang et al., 2022). Similarly, Lu et al. (2021) applied digital twin to the design process of automotive constant velocity joint, replacing traditional physical testing with virtual testing of the product implemented through digital twin to enhance the efficiency of tests during the design process. In terms of remote testing capabilities, Leng et al. (2021) have implemented remote semi-physical testing of products in the design phase through a digital twin system, significantly reducing the impact of Covid-19 pandemic that prevented physical testing of products in the field. Wu et al. (2022b) integrated multi-disciplinary collaboration into the digital design process through a digital twin platform, providing real-time verification of problems caused by the intersection of multiple disciplines, reducing design costs while promoting collaborative optimisation between disciplines in the product design phase.

Manufacturing phase

Manufacturing is the main phase in which digital twin is applied, and it refers to the process of assembling, manufacturing or producing a product based on specifications defined in the design phase (Son et al., 2022). During this phase, the digital twin has been investigated for flexible scheduling and production, process optimisation and production improving, equipment maintenance and fault diagnosis, energy management, human factors engineering optimisation, as well as real-time data management and tracing. In terms of digital twin implementation to assist production scheduling, intelligent scheduling of workshops enabled by digital twin could solve the problem of inconsistent resource allocation to physical production sites caused by information imbalance, and real-time active workshop scheduling was achieved through data provided by digital twin (Zhang et al., 2022). Nie et al. (2021) enhanced the allocation of resources and resistance to disruption in the production process through the integration of physical and virtual shopfloor with digital twin service systems, enabling a more efficient allocation of resources. In addition, a digital twin-based mixed integer linear programming (MILP) scheduling model has been developed, realising flexible scheduling of production based on internal and external temporary events (Tliba et al., 2022).

Digital twin can also be used to optimise the process and improve the production of products. As one of the main concerns of product production, quality improvement is an important aspect of digital twin applications. Reisch et al. (2022) were able to achieve real-time defect detection during the machining of large metal parts through digital twin and make quantitative assessments to improve the sensitivity of defect detection thereby ensuring machining quality. Also, quality control methods driven by digital twin can be used to accurately predict product quality, evaluate processes and optimise process parameters related to product quality (Zhu & Ji, 2022). In addition, improvements in the production are also manifested in optimisation in the machining and assembly processes. The machining state during the manufacturing process could be simulated by digital twin in real time and enable timely correction and optimisation of machining solutions to improve the machining process (Zhang & Zhu, 2019). Yi et al. (2021) also introduced an intelligent assembly process enabled by the digital twin, capable of being used for assembly process planning, simulation and prediction. Additionally, the digital twin-driven assembly commissioning method developed by Sun et al. (2020) enabled the assembly process prediction and optimization, ensuring the high precision required for the assembly of multi-disciplinary coupled products.

Maintenance during production is important for the production process, which can ensure that sufficient production resources are available during production to achieve the desired productivity and quality of production (Celen & Djurdjanovic, 2012). In production processes, the digital twin has shown capabilities in equipment maintenance, fault prediction, intervention and diagnosis. Guo et al. (2021) proposed a digital twin-based shopfloor equipment life prediction and preventive maintenance method to guide the maintenance of relevant components of shopfloor production equipment. Also, predicting possible anomalies during production could be achieved with the digital twin, ensuring the stability of the manufacturing process (Wang et al., 2021a, 2021b, 2021c). To quickly resolve faults in the event of future breakdowns, digital twin-based factory system platform can provide operators with tools for monitoring the production process, making it possible to intervene in time in the event of a production breakdown (Franceschi et al., 2022). In addition, to deal with faults efficiently, digital twin has been used as fault diagnosis aids. Combined with deep migration learning, digital twin-assisted fault diagnosis methods allow the extraction and exchange of simulated data for training from the virtual to the physical space, improving fault prediction accuracy and achieving efficient fault-assisted diagnosis of production processes (Deebak & Al-Turjman, 2021).

Another major application in production processes is energy management, a good energy management system could effectively contribute to efficiently managing energy in manufacturing processes (Wen et al., 2021). The energy management system based on digital twin is driven by operating conditions, parameters and real-time data on production loads. With the integration of a hybrid Petri-net (DDHPN) driven by data, the system can reflect the energy usage of the production process in real-time for efficient energy management (Li et al., 2022). Besides, by combining the digital twin with agent-based decision making, the movement of the robots in the production process can be optimised in real-time, thus enabling the energy consumption of the manufacturing process to be reduced (Barenji et al., 2021).

Human–robot collaboration allows for the combination of the high precision, speed and repeatability benefits of robots with the flexibility and cognitive skills of workers, but challenges remain in how to efficiently implement human–robot interaction in production processes (Villani et al., 2018). The application of digital twin in human factors engineering could effectively promote efficient human–machine collaboration. Sun et al. (2022) produced a framework for human–robot collaboration (HRC) commissioning driven by digital twin, which was able to improve the cognitive ability and adaptability of the robot units to the task, adaptively adjust the robot motion path during HRC, and optimise the efficiency of HRC. In addition, via the digital twin of flexible assembly unit developed, the simulation model has been used for live control, dynamic task allocation as well as sequencing between man and machine, which achieved more efficient collaborative human–machine assembly (Bilberg & Malik, 2019).

The tracing of information and managing data in real-time is a matter of concern during the production of a product. Especially in the production of complex products, owing to the high degree of unpredictability, complexity and frequent rework and repair, the importance of data management and traceability of process information in production is even more prominent (Zhuang et al., 2021). The intelligent machine digital twin tool developed by Wang et al., (2021a, 2021b, 2021c) has allowed isolated physical machines to be connected to the digital system and to monitor and manage machine operating conditions, production times and machine efficiency in real-time. Moreover, the digital twin has been introduced into the production process, achieving synchronous mapping of physical and virtual space in real-time, therefore achieving the goal of production site monitoring and communication, as well as inspection of the geometric features of the product in a timely manner (Zheng et al., 2021a, 2021b).

Transportation phase

After manufacturing, the logistics process in which the manufacturer transports the product to the selling point in accordance with purchase order is called transportation (Son et al., 2022). In the era of Industry 4.0, more and more new technologies are being used to change the competitive landscape of logistics and transport in the manufacturing industry (Tang & Veelenturf, 2019). The digital twin has been applied in the manufacturing transportation in areas such as real-time logistics management and tracking, storage or transport planning optimisation and controlling the risk of logistics processes.

The digital twin can be combined with cloud computing systems to capture the dynamics of the physical world in IoT-driven production-synchronous logistics systems, thereby enabling monitoring and controlling of logistics systems in real-time (Pan et al., 2021). In addition, integrating the digital twin platform with a multi-dimensional immersive virtual reality system and an IoT system allowed for the visualisation of cargo loading, while data captured by sensors can be used to optimise loading and transport planning, and these functions (Wong et al., 2021). Furthermore, the precise positioning and behavioural detection realised by the digital twin can enhance the safety of people working in the logistics process and the perception of risks, thus controlling the risks in the logistics (Zhao et al., 2021).

Sales phase

Sales is the process of selling products to companies or individuals (Son et al., 2022). In the product sales process, Sun et al. (2021) have successfully implemented a digital twin-based virtual shop by combining IoT and artificial intelligence (AI) analytics. It provided real-time feedback to users on product details and the development of intelligent soft robotic manipulators to automatically recognise grabbed items, thus providing a better remote interactive shopping experience for customers during the product sales process.

Utilisation and after-sales service phase

During the utilisation and after-sales service process, the customer operates the product according to the product's manual, meanwhile, the manufacturer provides maintenance and service for the product during the customer's use phase (Son et al., 2022). Improving product lifecycle maintainability is becoming increasingly important for manufacturers to maintain their competitiveness in the current market (Guo et al., 2020). During this phase, predictive maintenance and fault detection, product operation optimisation and health status monitoring can all be achieved by the digital twin. By combining digital twin with deep learning, product operating conditions can be simulated from digital twin models for model training, thereby enabling intelligent predictive maintenance of products with limited measurement data, as well as intelligent fault diagnosis of products (Xia et al., 2021; Xiong et al., 2021). A study by Li et al. (2021) applied digital twin in studying the operating conditions of gasoline engines. The digital twin simulation and optimisation platform combined with algorithms could identify the best operating conditions for engines, reduce product energy consumption and optimise product operation. In addition, detecting health conditions and predicting the remaining lifespan of products in use are also possible with the digital twin. For example, a deep migration learning-based digital twin model driven by data proposed by Meraghni et al. (2021) can be used to update the digital twin model of products, making cell product life prediction and health management a reality. In the area of renewable energy, Saini et al. (2022) developed a digital twin of a real time microgrid (MG), installed at the commercial building, that can be used to evaluate the electrical, financial, and environmental performance of the MG. Li et al. (2022) developed a digital twin driven information architecture of sustainability assessment oriented for dynamic evolution under the whole life cycle based on the classic digital twin mapping system. The sustainability assessment method segment of the architecture includes indicator system building, indicator value determination, indicator importance degree determination and intelligent manufacturing project assessing (Li et al., 2022).

Recycling and disposal phase

In the final phase of the manufacturing product lifecycle, recycle and disposal refers to the disposal or reuse of a product after it has been used by the customers (Son et al., 2022). Manufacturers are currently facing significant challenges in the disposal of used products, therefore it is important to explore ways to reuse, remanufacture and recycle products or their components during the product lifecycle (Kuik & Diong, 2019). In this phase, combined with deep learning, the utilisation of digital twin can provide manufacturers with information to make inform decisions on whether to remanufacture, upgrade or repair products (Zacharaki et al., 2021). The virtual model of the digital twin can also help for analysing components that should be scrapped and to understand the disassembly process of scrapped components (Cheng et al., 2020). In addition, digital twin can be used to predict market demand in the remanufacturing process, reduce uncertainty and support remanufacturing operations across the product lifecycle (Wang et al., 2020).

The barriers to implementing digital twin in manufacturing

In this section, the barriers to the adoption of digital twin in manufacturing will be examined. Table 5 provides the search terms used in identifying the literature related to impediments to digital twin deployment in manufacturing.

Using the search terms of Table 5, the barriers identified have been captured in the Word cloud of Fig. 11.

On conducting a detailed exploration, the literature resulting from Fig. 11, barriers to the adoption of digital twin will be discussed in the ensuing paragraphs.

Firstly, visibly, it appears from Fig. 11, that proper design is still a challenge in the digital twin application in manufacturing, and difficulties still exist with synchronous simulation, computer modelling, data fusion and transmission.

Secondly, the lack of a uniform definition and systematic understanding of the digital twin concept has hindered its application in manufacturing. Although studies about digital twin is increasing and definitions are converging, there is still no complete agreement on many of the characteristics of the digital twin (Liu et al., 2022a, 2022b, 2022c, 2022d). The comprehension of the concept, background and development methodology of the digital twin is important to its application, but systematic understanding of the digital twin is still lacking, which poses a challenge to the widespread use of this technology in manufacturing (Kantaros et al., 2022).

Thirdly, the lack of standardisation impedes the digital twin's deployment in manufacturing. Interoperability and uniformity between technology modules are still lacking. Difficulties in digital twin scalability and interoperability, data access and exchange between modules make it challenging to combine modules into larger systems, hindering its integrated application throughout the product lifecycle (Qamsane et al., 2022). In the manufacturing product delivery, digital twin models may be created by different stakeholders in different phases of product lifecycle, and different tools or development standards may be adopted, which also creates difficulties in its application and integration (Zheng et al., 2021a, 2021b).

Fourthly, due to the complexity of physical systems, there are still difficulties in achieving accurate simulations and precise real-time synchronisation between physical and virtual entities. For accurate and reliable simulation of the digital twin model, many factors should be given consideration. This is a challenge for the hardware capabilities of the computers in manufacturing plants, where in some plants the computers are still not efficient enough to achieve accurate and fast simulations (Chabanet et al., 2022; Gunasegaram et al., 2021). Also, the complexity, variability, uncertainty and ambiguity of the physical environment, combined with the constant generation of physical data, makes it harder to interact in real-time with the physical and virtual environments (Pires et al., 2019).

Finally, there is the obstacle posed by the lack of trust and consensus between stakeholders in the product delivery process and the poor interaction of information. Due to considerations of sensitivity and security of core data or important information between the various stakeholders, and the fact that the technology platform cannot be fully trusted by the stakeholders, making information interaction insufficient (Tao et al., 2022). Together with the fact that most organisations currently have their own systems and ways of processing information, with very little information sharing and interaction, thus making it more difficult to apply the digital twin to the manufacturing process (Pires et al., 2019).

Digital twin applications in the construction industry

Table 6 shows the literature search terms and outcomes for digital twins' applications in the construction industry. Figure 12 is the word cloud exported from VOSviewer about the digital twin applications in construction.

It is important to note that search result for digital applications in construction is 72, slightly more than 61 for the literature on digital twin in construction as indicated in Table 3. This is due to the addition word "Application" included in the search term 'Digital Twin Application' AND 'Construction' that brought about the extra number of articles. Also, on using the search term, 'Digital Twin Application' AND 'Project Delivery', the output was zero as indicated in the last row of Table 6.

Table 5 Literature on the barriers to the digital twin application in manufacturing. *Source* by authors

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Manufacturing' AND 'Barrier'	27	21	7	61
'Digital Twin' AND 'Production' AND 'Barrier'	17	9	4	
'Digital Twin' AND 'Manufacturing' AND 'Challenges'	443	256	44	
'Digital Twin' AND 'Production' AND 'Challenges'	311	177	30	

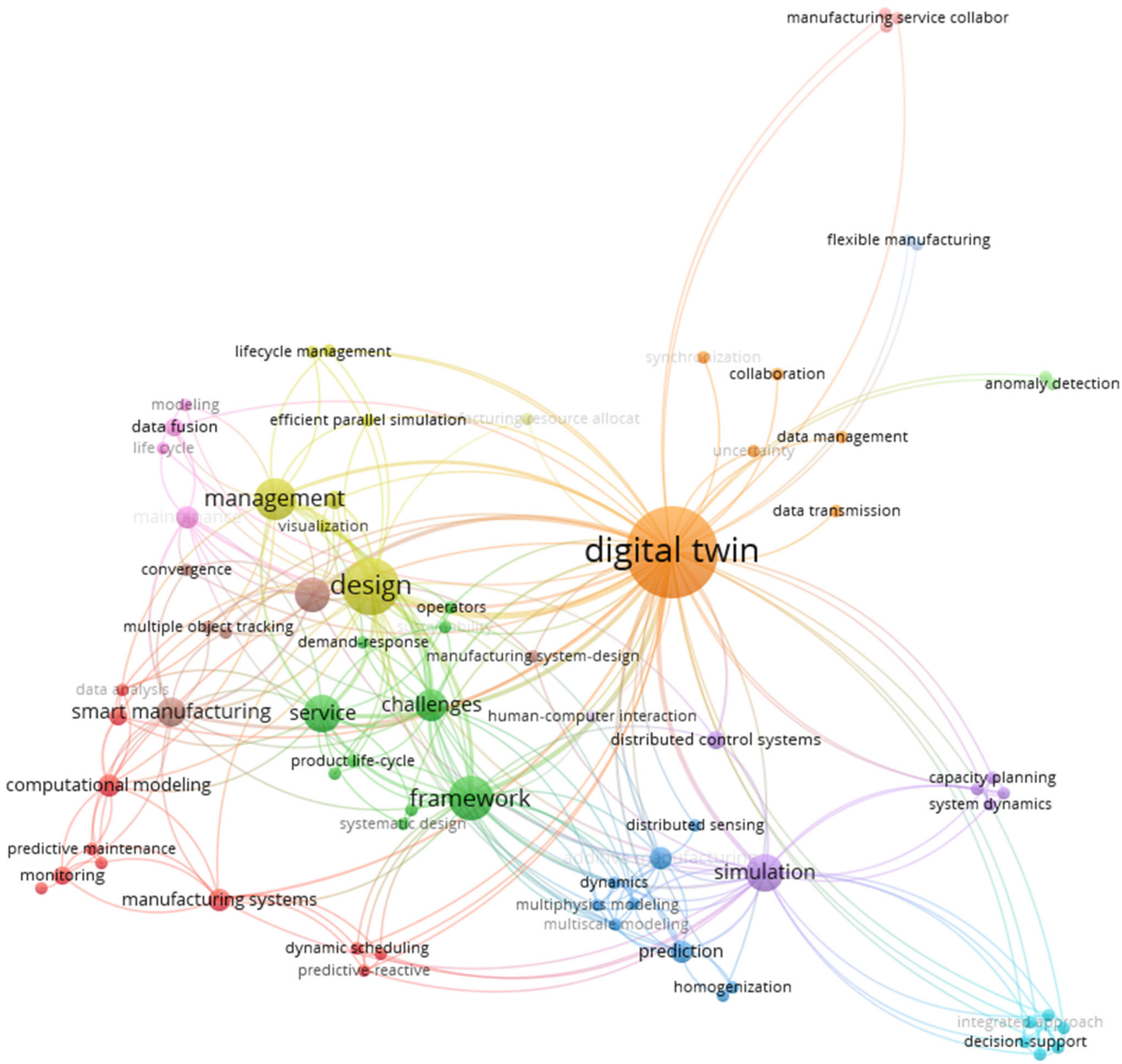

Fig. 11 Word cloud of challenges to digital twin's application in manufacturing. *Source* by authors

Table 6 Literature on digital twin applications in construction. *Source* by authors

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Construction'	502	350	40	72
'Digital Twin' AND 'Building'	1078	710	51	
'Digital Twin Application' AND 'Construction'	174	117	26	
'Digital Twin Application' AND 'Project Delivery'	0	0	0	

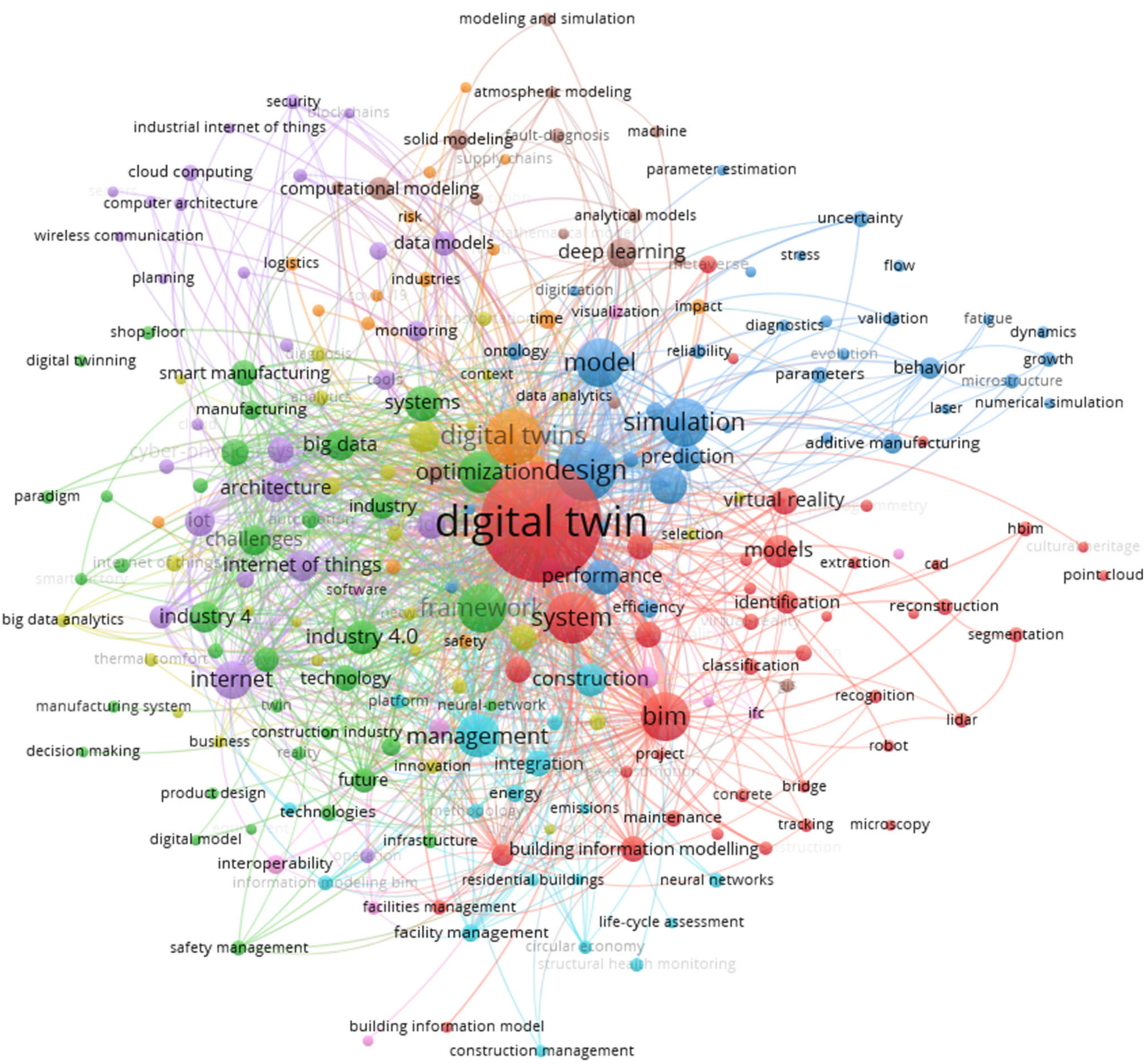

Fig. 12 Word cloud of digital twin applications in construction. *Source* by authors

On generating the Word cloud for the digital twin applications in construction, the result is presented in Fig. 12.

Figure 12 shows that, in the construction industry, with the maturation of technologies such as BIM, augmented reality, geographic information systems (GIS) and big data, digital twin applications are beginning to emerge, particularly in the construction of buildings and infrastructure projects. The most prominent research clusters of digital twins' applications include asset and facility management, construction safety management, hazard identification, automated construction, sustainable development, and structural health monitoring. To develop a detailed and specific understanding of how digital twin could be applied in the lifecycle of construction projects, the information gathered from the systematic review is discussed under a four-part project delivery lifecycle model comprising design and engineering, construction, operation and maintenance, and demolition and recovery was adopted.

Design and engineering phase

The design and engineering is the phase to organise and design the project plan, sign various documents with project stakeholders, carry out pre-construction surveys and audits, and obtaining approvals (Xu et al., 2014). Within this process, information sharing and design solution optimisation could be achieved by the use of digital twin. Kaewunruen and Lian (2019) proposed a six-dimensional Building Information Model (BIM)-based digital twin that could fully utilise information from the construction site to improve the flow of information for project planning and design. By applying it to a railway construction project, it was shown that the digital twin can simplify technical communication by improving information sharing on the construction project, thus achieving improved project design quality. Zhao et al. (2022) used BIM-based digital twin to simulate and evaluate ventilation options for public sanitation constructions, demonstrating the ability of digital twin to optimise the building environmental performance during design. Also, the integration of the digital twin with multi-criteria decision making (MCDM) and geographic information systems (GIS) enabled optimisation of complex road planning and construction the during road construction design (Jiang et al., 2022). Moreover, by simulating the UK's King's Cross station, Kaewunruen and Xu (2018) implemented a BIM-based digital twin in planning, design and operating environmentally efficient construction projects. Their study on the application of BIM in railway station construction projects proves that BIM-based digital twin can not only help in the design of construction projects, but can also take full account of economic and environmental benefits.

Construction phase

The construction phase is when the building project is formed and plays a prominent role in the overall delivery of the building project (Opoku et al., 2021). In this phase, the digital twin was applied in the areas of real-time construction monitoring, project information sharing and tracing, safety evaluation and risk control, construction quality and process optimisation. Han et al. (2022) developed the BIM-IoT platform as a prototype for implementing the digital twin, providing data monitoring during road construction, enabling real-time construction inspection and quality management. In combination with the IoT to update building information models in real-time, the joint use of digital twin and blockchain technology can significantly improve information sharing and traceability on construction projects (Lee et al., 2021). With reference to Wu et al. (2022a), by combining digital twin with deep learning and mixed reality, it was able to achieve real-time visual warning, making self-safety assessment of construction workers during the construction process a reality so that the risks during project construction can be controlled. These developments and applications are supported by the integration of the digital twin with other technologies, allowing it to provide accurate information on the project status during the construction process. Moreover, based on the large amount of accurate information provided, the digital twin could help to improve project quality and optimise the construction process. A study by Tran et al. (2021) demonstrated that geometric errors during construction can be assessed in an efficient way to improve construction quality by comparing the 3D as-built digital twin based on the construction process with the 3D design model. Additionally, the digital twin was able to simulate and calculate the construction situation and material situation on site in the virtual model, implementing intelligent planning for the deployment of materials and site logistics, thereby enabling a better construction process (Greif et al., 2020; Liu et al., 2022c).

Operation and maintenance phase

The main task during the operation and maintenance of construction projects involves the development and implementation of a proper maintenance programme while operating the building, which is an aspect of good performance and a comfortable environment for the users (Xu et al., 2014). During this phase, the completed buildings are generally not under the control of the builders, thus makes managing and accessing building data more challenging (Opoku et al., 2021). Nevertheless, the use of the digital twin has brought relief to the problem, as it could be useful in the areas of construction maintenance and repair, energy management, safety management, and facilities and asset management. Applying digital twin to the maintaining and repairing of buildings could provide opportunities for the building's maintenance staff to enable manual intervention and predictive maintenance before damage or failure occurs. For example, the digital twin can be integrated with cloud computing and deep learning to build a digital twin framework for building health inspection, enabling accurate detection of building damage and human intervention for efficient real-time monitoring and proactive maintenance (Dang et al., 2022). Besides, many researchers have explored opportunities to apply digital twins to building energy management. Zhao et al. (2021) used 3D laser scanning technology to efficiently create digital twin models of buildings and evaluate retrofitting options for existing buildings in terms of improving energy use through simulation. Their case study showed that this method was effective in reducing building energy costs, bringing opportunities for more efficient energy use in building operations and maintenance. Peng et al. (2020) have applied the digital twin to the operation of a hospital to continuously monitor the energy consumption of the hospital building in terms of water and electricity, and to count the absolute amount of energy consumed by different categories, thus demonstrating the important role played by digital twin in the energy management of hospitals. Moreover, they have also proven the value of digital twin applications in safety management. By interfacing the digital twin platform with the hospital's video surveillance platform, the system was able to call up surveillance video in real-time, and in the event of a security situation, the system was able to quickly locate and respond to it, enabling intelligent security management in the building. In addition, the study conducted by Lu et al. (2020a) provided a digital twin system for asset monitoring, based on an extended industrial foundation classes (IFC) data integration approach, achieving the automated and efficient management and monitoring of building assets in daily operations and maintenance management. In general, it appears that the powerful structural and visual presentation enabled by the digital twin makes a significant difference in these applications during the operation and maintenance phase of a construction project (Opoku et al., 2021). Nie et al. (2021) developed a digital twin application that uses real-time and historical data of selected features of historic buildings to predict energy consumption, and control energy-consuming equipment autonomously to reach the balance of energy efficiency, building conservation, and human comfort. Darwish and Hassanien (2022) developed a BIM model powered by Digital Twins (DT) that can be used for monitoring and inferring the behavior, deterioration of heritage structures, performance, collecting and classifying varied data that can co-exist in the model of an asset for artifact preservation. Falcone et al. (2021) developed a digital twin application that can be used for the automated analysis of the state of degradation of a cultural heritage artefact. Jouan and Hallot (2019) developed a digital twin application that captures analysis and simulation data using onsite sensors that can be used in predicting threats to the site integrity and corresponding preventive solution. The digital twin can support site managers in the preventive conservation of their assets. In the area of environmental sustainability, Fokaides et al. (2022) developed a digital twin that can be used in facilitating the to a smart, sustainable, resilient and carbon neutral built environment. Ospina-Bohórquez et al. (2022) created a digital twin for monitoring the construction of a wind farm.

Demolition and recovery phase

The obsolete and unusable buildings need to be demolished and replaced by new buildings by the end of the construction project's lifecycle (Ginga et al., 2020). Ensuring activities in the final phase of a building project's lifecycle are sustainable is a challenge. This is because a large amount of waste with environmental impacts is often generated, and this phase is often overlooked by researchers (Ginga et al., 2020; Liu et al., 2021). Some studies have investigated the use of digital twin in construction demolition and recovery phase. Kang et al. (2022) have developed a BIM and IoT-based digital twin framework to support information collection and analysis for activities in the demolition and recovery phases of buildings. The framework they proposed will be capable of assessing the volume of waste, planning the building demolition process and waste disposal routes, thus making it easier to choose an appropriate waste management strategy for building demolition. Zust et al. (2021) suggested an approach to deploy and process materials generated during excavation and demolition of buildings with digital twin, realising the recycling of demolition waste and reducing the demand for construction raw materials. Besides, BIM-based digital twin has its application in building renovation. The use of BIM-based building toolkits for the renovation of existing residences could enhance the flow of information, achieving the performance and quality improvement of buildings (Daniotti et al., 2022).

Barriers to implementing digital twin in construction

In Table 7, the search terms and outcomes on the impediments to the adoption of the digital twin in construction projects lifecycle are listed. These are then visualised in a word cloud map in Fig. 13.

According to Fig. 13, the application of digital twin is faces a number of challenges including integration of technologies, standardisation, model simulation, real-time interoperability, etc. The difficulties of data and technology integration are a barrier to the deployment of digital twin. In the semi-structured interviews conducted by Broo and

Table 7 Literature on the barriers to the digital twin application in construction

Search terms	Outcome	Screening		
		1st	2nd	3rd
'Digital Twin' AND 'Construction' AND 'Barrier'	12	11	3	26
'Digital Twin' AND 'Building' AND 'Barrier'	22	13	2	
'Digital Twin' AND 'Construction' AND 'Challenges'	129	89	16	
'Digital Twin' AND 'Building' AND 'Challenges'	251	159	18	

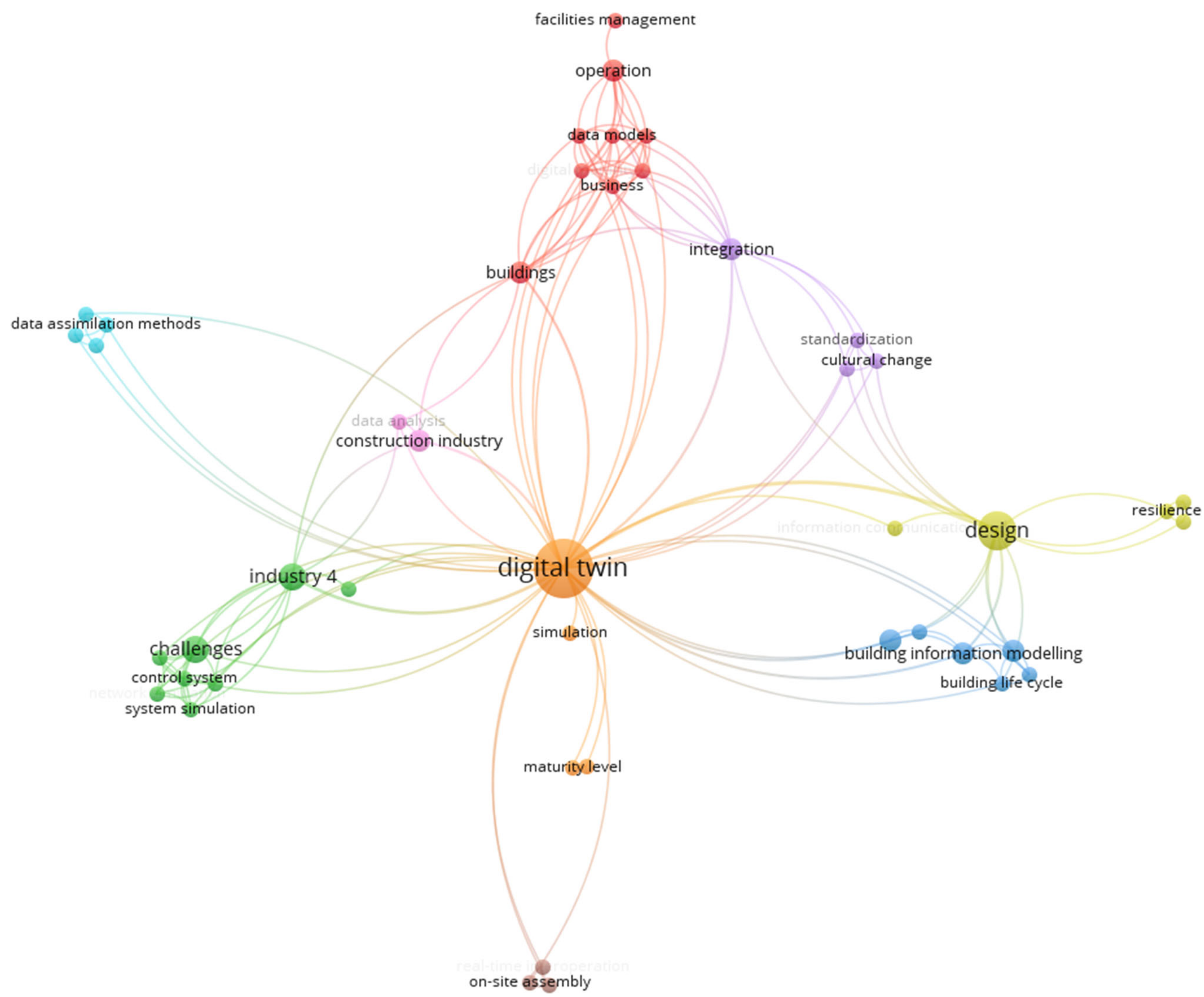

Fig. 13 Word cloud of obstacles to digital twin's application in construction

Schooling (2021) with executives from the UK infrastructure industry, it was mentioned that in cases where different stakeholders are using different software or different versions of the same software, the lack of common data standards and interoperability can make it very difficult to share project data and integrate technologies, therefore posing huge challenges to applying digital twin. Moreover, data security is a concern in the current delivery of construction projects. Data ownership remains ambiguous, and issues related to intellectual property rights associated with the digital twin remain. Especially in a web-based environment, with concerns about intellectual property and legal issues creating difficulties in the digital twin adoption (Madni et al., 2019;

Shahzad et al., 2022). Also, the deployment of technologies and facilities related to the digital twin is still a major issue in construction. Many facilities associated with digital twin, such as sensors, RFID (radio frequency identification), cyber-physical systems or WiFi networks, have yet been fully adopted in construction sites (Hoeft & Trask, 2022). Moreover, the availability and technical reliability of the facilities associated with the deployment of digital twin in the development of the building projects is wanting (Ammar et al., 2022). All of these factors have combined to make the digital twin implementation difficult.

Furthermore, organisational challenges such as the ambiguity in terms of budget of digital twin in construction and resistance to change are still of concern. The construction sector is still unclear about the cost of software and hardware required to deploy the digital twin in project development. The return on investment and impact on the cash flow profile of digital twin application has not been demonstrated on many projects. Also, the amount of training required for the technical expertise required to apply digital twin and the additional costs associated with training is still uncertain (Ammar et al., 2022). Cost uncertainty is also a major concern for the digital twin application in construction. The resistance of organisations or individuals to change is another concern for hindering the digital twin's adoption. Given the fragmented and uncertain nature of the construction industry, organisations or decision makers in the construction industry do not usually consider adopting new technologies or platforms for reasons of commercial and financial risk avoidance (Hoeft & Trask, 2022). Sacks et al. (2020) also noted that traditional business practices in the construction industry can resist the adoption of technological innovations. Existing approaches to construction project management and practices, particularly the workforce already skilled in implementing these practices, are difficult to change, which poses a considerable barrier to the digital twin deployment when developing construction projects.

Finally, the fickle and unique nature of the construction industry also impede the use of digital twin, due to the fact that it is almost impossible to identify two identical construction projects, each one is unique (Madubuike et al., 2022). The uniqueness and complexity of projects, combined with the fact that there are no agreed standards for the digital twin utilisation in construction, therefore make the digital twin development and application even more difficult.

Discussions

Comparison of digital twin in manufacturing and construction

The implementation of digital twin in product and project development in both the manufacturing and construction industries has attracted considerable attention from researchers. To assess the digital twin's applications and implications in product and project development, six different aspects or themes: the nature of products/project/service, the industry context, key technologies, applications and functions, benefits and barriers will be used as a lens upon which to compare the two industries.

The nature of product/project/service: In the manufacturing industry, products are typically mass-produced goods that are created through standardized processes. These products can range from consumer electronics, automobiles, and appliances to furniture, clothing, and packaged food items.

On the other hand, the construction industry is focused on the creation of infrastructure and buildings. Instead of producing standardized products, construction projects involve the development of unique structures tailored to specific requirements. Peharps, partly because of the standardised nature of products, digital twins is easily applied in the manufacturing than in the construction sector. This aligns with the view by Abanda et al. (2017) where, they argued that BIM can easily be applied on modular construction as it is standardised compared to traditional construction. However, due to the unique nature of projects and the challenge to understand and make informed decisions about their performance, the need of implementing digital twin in construction is urgent and and should be a par with the manufacturing sector to say the least. The issue of performance draws in other concepts such as an intelligent or smart project or building, which opens up another discussion about its relationship between BIM, digital twins and smart buildings. It is important to note that this continuum is not strictly linear, and there can be overlaps and interactions between these concepts. For example, a BIM model can serve as the basis for developing a Digital Twin, and a Digital Twin can inform ongoing updates and modifications to the BIM model. Ultimately, the goal is to leverage these technologies and approaches to improve construction processes, building performance, and operational efficiency throughout the lifecycle of a building.

Industry context: In manufacturing, the advent of the new paradigm of Industry 4.0, has led to an increase in interconnection and computerisation of products (Lu, 2017). Manufacturing has evolved to a state where it is feasible to combine intelligent objects and cyber-physical systems. The novel technologies that allow the development of digital copies in a digital environment, enabling real-time communication and making the physical and virtual worlds exchanging a reality (Cimino et al., 2019). The digital twin performs a key role in the context of Industry 4.0 and Smart Manufacturing, attracting significant interest from researchers and manufacturing practitioners (Lu et al., 2020b). The difference between the industry context in the manufacturing and the construction industry is that the latter has long been regarded as a sector with a slow pace of innovation, low levels of digitalisation and low efficiency in project development (Leviäkangas et al., 2017). Despite the slow adaptation to digitisation and informatisation, digital tools have improved task realisation, communication and information interaction in construction, leading to the development of many construction-related concepts such as smart buildings and smart cities (Ozturk, 2021). The great potential has been shown by digital twin in enhancing the construction project delivery (Al-Sehrawy & Kumar, 2021).

Key technologies: With regard to key technologies, the evolution of various kinds of new-generation technologies has made possible that the physical world and the virtual world can be gradually converged. The digital twin has greatly facilitated the digitalisation process in various industries by combining these technologies to digitise physical entities as a whole (Qi et al., 2021). The application of digital twin is closely related to the integration of various technologies. Technologies related to the digital twin, including the Internet of Things (IoT), big data, deep learning (DL) and blockchain, are all being researched and applied to some extent in the manufacturing and construction industries. However, the difference between the two is that, in construction projects, the BIM-based digital twin is the most common form of its application. As far as the digital twin is currently being applied, digital twin models are used as synonyms for BIM models in construction (Opoku et al., 2021), which is not accurate as both are not synonymous. Furthermore, in this study, examples of the use of digital twin in conjunction with Geographic Information Systems (GIS) was explored in the construction industry, while no relevant applications were found in the manufacturing industry. For manufacturing, in the transformation process to smart manufacturing, in addition to several technologies that are common in both industries, there is a preference for applications related to cyber-physical integration, such as finite element simulation, virtual reality and CPS (Qi & Tao, 2018).

An important aspect often demanded by practitioners are the various digital twin software systems. Unfortunately, upon browsing the literature identified through the systematic review, the different digital twin software systems were not uncovered. As a result, a manual search through leading vendors' or manufacturers' website led to the identification of the different digital twin software systems. The digital twin software for manufacturing will be discussed in the ensuing paragraph.

- Siemens Digital Twin: Siemens offers a comprehensive suite of digital twin solutions, including Simcenter for simulation and testing, Mindsphere for IoT connectivity and analytics, and Tecnomatix for digital manufacturing and plant simulation.
- Dassault Systèmes 3DEXPERIENCE: Dassault Systèmes provides a platform for digital twin development and management. It includes applications such as DELMIA for manufacturing operations management, SIMULIA for simulation and analysis, and CATIA for product design.
- PTC ThingWorx: ThingWorx is an Industrial IoT platform that enables the creation and management of digital twins. It provides tools for connecting assets, collecting and analyzing data, and creating virtual representations of physical products and processes.
- AVEVA Asset Performance Management: AVEVA offers a digital twin solution focused on asset performance management. It combines real-time data, predictive analytics, and simulation capabilities to optimize asset performance, maintenance, and reliability.
- Ansys Twin Builder: Ansys Twin Builder is a simulation-based digital twin platform. It allows manufacturers to create and simulate virtual models of products and processes, enabling optimization, predictive maintenance, and performance analysis.
- GE Digital PlantSight: GE Digital's PlantSight is a digital twin solution for the manufacturing industry. It integrates 3D models, engineering data, and real-time information to provide a holistic view of assets, improve operational efficiency, and enable data-driven decision-making.
- AspenTech Asset Performance Management: AspenTech offers a suite of solutions for asset performance management, including asset optimization, predictive maintenance, and process modeling. It enables manufacturers to create digital twins to monitor and optimize equipment and processes.
- Honeywell Forge Asset Performance Management: Honeywell Forge is an Industrial IoT platform that includes asset performance management capabilities. It allows manufacturers to create digital twins of assets, monitor performance, and leverage predictive analytics for maintenance and optimization.
- Microsoft Azure Digital Twins: Microsoft Azure provides a cloud-based platform for building and managing digital twins. It offers tools and services for modeling and visualizing assets, analyzing data, and integrating with other Azure services.

While digital twin software is not as prevalent in the construction sector as it is in manufacturing, there are still some software platforms and solutions available for implementing digital twins in construction. Here are a few examples:

- Autodesk Tandem: Autodesk Tandem aims to leverage Building Information Modeling (BIM) data and combine it with real-time project data to create a comprehensive digital representation of a built asset. This digital twin would allow construction teams, facility managers, and owners to visualize, analyze, and interact with the asset throughout its entire lifecycle.
- Bentley iTwin: Bentley iTwin is a comprehensive platform that combines reality modeling, BIM, and asset performance modeling. It enables the creation and management of digital twins for infrastructure projects, supporting design, construction, and ongoing operations.
- Hexagon HxDR: Hexagon HxDR is a cloud-based reality capture and digital twin solution for construction and infrastructure projects. It integrates high-resolution imagery, laser scanning, and other data sources to create accurate and detailed digital twins.
- Siemens COMOS: Siemens COMOS is a digital twin platform that caters to various industries, including construction. It provides tools for managing data and information throughout the entire lifecycle of a project, from design and engineering to construction and maintenance.
- IBM Maximo for Construction: IBM Maximo for Construction is an asset management software that can be extended to incorporate digital twin capabilities. It enables construction companies to monitor and manage assets, track maintenance activities, and optimize performance.
- Unity Reflect: Unity Reflect is a real-time 3D visualization and collaboration platform that supports the creation of digital twins for construction projects. It enables stakeholders to explore and interact with BIM models, improving communication and decision-making.
- SmartReality: SmartReality is a mobile application that combines augmented reality (AR) with digital twin technology. It allows construction teams to overlay 3D BIM models onto real-world construction sites, providing an immersive visualization experience.

Application and the main functions: The manufacturing and construction industries have different product and project lifecycle models and there is a difference in the extent to which digital twin is applied. Typically, manufacturing products have a more complex lifecycle than construction. In construction, the main functions and areas of application of the digital twin include building information visualisation and traceability, facilities management, energy simulation and management, real-time monitoring, structural and building inspection, construction process optimisation and construction risk management. The operation and maintenance (O&M) phase of the construction project lifecycle is where the digital twin is mostly applied. For manufacturing, the digital twin has even wider applications than manufacturing, including not only applications in information and data management, flexible scheduling, energy management, real-time monitoring, facilities maintenance and fault diagnosis, process optimisation and risk control, but also in rapid design, remote virtual verification, requirements exploration and function development, and human factors engineering. Unlike construction, the design and manufacturing phases of a product are what digital twin in manufacturing product lifecycle is currently more focused on. However, a similar situation in manufacturing and construction is that studies on the use of digital twin in the final stage of the lifecycle are lacking compared to other stages.

Benefits of digital twin application: The benefits of digital twin applications are quite similar in both manufacturing and construction industries, delivery time shortening and efficiency gains, project risk reduction, quality assurance, and management assistance of facilities brought about by digital twin have positively affected project delivery. However, the difference is that in the manufacturing industry, the improvements in economic benefits brought about by digital twin applications are more evident, specifically in terms of lower production costs, reduced energy consumption, etc. (Zhou et al., 2020). In construction, although digital twin applications can lead to increased energy efficiency, whether they are effective in reducing construction costs is still to be investigated. In this study, the use of the digital twin contributed to helping manufacturing sector or manufacturers to explore new business opportunities.

Lessons learned

The comparison shows that the construction industry is still in its infancy when it comes to implementing digital twin in project delivery and still lags behind the manufacturing industry. The construction industry needs to learn lessons from the current digital twin use in manufacturing to drive its own better application.

Digital twin technologies: The construction sector needs to strengthen the deployment of digital twin-related technologies. Digital twin-related technologies are still underdeployed in construction compared to manufacturing, for example, RFID or wireless networks, which are common in the manufacturing industry, are still rarely deployed in the delivery of construction projects (Hoeft & Trask, 2022). Therefore, the construction industry should follow the lead of the manufacturing industry in the deployment of technological facilities, complementing the relevant hardware to provide the conditions for a wider digital twin adoption.

Definition and standards for digital twin: Establishing unified and generally accepted definition of digital twin and its development standards is imperative. The lack of a common definition or development standard for the digital twin is currently a significant barrier to its adoption in both manufacturing and construction. In different disciplines, the digital twins' areas of focus are different (Kritzinger et al., 2018). Therefore, accelerating identification of a common definition can help drive further research into applications related to the digital twin and make progress towards integrated multidisciplinary applications. Furthermore, the current level of integration of digital twin with related technologies in construction is still insufficient compared to manufacturing. Facilitating the establishment of a unified standard for digital twin development and integration could enhance the integration with related technologies and their wider application.

Digital twin application for full project lifecycle: The implementation of digital twin throughout the whole lifecycle of a project should be given attention. Even though the digital twin provides many benefits for product development in manufacturing and its application is more mature than in the construction industry, research varies considerably according to different phases of product or project lifecycle. Most application cases were focused on a single or specific few phases and did not form an integrated application for the whole lifecycle. In construction, the major emphasis in digital twin usage is currently on the operations and maintenance phase of construction projects. Hence, in construction projects, paying attention to the digital twin's integrated application across the full lifecycle would help to fill the gaps and bring wider benefits to project delivery.

Data protection and sharing: To promote better digital twin adoption, the construction industry needs to improve its intellectual property and data protection regulations. As industrial big data becomes more widespread, the challenge with information interaction and sharing between project stakeholders due to information security concerns has slowed down the pace of digital twin adoption. This is even more evident in the manufacturing sector where industrial internet platforms are the main method of collaboration (Tao et al., 2022). The construction industry should learn from it, strengthen privacy protection and data security, improve provisions for information ownership and data protection, and create conditions for better information interaction between stakeholders to promote the digital twin adoption.

Openness to change: Last but not least, the construction industry needs to embrace change. Given the nature of the fragmentation and uniqueness of the construction industry, the adoption of new technologies inevitably brings business risks to construction project development, so many construction industry practitioners are conservative and reluctant to try out new technologies in the project development process (Hoeft & Trask, 2022). Nevertheless, the digital twin has demonstrated in manufacturing that it can bring many benefits to project development, and its potential for the construction sector is also becoming apparent. The construction industry should therefore be open to the adoption of new technologies while considering the risks, and it would be beneficial to actively explore the use of digital twin and embrace new opportunities in project development.

Conclusions

The aim of the study was to review both the application of digital twins in manufacturing and construction, and to draw out lessons learned from the digital twin applications. Through a systematic literature review and bibliometric analysis, this paper first reviewed the current state of digital twin for manufacturing and construction, providing an overview of research landscape in these two industries since 2012, the year in which digital twin started gaining popularity. The study investigated the application of digital twins and the barriers in the product and project lifecycles for the manufacturing and construction industries respectively. Following this, a comparative analysis of digital twin applications, barriers and benefits in the two industries was undertaken. However, the overall level of digitalisation is still low in construction, and the digital twin deployment still lags behind the manufacturing industry. From this comparative analysis, lessons were drawn under five categories that include digital twin technologies, digital twin definition and standards, digital twin application for full product and project lifecycle, data protection and sharing and openness to change. However, this study has some limitations. The records for the study were only collected from a single source, i.e., the Web of Science, rather than from several databases simultaneously. Coupled with the limited scope of this study, only a few of the most relevant keywords and their synonyms were selected for the literature search, thus possibly resulting in an under-complete collection of literature, which may consequently make the overview and collation of the digital twin's application across the project lifecycle less comprehensive.

Secondly, the subjectivity of judgement when reviewing the articles may influence the accuracy of the conclusions. The process of summarising findings involves concluding and categorising the scattered applications of the digital twin in a variety of areas of project (product) lifecycle. Thirdly, the phases considered in the lifecycles were different, e.g., manufacturing and construction in the manufacturing and construction sectors are different terms, although their meanings are largely the same with regards to their respective sectors. However, the scope of their boundries may be different, especially given the authors chosed 7 and 4 phases for the manufacturing and construction sectors respectively. Given the prelimary nature of this study and the fact that the goal was to provide a high-level overview, the authors chose to focus on articles that could fit with the different phases as difined in the different literature. As part of future studies, it will be imperative to provide a unique lifecycle with scopes clearly defined, such that it can serve as the lenses on which a detailed comparative analysis can be conducted. Fourthly, the unique nature of project versus products that can often be standardised is a limitation of the analysis of the application of digital twin on products and projects, as it cannot be granular if specific products and projects are not employed as case studies. As part of future study, specifc case study products and projects should be used in conducting detailed comparative analysis.

Lastly, the authors' personal subjective judgement may lead to inaccurate identification of digital twin applications or a less comprehensive generalisation of applications at some lifecycle phases. Based on the limitations mentioned, some recommendations on the research are proposed to provide insight for researchers to better conduct research in this area in the future. It is recommended that literature should be collected from a wider range of sources for future research. For example, using various databases such as Scopus, Web of Science and Science Direct, as well as expanding the scope of relevant keyword searches. This will enable the study to include more relevant literature and provide a wider picture of how digital twin is being applied in the relevant industries.

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Declarations

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