Automation in Construction 152 (2023) 104931

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

# Technologies for digital twin applications in construction

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ARTICLE INFO

*Keywords:*
Digital twin
Digital construction technologies
Building information modelling (BIM)
Internet of Things
System architecture
Systematic literature review

ABSTRACT

The construction industry is facing enormous pressure to adopt digital solutions to solve the industry's inherent problems. The digital twin has emerged as a solution that can update a BIM model with real-time data to achieve cyber-physical integration, enabling real-time monitoring of assets and activities and improving decision-making. The application of digital twins in the construction industry is still in its nascent stages but has been steadily growing over the past few years. A wide variety of emerging technologies are being used in the development of digital twins in diverse applications in construction but it is not immediately clear from the literature which ones are key to the successful development of digital twins, necessitating a systematic literature review with a focus on technologies. This paper aims to identify the key technologies used in the development of digital twins in construction in the existing literature, the research gaps and the potential areas for future research. This is achieved by conducting a systematic review of studies with demonstrative case studies and experimental setups in construction. Based on the observed research gaps, prominent future research directions are suggested, focusing on technologies in data transmission, interoperability and data integration and data processing and visualisation.

## 1. Introduction and research background

The digital twin is a revolutionising technology in the industry 4.0 era. The advent of the concept can be traced back to Grieve's presentation for a Product Lifecycle Management module at the University of Michigan in 2002 [1]. The concept was not conclusive at the time but elaborated the components of a digital twin to be a 'physical product in real space', a 'virtual product in virtual space' and a connection between both the physical and virtual products for data exchange. It became more evident in 2010 when it was published in the National Aeronautics and Space Administration (NASA) modelling, simulation, information technology processing roadmap where a digital twin was defined as "an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [2]. Several definitions of the concept have been made in the following years. For example, a digital twin has been referred to as a "realistic model" [3], "digital representation" [4], "dynamic virtual model" [5] that possesses the properties and behaviour of a system in the physical world. This study adopts the early definition of digital twins by Grieves [1]. The digital twin was first practically applied in NASA's Apollo program in 2010, and its application has evolved and has spread to other industries since then. Digital twin applications have been mainly investigated in manufacturing, aviation, and healthcare [6].They have been reported to improve, automate and enhance the efficiency of various activities in those industries. The promising abilities of digital twins and the rapid advances in emerging smart technologies have attracted interest in their application for the construction industry.

The term 'digital twin' is relatively new in the construction research literature. However, there is quite some lack of clarity in the concept because of its confusion with the term 'BIM'. Some authors use the two terms interchangeably while others consider them to be different. For

*Abbreviations:* ANN, Artificial Neural Network; ANOVA, Analysis of Variance; API, Application Programming Interface; AR, Augmented Reality; BACnet, Building Automation and Control Networks; BIM, Building Information Modelling; BMS, Building Management System; CoBie, Construction-Operations Building information exchange; GPS, Global Positioning System; HTTP, Hypertext Transfer Protocol; IFC, Industry Foundation Classes; IoT, Internet of Things; LAN, Local Area Network; LiDAR, Light Detection and Ranging; MQTT, Message Queuing Telemetry Transport; MR, Mixed Reality; RESTful API, Representational State Transfer Application Programming Interface; RFID, Radio Frequency Identification; SQL, Structured Query Language; SVM, Support Vector Machine; UAV, Unmanned Aerial Vehicle; UWB, Ultra-Wide Band; VLAN, Virtual Local Area Network; VR, Virtual Reality; WSN, Wireless Sensor Networks.

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https://doi.org/10.1016/j.autcon.2023.104931
Received 21 October 2022; Received in revised form 1 April 2023; Accepted 5 May 2023
Available online 13 May 2023

example, the digital twin has been referred to as BDOs (BIM Digital Objects) [7] and as a BIM model with lifecycle data and the ability to carry out simulations [8] . The confusion in the usage of the terms might hinder the acceptance of digital twins as a new concept in the construction industry [9] . Therefore, it is essential to differentiate between digital twins and BIM. BIM has been defined by the UK BIM task group as "a collaborative way of working, underpinned by the digital technologies which unlock more efficient methods of designing, delivering and maintaining physical built assets" [10] . A key feature of BIM is the 3D model commonly known as the BIM model which is realised with object-oriented software [11]. The BIM model acts as a rich data repository that contains information on geometric and functional aspects of an asset [12] and other related data like time schedules (4D) [13], cost (5D) estimation [14], asset management [15], etc. It can be used to integrate multi-disciplinary information from different project lifecycle phases to promote communication [16]. When properly developed and managed, the BIM model can provide a wealth of accurate geometric, descriptive and operable metadata that can be used to enhance project delivery practices [17]. However, the BIM model is limited in providing dynamic real-time data of the physical environment. Construction projects and assets are both implemented within a dynamic physical environment generating a vast amount of non-geometric data. A significant volume of this data is not fully taken advantage of yet it is critical for informed decision-making [18] .Thus, the need to collect this data by monitoring assets and projects in real time is required. Also, the BIM model has limited capability to process large sets of dynamic and multi-form data that require advanced technologies for storage and processing. These limitations of BIM models can lead to underutilisation of data, ineffective decision-making and inefficient practices with significant cost implications. The emerging concept of the digital twin offers an opportunity to address the limitations of BIM. In a digital twin system, the physical entity is connected to its equivalent virtual model by a data connection that allows data exchange between both entities. This implies that a BIM model is a merely starting point for the development of a digital twin in construction. With digital twin technology, the BIM model is connected to the physical environment to enable the bi-directional transfer of data between both entities. This enables the BIM model to be updated with real-time data which facilitates improved decision-making in the implementation and management of assets. Moreover, digital twins leverage advanced data analytics techniques like artificial intelligence for processing large sets of data to enable condition monitoring, predictions, diagnostics, prognostics and system optimisation . These digital twin capabilities have the potential to significantly improve information management and decision-making in various construction practices which in turn enhances the efficiency of construction and asset management activities.

The application of digital twins in the construction industry is a growing area of research. Five systematic literature reviews that include Boje, et al. [19], Jiang, et al. [20], Opoku, et al. [21], Deng, et al. [22] and Ozturk [23] on digital twin applications in construction already exist. Ozturk [23] conducted a bibliometric analysis to provide an overview of the research landscape for digital twins in the AECO-FM industry. Boje, et al. [19] analysed the perceived abilities of a digital twin as applied across various engineering domains and identified potential areas in BIM application in the construction phase that can be enhanced by a digital twin. Opoku, et al. [21] investigated digital twin applications in various project lifecycle phases while Deng, et al. [22] examined the built areas that concern digital twins and the capabilities of current state-of-the-art digital twins. Jiang, et al. [20] investigated the applications of digital twins in the civil engineering sector. None of the reviews has focussed on establishing the state of the art of existing technologies for digital twin development in the literature. It has been reported that digital twins present significant challenges in their development from a technological perspective [24–26]. A wide variety of emerging technologies are being used in their development for various applications but it is not immediately clear from the literature which ones are key to their successful development, necessitating a systematic literature review with a focus on technologies. Although the focus here is on technologies, it has to be acknowledged that the application and adoption of digital technologies in the AEC industry is affected by several organisational challenges such as inadequate expertise [27,28], financial constraints [29], cultural barriers [30], resistance to change [31] and competing initiatives [32,33] etc., which are out of the scope of this study. This paper aims to identify the key technologies used in the development of digital twins in construction in the existing literature, the research gaps and the potential areas for future research.

Typically, the development of a digital twin requires a data connection between a physical entity and its equivalent virtual model. Modelling technologies are used to generate a virtual model which mirrors the parameters of the physical environment such as the geometric structure, functionality, state, location, process, and performance [25]. The Internet of Things (IoT) technologies enable data connection, which allow for the bi-directional flow of data between physical and virtual entities [34]. The IoT technologies collect data from the physical environment which is then transmitted to the virtual model using communication transmissions in application layer protocols. The collected data is of high volume and can be multi-source, requiring big data storage technologies. The dynamic data from the physical environment is then integrated and fused into the virtual model to provide human-understandable abstractions and inferences [35]. The digital twin data can be processed using advanced data analytics technologies to provide various services to the users. The processed data is finally available to the end users straightforwardly and interactively through data visualisation which is supported by visualisation technologies [36]. These technologies collectively form the basis for implementing a viable digital twin consisting of a high-fidelity model with bi-directional data transfer and data processing capabilities. The technologies have been conceptualised into a digital twin system architecture with five development layers that include data acquisition, data transmission, digital modelling, data/model integration and the service [37]. The data acquisition layer consists of technologies for data collection and the collected data set. The transmission layer consists of the networking, communications and transmission protocols technologies. The digital modelling layer considers the technologies for measuring the parameters of the physical entity and for modelling the virtual model. The data/model integration layer consists of technologies that support data storage, data/model integration and fusion, data processing and analysis, visualisation and AI, machine learning and simulation engine. For this study, four broad categories that include data storage, data/model integration and fusion, data processing and analysis and data visualisation are treated as sub-categories of the data/model integration layer. The study uses this architecture as a guiding framework to identify the various technologies used in the five development layers of digital twins. The study adopts a systematic literature review methodology of selected digital twin application studies with construction-related demonstrative case studies and experimental setups. Firstly, the generic composition of digital twins in the studies is examined. This is followed by the elicitation of data about the technologies against the five conceptual digital twin development layers by [37]. Moreover, gaps and research issues for digital twin applications are discussed in this paper.

Following this introduction, the research design is presented in Section 2 followed by data collection in Section 3 and data extraction in Section 4. This is followed by Section 5 which presents the findings and discussions and Section 6 that presents the research gaps and future research. Finally, the conclusions and limitations are presented in Section 7.

## 2. Research design

### 2.1. Research methodology

A systematic literature review (SLR) is applied in this paper because it follows a rigorous and explicit procedure to identify, evaluate and synthesise the existing body of knowledge on a specific subject [38]. This approach helps in establishing the current state of the art on a subject which aids in identifying research gaps and determining future research directions in that subject field. Kitchenham, et al. [39] propose that an SLR comprises three stages which include: planning, implementation and reporting. The planning phase involves framing the research questions and creating criteria for locating the material and search methods. This is followed by the implementation phase where the material is collected and selected for the study. Lastly, the literature is combined and analysed in the reporting phase. This paper applies the preferred reporting items for systematic reviews and meta-analyses (PRISMA) method for collecting data for the systematic review. The PRISMA method is widely used in systematic reviews since it clearly describes the rationale and procedures for identifying, selecting, excluding and including literature to improve the accuracy of the systematic review [40]. The methodology of the study consists of 1) framing the research questions, 2) data collection and processing, 3) data extraction and analysis and 4) summary of findings and discussions.

### 2.2. Research questions

To define the scope of interest of the SLR, the following research questions were addressed:

Q1: What are the components of digital twins in digital twin

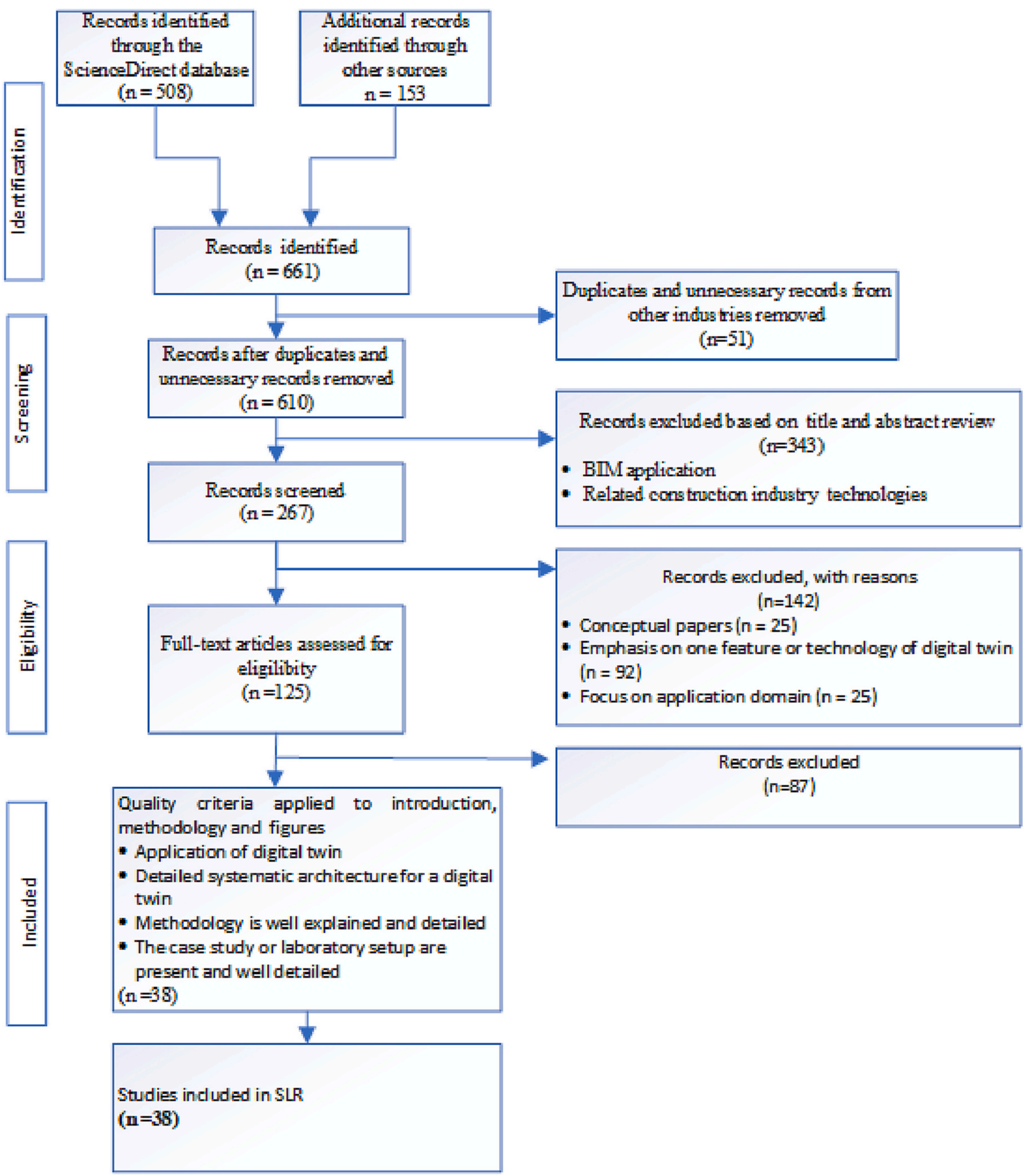


**Fig. 1.** PRISMA workflow diagram.

applications in construction?

Q2: What are the existing technologies used in the development of digital twins?

Q3: What are the research gaps and potential areas for future research?

## 3. Data collection for the literature

This section describes the steps taken to collect the relevant literature for the study. A PRISMA workflow diagram for the study is shown in Fig. 1.

### 3.1. Performing the search process

An initial literature search was conducted in the ScienceDirect database because it is one of the biggest databases covering a wide range of scientific publications. Moreover, it possesses desired attributes for conducting search queries like advanced search fields where systematic searches can be conducted [41]. An advanced search with keywords executed in the ScienceDirect database with a search string set to (“digital twin OR “virtual twin“ OR “cyber-physical system“) AND (“construction industry” OR “AEC” OR “construction management” OR “construction engineering“), for publications between 2015 and September 2022 and set to only research and review articles. The period selected for the search is appropriate because there are very few publications on digital twins before 2015. This search yielded a result of 508 records. A similar search using the keywords of “digital twin” and “construction industry” was run in similar databases like Web of Science and Google Scholar. An additional 153 records were identified by reading through the titles of the papers in the databases and selecting only those that had not been found in ScienceDirect.

### 3.2. Inclusion and exclusion criteria

The study gathered a total of 661 articles from both ScienceDirect and other additional databases. Inclusion and exclusion criteria were applied in three phases. The screening phase began by removing 51 records that were duplicates and studies that are not construction-industry related leaving a total of 610 articles. The second phase of screening involved reading of titles and abstracts of the publications and 343 articles were excluded because they were BIM application studies and on other related technologies in the construction industry. This left behind a total of 267 records. In phase three, 142 records were excluded of which, 25 were conceptual papers, 92 focused on one feature or technology of the digital twin and 25 records emphasised the service or function area for which the digital twin is developed. A total of 125 records remained for full-text assessment. An inclusion criterion was applied to the remaining 125 records. The inclusion criteria considered having 1) a detailed systematic architecture for a digital twin application 2) a methodology for the implementation 3) the technologies used for the implementation and 4) the demonstrative case studies and laboratory setups presented. The introduction, methodology and figures of the remaining studies were assessed and scored up to 4 in terms of those 4 criteria. The eligible papers obtained for the review were 38 in total and these are shown in Table 1.

## 4. Data extraction and analysis

The study uses Grieve’s [1] generic components of a digital twin to identify the essential components of a digital twin in the selected studies as indicated in Table 2. We identified the essential components of a digital twin using Grieve’s three dimensions of a digital twin namely physical entity, virtual entity and the data connection between both entities in the various studies. Table 2 shows the elicited data on the composition of digital twins in the selected studies. Table 2 comprises 4 columns for the article reference, physical entity, virtual entity and data

**Table 1**
Selected practical studies for the systematic review.

| Item | Title of paper | Aim of study | Reference |
|---|---|---|---|
| 1 | Towards Civil Engineering 4.0: Concept, workflow and application of Digital Twins for existing infrastructure | To propose a step-by-step workflow process for developing a digital twin for an existing asset in the built environment | Pregnolato, et al. [42] |
| 2 | Digital Twin-driven approach to improving the energy efficiency of indoor lighting based on computer vision and dynamic BIM | To consider the linkage between the lighting and surveillance systems and propose a digital twin lighting system. | Tan, et al. [43] |
| 3 | Using IoT for automated heating of a smart home by means of Open HAB software platform | To develop an IoT based application for managing automated heating in a smart home | Borissova, et al. [44] |
| 4 | Digital twin-enabled real-time synchronisation for planning, scheduling, and execution in precast on-site assembly | To develop a digital twin-enabled real-time synchronisation systems to facilitate planning, scheduling and execution during on-site assembly in prefabricated construction | Jiang, et al. [45] |
| 5 | A BIM-IoT and intelligent compaction integrated framework for advanced road compaction quality monitoring and management | To propose a BIM-IoT based framework combined with intelligent compaction prototype for real-time compaction quality monitoring and management | Han, et al. [46] |
| 6 | A digital twin predictive maintenance framework of Air handling units based on automatic fault detection and diagnostics | To propose a digital twin predictive maintenance framework of AHU | Hosamo, et al. [47] |
| 7 | Digital twin-enabled smart modular integrated construction system for on-site assembly | To propose a digital twin-enabled smart modular integrated system with a testbed robotic demonstration for collaborative decision-making and daily operation during on-site assembly. | Jiang, et al. [48] |
| 8 | Augmented reality and digital twin system for interaction with construction machinery | To develop an Augmented Reality (AR) and Digital Twin (DT) based Digital Physical Link (DPL) of computing devices found in most construction projects with construction machinery. | Hasan, et al. [49] |
| 9 | BIM- and IoT-based virtual reality tool for real-time thermal comfort assessment in building enclosures | To investigate the synergistic benefits of BIM, the Internet of Things (IoT) and Virtual Reality (VR) for developing an immersive VR application for real-time monitoring of thermal comfort conditions. | Shahinmoghadam, et al. [50] |
| 10 | Data driven indoor air quality prediction in | To investigate how to activate the control of | Tagliabue, et al. [51] |

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**Table 1** (*continued*)

| Item | Title of paper | Aim of study | Reference |
|---|---|---|---|
| | educational facilities based on IoT network | the indoor conditions according to the occupancy rate by integrating of indoor air quality data gathered by the internet of things (IoT) sensors. | |
| 11 | IoT open-source architecture for the maintenance of building facilities | To integrate IoT alert systems with BIM models to monitor building facilities | Villa, et al. [52] |
| 12 | A BIM-data mining integrated digital twin framework for advanced project management | To develop a digital twin-based framework to control and optimise the complex construction process | Pan and Zhang [53] |
| 13 | Integrated digital twin and blockchain framework to support accountable information sharing in construction projects | To develop an integrated digital twin and blockchain framework that can selectively store and share important project-related information traceably | Lee, et al. [54] |
| 14 | Digital Twin-Based Safety Risk Coupling of Prefabricated Building Hoisting | To propose a digital twin-based safety risk management framework for prefabricated building hoisting | Liu, et al. [55] |
| 15 | Intelligent Safety Assessment of Prestressed Steel Structures Based on Digital Twins | To propose an intelligent safety assessment method of prestressed steel structures based on digital twins. | Liu, et al. [56] |
| 16 | Digital Twins and Road Construction Using Secondary Raw Materials | To establish a fully functioning digital twin of a road constructed using Secondary Raw Materials (SRM) | Meža, et al. [57] |
| 17 | Digital twin for supply chain coordination in modular construction | To develop a digital twin framework for real-time logistics simulation to predict potential logistics risks and accurate module arrival time. | Lee and Lee [58] |
| 18 | Towards an Occupancy-Oriented Digital Twin for Facility Management: Test Campaign and Sensors Assessment | To facilitate the optimisation of building operational stage through advanced monitoring techniques and data analytics | Seghezzi, et al. [59] |
| 19 | Developing a Digital Twin at Building and City Levels: A Case Study of West 1 Cambridge Campus | To present a system architecture for digital twins at both building and city levels. | Lu, et al. [37] |
| 20 | Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance | To propose a digital twin-enabled anomaly detection system for asset monitoring and its data integration method based on extended industry foundation classes (IFC) in daily O&M management. | Lu, et al. [60] |
| 21 | Digital Twin Hospital Buildings: An Exemplary Case Study through Continuous Lifecycle Integration | To present a digital twin for a hospital building based on the concept of continuous lifecycle integration | Peng, et al. [61] |
| 22 | Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms | To develop an integrated data-driven framework based on BIM and IoT technologies for predictive maintenance of building facilities. | Cheng, et al. [62] |
| 23 | Cyber-physical system for safety management in smart construction site | To propose a smart construction site framework for safety management | Jiang, et al. [63] |
| 24 | Visualised inspection system for monitoring environmental anomalies during daily operation and maintenance | To explain the development of an AR-supported automated environmental anomaly detection and fault isolation method to improve building occupants' thermal comfort. | Xie, et al. [64] |
| 25 | Cyber-physical postural training system for construction workers | To propose a cyber-physical postural training environment that integrates virtual reality and embodied interaction for construction workers to undergo repetitive training and obtain feedback. | Akanmu, et al. [65] |
| 26 | Prototype of a cyber-physical façade system | To systematically test the application of individual cyber-physical system criteria to facades using a prototype. | Böke, et al. [66] |
| 27 | Real-Time Process-Level Digital Twin for Collaborative Human-Robot Construction Work | To propose human-robot interaction and collaboration within a real-time, process-level, immersive virtual reality (VR) digital twin | Wang, et al. [67] |
| 28 | Development of a Twin Model for Real-time Detection of Fall Hazards | To propose and test a digital twin for health and safety management on construction sites | Messi, et al. [68] |
| 29 | Cyber-physical-system-based safety monitoring for blind hoisting with the Internet of things: A case study | To develop a cyber-physical safety monitoring system for blind hoisting in metro and underground constructions | Zhou, et al. [69] |
| 30 | Linking energy-cyber-physical systems with occupancy prediction and interpretation through WiFi probe-based ensemble classification | To propose an occupancy-linked energy-cyber-physical system that incorporates WiFi probe-based occupancy detection. | Wang, et al. [70] |
| 31 | Office building occupancy monitoring through image recognition sensors | To investigate image recognition (ImR) to detect users' movements in an office building, and to provide real-time occupancy data. | Antonino, et al. [71] |
| 32 | Digital twin: vision, benefits, boundaries and creation of buildings | To explore issues related to the creation of a building's digital twin and propose a method for its implementation for a building facade | Khajavi, et al. [72] |
| 33 | Wireless electric appliance control for smart buildings using | To present an intuitive point-and-click framework to control | Rashid, et al. [73] |

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**Table 1** (*continued*)

| Item | Title of paper | Aim of study | Reference |
|---|---|---|---|
| | indoor location tracking and BIM-based virtual environments | electrical fixtures in a smart built environment. | |
| 34 | An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction | To propose an Internet of Things (IoT)-enabled platform for prefabricated public housing projects in Hong Kong. | Li, et al. [74] |
| 35 | An automated IoT visualisation BIM platform for decision support in facilities management | To describe an attempt to represent and visualise sensor data in BIM with multiple perspectives to support complex decisions requiring interdisciplinary information. | Chang, et al. [75] |
| 36 | BIM- and IoT-based monitoring framework for building performance management | To propose a new monitoring framework based on BIM and IoT. | Kang, et al. [76] |
| 37 | BIM integrated smart monitoring techniques for building fire prevention and disaster relief. | To construct a BIM-based Intelligent Fire Prevention and Disaster Relief System | Cheng, et al. [77] |
| 38 | Cyber-physical systems for temporary structure monitoring | To propose CPS-based temporary structures monitoring system that integrates the virtual model of a temporary structure and the physical structure on the construction job site. | Yuan, et al. [78] |

connection between the physical and virtual entities.

This is followed by elicitation of data on the technologies for the five conceptual digital twin development layers proposed by Lu, et al. [37]. In this section, the data on the technologies from the system architectures of the selected studies is elicited for the five development layers of a construction digital twin system architecture namely data acquisition, data transmission, digital modelling, data/model integration layer and the service layer by Lu, et al. [37] as explained in Section 1. The analysis is divided into two parts. The first part focuses on the first three layers of data acquisition, data transmission and digital modelling layers as shown in Table 3. The second part elaborates on the last two layers which include the data/model integration layer and the service layer as shown in Table 4.

## 5. Findings and discussions

This section presents the findings from the data extraction and analysis of the selected studies (Table 1) that is indicated in Table 2, Table 3 and Table 4.

### 5.1. Components of digital twins in construction applications

The digital twin applications consisted of various physical entities. Most of the studies used buildings and the associated building spaces [44,50,51,59,61,64,67,68,70,71,73,75–77]. Some studies focused on specific building components and systems such as lighting and surveillance system [43], air handling unit [47], fan coil [52], building systems [37], centrifugal pumps [60], chiller for an HVAC system [62] and building façade [66,72]. Other studies considered the construction and assembling sites for buildings [45,48,49,53–56,58,63,65,74,78] and road construction sites [46,57,69]. In these environments, various

**Table 2**
Components of digital twin in the selected studies.

| Reference | *Physical entity* | *Virtual entity* | *The data connection between physical and virtual entities* |
|---|---|---|---|
| Pregnolato, et al. [42] | Suspension bridge | 3D FEM (Finite Element Model) | IoT sensors |
| Tan, et al. [43] | Building with a lighting and surveillance system | BIM model of lighting system in the building | Surveillance system with cameras |
| Borissova, et al. [44] | Rooms in a single apartment | 3D model of apartment | IoT sensors |
| Jiang, et al. [45] | Robotic testbed assembling structure site | 3D model of assembling site | RFID (Radio frequency identification) and UWB (Ultra-Wide Band) technology |
| Han, et al. [46] | Section of a road being compacted | IFC BIM model to 3D models on a web browser (virtual assets) | IoT sensors and Satellite positioning and recognition devices |
| Hosamo, et al. [47] | Building Air handling units with (AHU) a rotary heat exchanger, bypass, heater and cooler | BIM model of AHU | Restful Application Programming Interface (API) over a conventional BMS |
| Jiang, et al. [48] | Assembly zone of a 3D printed modular building | 3D model of assembly zone | Smart objects |
| Hasan, et al. [49] | Analogue of a stationary tower crane | 3D model of tower crane | IoT sensors, |
| Shahinmoghadam, et al. [50] | The living room of a two-bedroom apartment | BIM model of the room | IoT sensors and thermography imaging |
| Tagliabue, et al. [51] | A laboratory in an education building | BIM model of laboratory | RESTful Application Programming Interface (API) |
| Villa, et al. [52] | Building and a room fan coil | 3D model of building and fan coil | Wired IoT sensor network |
| Pan and Zhang [53] | Construction site of a 3 storeyed building | 3D point cloud model, As-built IFC mode | Sensors in laser scanner |
| Lee, et al. [54] | Two industrial robots building a small mock-up bridge using prefab interlocking bricks | The virtual robotic construction project for a small mock-up bridge | RFID and GPS (Global positioning system) technology |
| Liu, et al. [55] | Real hoisting site for a prefabricated building | A virtual model of hoisting site | IoT network (Mesh) and RFID |
| Liu, et al. [56] | Prestressed steel construction site | 3D model of the construction site, physical model and behaviour model in the finite element model. | IoT sensors |
| Meža, et al. [57] | 300 m access road project in Maribor, Slovenia, | BIM model | IoT sensors |
| Lee and Lee [58] | Truck and prefabricated modules | BIM model | IoT sensors |

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**Table 2** (*continued*)

| Reference | *Physical entity* | *Virtual entity* | *The data connection between physical and virtual entities* |
|---|---|---|---|
| Seghezzi, et al. [59] | Spaces in an Education building | BIM model | IoT sensors |
| Lu, et al. [37] | A university building and building systems | BIM model of building and building systems like HVAC, etc | RESTful Web API and BMS data integrator application, Other IoT sensors and QR code-based asset management network |
| Lu, et al. [60] | Two centrifugal pumps of the HVAC system in a building | BIM model of building and pumps | IoT sensors |
| Peng, et al. [61] | Hospital building | BIM model of building | API |
| Cheng, et al. [62] | Chiller for a building HVAC system. | BIM model of building and chiller. | IoT sensor network with sensors and a Dedicated Digital Controller (DDC) system |
| Jiang, et al. [63] | Construction site with machinery, people, tower crane, etc. | BIM model of people, machinery, components and site environment | IoT sensors and positioning technologies |
| Xie, et al. [64] | A three-storeyed education building | BIM model of building | IoT sensors |
| Akanmu, et al. [65] | Real-life construction site with a trainee | Virtual construction site containing a wooden frame and human avatars | Vision and component-based sensing systems |
| Böke, et al. [66] | Experimental facade | 3D model of facade | IoT sensors |
| Wang, et al. [67] | A drywall installation with a 6DOF KUKA robot | As design BIM model and as-built point clouds of workspace | Camera sensors on the virtual construction site in Gazebo |
| Messi, et al. [68] | Ladder in a laboratory room | BIM model of laboratory room with a ladder | Ultra-wideband (UWB) sensor network |
| Zhou, et al. [69] | Road tunnel | BIM model of road tunnel | IoT sensors and actuators |
| Wang, et al. [70] | Large office space | BIM model used to develop energy cyber models | IoT sensors |
| Antonino, et al. [71] | Rooms in an office building | BIM model of building | Image sensors coupled with image recognition (Im) artificial intelligence on Raspberry board |
| Khajavi, et al. [72] | A building facade | BIM model of facade | Wireless sensor network |
| Rashid, et al. [73] | Office room | BIM model of office room | UWB-based real-time location tracking system and UWB localisation tag in a microcontroller |
| Li, et al. [74] | Construction site of a storeyed building | BIM model of storeyed building | RFID technologies |
| Chang, et al. [75] | Classroom in an education building | BIM model | IoT sensors |
| Kang, et al. [76] | Office in a building | BIM model of building | IoT sensors |
| Cheng, et al. [77] | Campus building | BIM model of building | IoT sensors |
| Yuan, et al. [78] | Scaffolding system on a construction site | 3D model of the scaffold frame | IoT sensors |

resources such as machinery, materials, and workers were monitored. Pregnolato, et al. [42] used an existing suspension bridge as their physical entity. All the studies contained a 3D model of the physical entity with the BIM model being the commonest virtual model. A 3D FEM (Finite Element Model) was used for the suspension bridge. The (IoT) Internet of Things sensors were the most used devices for creating a data connection between the physical entities and their corresponding virtual models. Other technologies that were used include RFID (Radio frequency identification), image sensors and image recognition artificial intelligence, vision and component-based sensing systems, satellite positioning and recognition devices, laser scanning and Restful APIs.

### 5.2. *Technologies in digital twin applications*

The data elicited in Table 3 and Table 4 for is categorised under five layers that include data acquisition, data transmission, digital modelling, data/model integration and service layers. The data/model integration layer is further classified into data storage, data/model integration and fusion, data processing and analysis and data visualisation.

#### 5.2.1. *Data acquisition layer*

Dynamic data from the physical environment is collected depending on the intended functionality of the digital twin. IoT sensors and technologies were the technologies used for data acquisition from the physical environment. The IoT sensor networks use sensing nodes to communicate the status of a parameter in a surrounding in a wireless manner [79]. They measure changes in physical, chemical and electrical properties of a surrounding and generate a response in the form of an electrical output. Various types of intelligent sensors are used to measure environmental parameters that include temperature, humidity, air quality, motion, pressure, airflow rates, air velocity, $CO_2$, lux levels, gas, particulate matter (PM) 10, smoke and acoustic levels. A wide range of sensors is available to collect data on various environmental parameters. For example, DHT11 sensors [50,76] and Monnit wireless sensors [64] were used for measuring temperature and humidity. Other types of sensors used include Rev. P wind sensors (MD0555 category) for air velocity [50], DHT22 sensors for ambient temperature, humidity and a light-dependent resistor (LDR) [52], TA465-X sensor system for airflow, temperature and humidity [70], Texas Instruments (TI) Sensortag CC2650 light sensors [72] and PT550 light sensors [76]. In other cases, sensor data is obtained from already existing monitoring systems of buildings. [47] used a Restful API (Application Programming Interface) over a conventional BMS (Building Management System) to collect data of the BMS hard-wired sensors that include NTC-12 K-sensors for temperature, TTH-6040–0 for the outdoor temperature and the IVL10 temperature-sensitive airflow transmitters and PTH-3202-DR for pressure. Similarly, a RESTful API was applied to collect sensor data from the Supervisory Control and Data Acquisition (SCADA) system for HVAC plants with temperature, humidity and CO2 sensors [51]. Cheng, et al. [62] obtained sensor data from a direct digital control (DDC) system in an IoT sensor network consisting of temperature sensors, humidity sensors, flow rate sensors and pressure sensors.

IoT sensor technologies are also used to collect mechanical data in

**Table 3**
Technologies used in the data acquisition, data transmission and digital modelling layers in a digital twin architecture.

| Reference | Data acquisition layer | | Transmission layer | | Digital modelling layer |
|---|---|---|---|---|---|
| | *Data collection* | *Data set* | *Network and communication* | *Transmission* | *Virtual (3D) modelling* |
| Pregnolato, et al. [42] | Temperature sensors, displacement transducers and strain gauges | Mechanical sensor data | Hybrid wired and WSN (wireless sensor network) | MQTT (Message Queuing Telemetry Transport) message broker | 3D FEM (Finite Element Model). Midas Gen Software |
| Tan, et al. [43] | Cameras | Video stream data | LAN (Local Area Network), Internet | Not stated | BIM model. Autodesk Revit, Three.js and Draco |
| Borissova, et al. [44] | Temperature sensors, motion sensors, door sensors, thermostats, smart contacts | Environmental sensor data | WiFi Raspberry Pi installed openHAB | MQTT | 3D model. |
| Jiang, et al. [45] | UWB, RFID tags | Positioning data | Smart mobile gateway | MQTT | 3D model. Unity 3D |
| Han, et al. [46] | Acceleration sensors, speed sensors. Real-time kinematic global navigation satellite system (RTK – GNSS) antenna | Mechanical sensor data, Positioning data | Bluetooth | MQTT | IFC BIM model converted to 3D models on a web browser (virtual assets) in Three.js program |
| Hosamo, et al. [47] | Restful API over a conventional BMS system with hard-wired sensors: NTC-12 K-sensors for temperatures, PTH-3202-DR for pressure, TTH-6040–0 for outdoor temperature and the IVL10 temperature-sensitive airflow transmitters. | Environmental sensor data | Internet and BACnet (Building Automation and Control Networks) for data communication among the various equipment, devices and sensors | Universal Resource Locator via the API | BIM model. Autodesk Revit |
| Jiang, et al. [48] | UWB tag, RFID tag and industrial wearable | Positioning data, control data | Mobile Gateway Operating System (MGOS) light middleware, wireless network | MQTT | 3D modelling. Solidworks and 3D Max |
| Hasan, et al. [49] | HC-SRo4 ultrasonic distance sensor and accelerometer and gyroscopic sensor(MPU-6050) Micro-controller unit (MCU) connects to sensor/actuator network using Arduino sketch | Positioning data, mechanical sensor data | Not stated | Not stated | Sketchup 3D for BIM model. Model imported to Unity 3D |
| Shahinmoghadam, et al. [50] | DHT11 sensors for air temperature and relative humidity and modern device Rev. P wind sensors (MD0555 category) for air velocity . IoT node for FLIR Lepton thermal imaging module VR-based module for user-defined input | Environmental sensor data, weather data, thermal image data | Wi-Fi | HTTP | BIM model. Autodesk Revit |
| Tagliabue, et al. [51] | RESTful API to collect data from temperature, humidity and $CO_2$ sensors | Environmental sensor data | Internet and Supervisory Control and Data Acquisition (SCADA) for HVAC plant | Not stated | Not stated |
| Villa, et al. [52] | SCT-013-000 current sensor, EU:77DE-06-09 voltage sensor, DS18B20 and PT100 temperature sensors for fan coil. DHT22 sensors for ambient temperature, humidity and a light-dependent resistor (LDR) | Mechanical and environmental Sensor data | WiFi, Raspberry Pi (RPi) 3B acts as a router using DNSmasq software. Node-Red installed on the RPi. | MQTT | 3D modelling. Autodesk Revit |
| Pan and Zhang [53] | UAV (Unmanned Aerial Vehicle) equipped with LiDAR scanner | 3D point clouds | Not stated | Not stated | Laser scanning to obtain 3D points cloud model. |
| Lee, et al. [54] | RFID and GPS tags | Positioning data | Internet, Azure blockchain platform to provide IoT hub, web server and blockchain network | Not stated | Unity Software for virtual environment modelling. |
| Liu, et al. [55] | Smart camera, wind speed, temperature, humidity and air quality sensors. Tower data recorder and RFID tags | Video and image data, environmental sensor data, state information data | Self-organising Wi-Fi network | Not stated | Not stated |
| Liu, et al. [56] | Cable compression-tension sensors (DH3815), RFID tags, Environmental sensors (wind speed and temperature) | Mechanical sensor data, environmental sensor data, component information | Not stated | Not stated | Autodesk Revit. Laser scanning using a Trimble TX5 3D scanner and Real works 8.0 to obtain 3D points cloud. |
| Meža, et al. [57] | Temperature sensor, Inductive displacement sensor, soil moisture sensor, asphalt strain sensor, horizontal inclinometer and pressure pads. | Mechanical sensor data | Not stated | Not stated | 3D modelling. Autodesk Civil 3D, Revit and Bexel manager BIM analysis and management tool |

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**Table 3** (*continued*)

| Reference | Data acquisition layer | | Transmission layer | | Digital modelling layer |
|---|---|---|---|---|---|
| | *Data collection* | *Data set* | *Network and communication* | *Transmission* | *Virtual (3D) modelling* |
| Lee and Lee [58] | The virtual server generating hypothetical IoT sensor data | Location and tracking data | Not stated | Not stated | Virtual modelling. Unity 3D |
| Seghezzi, et al. [59] | High quality Bullet Pro Camera sensors | image data | Virtual local area network (VLAN) and use of static IPs | Data stored in an online database and downloaded as CSV files | Online platform SophyAI. |
| Lu, et al. [37] | Monnit wireless sensors for environmental parameters like temperature and humidity, BMS sensor network and QR codes. | Environmental sensor data, component information data | Ethernet gateways in a wireless communication network | HTTP (Hypertext Transfer Protocol) | 3D model. Autodesk Revit and AECOsim building designer. Laser scanning and photogrammetry. |
| Lu, et al. [60] | Vibration sensors | Mechanical sensor data | Not stated | Not stated | 3D model. Autodesk Revit |
| Peng, et al. [61] | Building automation systems (BAS), energy monitoring systems, security monitoring systems, medical gas pipeline systems and armarium system sensor networks | Environmental sensor data, energy data, video data | Building systems communication networks | HTTP | Laser scanning and Mixed Reality (MR) application. |
| Cheng, et al. [62] | Direct digital control system that receives data from temperature sensors, pressure sensors and flow rate sensors | Environmental sensor data | Direct digital control system and BACnet protocol for communications between devices | Not stated | 3D model. Autodesk Revit |
| Jiang, et al. [63] | Positioning base stations, positioning labels for workers, hoisting positioning devices, ultrasonic positioning sensors, laser ranging and 3D gyroscope sensor | Positioning data, location label data | Bluetooth and Wi-Fi | HTTP and socket protocol | Not stated |
| Xie, et al. [64] | Monnit wireless sensors for temperature and humidity and sensor data from BMS | Environmental Sensor data | Not stated | HTTP | Not stated |
| Akanmu, et al. [65] | Vision and wearable IMUs (Inertia Measurement Units) with a 3-axis accelerometer, gyroscope and magnetometer,<br>Vive trackers using a velcro | Kinematic data (body movement data) | Wi-Fi. HTC VIVE Pro's base station and USB connection | Not stated | VR environment created using the Unity game platform and HTC VIVE Pro device. Autodesk 3D Max for creating a human avatar, imported to Unity |
| Böke, et al. [66] | Light, gas, temperature, humidity and acoustic sensors connected to NodeMCU microcontroller | Environmental sensor data | Wireless local area network (WLAN) | MQTT | Rhinoceros 6 software for the 3D model |
| Wang, et al. [67] | Three Microsoft Kinect cameras | Image data converted to point clouds | Not stated | gazebo_ros_pkg | VR (Virtual Reality) environment using Unity 3D and Unified Robotics Description Format (UDRF) for building Robot arm model |
| Messi, et al. [68] | UWB tags on the ladder | Positioning data | Node-RED programming tool for connecting UWB data to the database | MQTT | Unity 3D. |
| Zhou, et al. [69] | Ultrasonic sensors, laser ranging sensors, Wind speed sensors, PM 10 sensors, noise sensors, humidity sensors and temperature sensor | Positioning data, tracking data, and environmental data | Self-organising Wi-Fi network | Not stated | Not stated |
| Wang, et al. [70] | TA465-X sensor system for airflow, temperature and humidity. Cameras for recording occupants. | Environmental sensor data, video data | Wi-Fi network | Not stated | BIM model |
| Antonino, et al. [71] | Cameras | Image data | Not stated | Not stated | 3D modelling. Autodesk Revit |
| Khajavi, et al. [72] | Texas Instruments (TI) Sensortag CC2650 light sensors | Environmental sensor data | Raspberry Pi 3B+ network gateway using Bluetooth | Not stated | 3D model. |
| Rashid, et al. [73] | UWB anchors and UWB tag in handheld clicker | Positioning and orientation data | UWB radio communication | Not stated | Virtual modelling. Game engine Unity 3D |
| Li, et al. [74] | RFID tags on precast building components | Positioning data | IoT gateway and Bluetooth | Not stated | Not stated |
| Chang, et al. [75] | Sensors for indoor temperature and humidity connected to an Aurdino Mega 2560 R3 microcontroller board | Environmental sensor data | Not stated | Not stated | 3D model. Autodesk Revit |
| Kang, et al. [76] | DHT11 sensors for temperature and humidity and PT550 light sensors connected to Arduino microcontroller | Environmental Sensor data | Wired or wireless network | MQTT protocol. Mosquitto service program to implement MQTT. Python and C# language. | BIM model. Autodesk Revit |

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**Table 3** (*continued*)

| Reference | Data acquisition layer | | Transmission layer | | Digital modelling layer |
|---|---|---|---|---|---|
| | *Data collection* | *Data set* | *Network and communication* | *Transmission* | *Virtual (3D) modelling* |
| Cheng, et al. [77] | Bluetooth smoke detector sensors connected to Raspberry Pi 3, Location data from mobile applications of users | Environmental sensor data, location data | Wi-Fi and Ethernet | Not stated | 3D model. Autodesk Revit |
| Yuan, et al. [78] | Load cells switch sensors, an accelerometer and displacement sensor | Mechanical sensor data | Cloud computing | Internet and cloud computing services. | 3D model. Autodesk Navisworks |

various applications. For a suspension bridge, temperature sensors were used to measure the temperature of the chain links while displacement transducers measured the displacement of the saddles [42]. The piezoelectric acceleration sensor was used to acquire the vertical acceleration of the vibration wheel to monitor the quality of road compaction [46]. To monitor the safety of a scaffolding system Yuan, et al. [78] and cables on a prestressed steel structure Liu, et al. [56], a column tension-compression sensor and accelerometer with a displacement sensor were used respectively. Lu, et al. [60] applied vibration sensors to monitor the mechanical condition of a chiller pump. To monitor the mechanical condition of a fan coil, SCT-013-000 current sensor, EU:77DE-06-09 voltage sensor, and DS18B20 and PT100 temperature sensors were used [52]. Meža, et al. [57] used various sensors that included temperature sensors, inductive displacement network sensor, soil moisture sensors, asphalt strain sensors, horizontal inclinometers network sensors and surface sensor pressure pads to obtain real-time data on a road construction project. Load cells, switch sensors, an accelerometer and displacement sensor were used to monitor the safety of a scaffolding system [78].

The IoT sensor technologies can also be used to obtain positioning data in dynamic environments. For example, the ultrasonic sensor and gyroscopic sensors were used to collect positioning data of resources to detect clashes and accurate placement [49] and track locations of resources on site [63]. Zhou, et al. [69] used both ultrasonic sensors and laser ranging sensors to track the location of machinery during tunnel operations. Akanmu, et al. [65] used vision and wearable IMUs (Inertia Measurement Units) with a 3-axis accelerometer, gyroscope and magnetometer as well as Velcro vive trackers to obtain body kinematic data. Another use of IoT sensors involved the application of cameras and laser scanners. Tan, et al. [43] used a building surveillance system to obtain video streams of scenes which were processed by an algorithm to detect pedestrians and perceive ambient brightness. A FLIR lepton 2.5 thermal imaging module was connected to the Raspberry Pi microprocessor to measure surface temperatures to monitor MRT (Mean Radiant Temperature) values at different points in the building enclosure [50]. Smart cameras provided video streams recording the wearing of safety equipment on site and uploaded to the cloud storage for analysis [55]. Seghezzi, et al. [59] used high-quality Bullet Pro Camera sensors to capture image data of occupant movement which was registered as a human by the deep learning algorithm embedded in the camera sensors to provide a count of occupants. Three Microsoft Kinect cameras acquired image data of a robot's workspace environment in Gazebo which was then converted to point clouds [67]. Antonino, et al. [71] used cameras with image sensors coupled with image recognition (Im) artificial intelligence to detect users' movements in an office building. Two overhead cameras were applied to record the entrance and exit events of occupants in a room which were then translated into counts of occupants [70]. On the other hand, 3D point clouds for a construction site were obtained using a UAV (Unmanned Aerial Vehicle) equipped with a LiDAR scanner [53].

To obtain positioning and location data, identification and tracking technlogies that include RFID tags, UWB tags and the global navigation satellite system (GNSS) were used. RFID systems consist of one or more readers and several RFID tags that contain a unique identifier which is applied to objects. A tag transmission is triggered by the readers using electromagnetic fields to automatically query for the possible presence of tags in the surroundings to receive their IDs (identifications) [80]. This enables the RFID systems to track or monitor physical objects in real time. On the other hand, UWB is a short-range and high-bandwidth communication technology that uses radio signals [81]. It can be used to locate and track human beings and objects in real time. The GNSS is an outdoor localisation system that uses a satellite-based navigation system at a global level. From the analysis, RFID and UWB tags were used to collect positioning data of prefabricated components on an assembling site (UWB) [48] and smart objects on a construction site [45]. Lee, et al. [54] used RFID tags and the GPS (Global Positioning System) to track and locate prefabricated blocks on a mock-up bridge site. RFID and UWB tags were used to locate precast building components [74] and the position of a ladder [68] respectively. UWB anchors and tags provided the position and orientation data on appliances in an office room [73]. The real-time kinematic global navigation satellite system (RTK – GNSS) was used to obtain location data for construction machinery [46]. The use of sensors, RFID and UWB devices, cameras and laser scanning in the construction industry, is growing and is well covered in the literature [81–85].

To be able to collect and transmit useful data, sensor systems consist of various functional layers like sensing and transduction, signal processing, data processing, signal transmission, etc., [86]. This follows that a high-level sensor system architecture can include a microcontroller, wired or wireless interface, memory, sensors, display and power. Examples of sensor platforms indicated in some studies include NodeMCU micro-controller Böke, et al. [66], Aurdino Mega 2560 R3 microcontroller board [75], Raspberry Pi 3B+ [72] and Raspberry Pi 3 [77]. The details on sensor architectures and platforms can be found in various studies such as [87–89] etc.

#### 5.2.2. Data transmission layer

Data transmission involves the processing and transporting of raw data from the data acquisition layer. The collected data is generally transmitted through the wire and wireless transmission technologies. The Wi-Fi wireless short-range technology was used in several applications [44,45,48,52,55,63,69,70,77]. Wi-Fi is a common communication technology that connects devices in a local area network using radio waves. Other examples of short-range wireless technologies included wireless local area network (WLAN) [66], Bluetooth [46,63,72,74] and ultra-wide-band (UWB) radio communication [68,73]. On the other hand, one study used Ethernet wired transmissions [37] while another study by Pregnolato, et al. [42] used a hybrid of both wired and wireless networks. In the case of sensor data obtained from a Building Management Systems (BMS), the internet and the BACnet (Building Automation and Control Networks) protocols were used for data communication among the various equipment, devices and sensors as indicated by [47].

The transmission of data must conform to communication layer protocols. These protocols are defined by different groups such as IEEE (Institute of Electrical and Electronics Engineers), IETF (Internet Engineering Task Force), etc., and are officially used as standards in the industry. They can be categorised into file transfer protocols and messaging protocols which are best suited for web applications and IoT

**Table 4**
Technologies for the data/model integration and service layers in a digital twin architecture.

| Reference | Data/model integration layer | | | | Service layer |
|---|---|---|---|---|---|
| | *Data storage* | *Data/model integration and fusion* | *Data processing and analysis* | *Data visualisation* | *Functionality* |
| Pregnolato, et al. [42] | Not stated | Metadata<br>APIs into Midas Gen software | Calculations and comparison of modelled and measured values | Midas gen software. Dashboards | Real-time monitoring, alerts when thresholds are reached |
| Tan, et al. [43] | MySQL, Cloud server and database | Three.js program. | Deep learning | Three.js program. Dashboards, Trend graphs, Pie charts, Pedestrian count | Detection of pedestrians, monitoring of pedestrian trends and pedestrian time |
| Borissova, et al. [44] | Internet my openHAB cloud | Not stated | Rule-based reasoning for time and temperature.<br>Energyplus for simulations | Colour coding, time series graphs | Simulation of effects of the digital infrastructure on the heating loads. |
| Jiang, et al. [45] | Not stated | Unity 3D | Time numerical models | Unity 3D. Analytic charts | Real-time monitoring of activities, ticket visualisation and real-time task alerts |
| Han, et al. [46] | MySQL | API into the Three.js program. | Computed intelligent compaction measurement values are compared against the target values | Three.js program. Dashboards, Colour coding, time series graphs and alert messages | Real-time monitoring of compaction progress and quality |
| Hosamo, et al. [47] | MSSQL | IFC data mapped into COBie and FM data using an ontology-based strategy in GraphDB,<br>Semantic data description for metadata using Brick schema,<br>Revit C#.NET API add-in plug-in using Microsoft Visual Studio | Machine learning involves the analysis of variance (ANOVA) and support vector machine (SVM) | Autodesk Revit. Time series graphs, Maximum and minimum sensor values, sensor's average value and historical value | Fault detection and prediction in AHU |
| Jiang, et al. [48] | Web Database | API into Unity 3D | Rule-based reasoning | Unity 3D. Real-time status Kanban, analytic charts that include line graphs and histograms | Real-time positioning tracing for smart objects, real-time control for the robots, instantiation for prefabricated modules |
| Hasan, et al. [49] | Unity 3D server | Script coded in Unity's game engine and the MCU sketch application. Augmented Reality (AR) viewfinder | Visibility analysis | Mobile application using marker-based Augmented Reality (AR). Dashboards, parameter values | Real Time monitoring of operations |
| Shahinmoghadam, et al. [50] | Google cloud platform | Unreal Engine 4 game engine using Oculus Rift S headsets<br>HTTP requests transmit calculated values based on sensor data into the game engine<br>VaRest plug-in to cloud storage module | Calculated indices namely predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) | Thermal comfort charts | Display environmental and thermography data in real-time, display thermal comfort levels using PMV/PPD and bioclimatic charts |
| Tagliabue, et al. [51] | Asset database | Not stated | Markov model preparation and ANN (artificial neural network) training | Time series graphs | comfort predictions and CO2 predictions |
| Villa, et al. [52] | MySQL database, PHP interpreter server and Apache web service are used to store data locally. | Autodesk forge API on the Raspberry Pi (RPi) 3B | Rule-based algorithm and alarm system | Autodesk Forge platform. Monitored fan coil variable values in real-time and dashboards for ambient variables. | Real-time visualisation of fan coil status. Alarm signals or real-time notifications to operators using telegrams or SMS. |
| Pan and Zhang [53] | BIM cloud database | Not stated | Data mining techniques | Colour coding, time series graphs | Bottleneck detection, simulation, real-time monitoring and construction progress prediction |
| Lee, et al. [54] | Azure Microsoft for cloud storage. | Add-in plug-in using Unity software | Compliance checking between as-built BIM and as-planned BIM, Blockchain | Unity platform. Dashboards in Azure Microsoft for the blockchain platform | Providing real-time information that was traced via a blockchain network |
| Liu, et al. [55] | Cloud server | Not stated | Apriori algorithms for association rules and complex network analysis | Line graphs and dashboards | Visualisation and monitoring for safety management |
| Liu, et al. [56] | Not stated | Not stated | Machine learning algorithm using Markov chain | Autodesk Revit. Line graphs and dashboard on a mobile terminal device | Simulating various working conditions for structural health predicting of structure and early warnings for maintenance |
| Meža, et al. [57] | Not stated | Open C# API in Bexel Manager. | Data analysis using Bexel Manager | Autodesk Civil 3D. Colour-coded element | Centralised data collection platform to analyse the safety of using secondary raw |

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**Table 4** (*continued*)

| Reference | Data/model integration layer | | | | Service layer |
|---|---|---|---|---|---|
| | *Data storage* | *Data/model integration and fusion* | *Data processing and analysis* | *Data visualisation* | *Functionality* |
| | | | | breakdown in a 3D model | materials for road construction |
| Lee and Lee [58] | Not stated | Unity engine API into Bing Maps | 3D simulations and data analytics | Unity engine. Colour coding | Real-time monitoring, Simulations of different scenarios |
| Seghezzi, et al. [59] | Online cloud database | SophyAI online platform | Visibility analysis | SophyAI online platform. Anonymous virtual agents, real-time occupancy count, trend graphs | Visualise real-time occupancy count and movements |
| Lu, et al. [37] | A mirrored database in a DynamoDB NoSQL database supported by the Amazon web services (AWS) | AWS DynamoDB, Autodesk forge API and web-based program design (i.e., .Net) using C# and Javascript. IFC schema mapping with the asset management system and sensors | Cumulative sum charts for anomaly point detection in pumps, comparison to predetermined comfort threshold to evaluate comfort levels and machine learning algorithms for predicting maintenance faults. | Autodesk forge platform. Time series graphs, colour coding, S curves and dashboards | Anomaly detection in pumps, real-time ambient environment monitoring and prediction of faults of boilers, and maintenance prioritisation. |
| Lu, et al. [60] | Amazon Web service (AWS) DynamoDB | Ifc Object matching table to describe the link between the BIM object Globally Unique Identifier (GUID) and corresponding item ID from different data sources. Autodesk forge API and .NET using C# and Javascript | Sequential analysis techniques and Bayesian online change point detection algorithm | Cumulative sum control charts (CUSUM) | Monitoring of the working condition of pumps and anomaly detection |
| Peng, et al. [61] | MySQL, Private cloud storage and Flink | Apache Kafka and Flink, Scheduled ETL (Extract, Transform and Load) | AI models using popular frameworks like TensorFlow, Keras and Pytorch deep learning | Dashboards, colour coding, line graphs, bar graphs, operation and alarm status, lists, trend charts and real-time animations | Visualisation for space management, monitoring of energy consumption in the building and building systems like the AHU and security system for fault detection |
| Cheng, et al. [62] | MSSQL | BIM and COBie data mapped onto facility data in FM system using a COBie connector plug-in<br>IFC 4 extension of sensor entities<br>Autodesk Revit plug-in | Comparison of real-time sensor data to historical maintenance and<br>Machine learning algorithms | Autodesk Revit. Time series graphs for temperature, pressure and flow rate. | Condition monitoring of the chiller and condition prediction of the chillers. |
| Jiang, et al. [63] | Not stated | Not stated | Algorithm engines for face recognition, personnel positioning and mechanical attitude positioning | Colour coding | Real-time monitoring of operations, worker and component tracking alerts for risks |
| Xie, et al. [64] | Dynamo DB NoQSL provided by Amazon web services | Not stated | Anomaly detection algorithms including moving average, cumulative sum and a binary segmentation-based change point detection method | Time series graphs, colour coding, Augmented Reality (AR) based visualisation | Identification of indoor environmental anomalies and corresponding failed assets |
| Akanmu, et al. [65] | Not stated | VR environment using Unity game platform | Rule-based reasoning | VR environment using Unity game platform. Colour codes for different risk levels | Monitoring of workers' postures during operations |
| Böke, et al. [66] | Cloud | 'Processing' development environment where the 3D model is loaded and sensor and actuator data is received | Comparison to thresholds, applying control logic | Node-RED dashboard for user interface. Data in form of flow charts | Real-time monitoring, and adaptive actions to the system |
| Wang, et al. [67] | Not stated | Virtual Reality (VR) environment in Unity 3D and Oculus Rift S VR headset, connected to ROS | Robot Operating Software (ROS) | Unity 3D and Oculus Rift S for VR interface. Visible agents on site | Real-time data that is used to control the Robot on site |
| Messi, et al. [68] | ArangoDB database | Unity 3D game engine for digital twin platform. IFC loader to import BIM model information | Checking against defined positions | Unity 3D. Colour coding and user notifications | Simulations using real-time data |
| Zhou, et al. [69] | Alibaba cloud server | Not stated | Visibility analysis and computation<br>Mechanical analysis and computation | Colour coding, parameter values | Monitoring of tunnel operations, early warnings about potential accidents |
| Wang, et al. [70] | Not stated | Not stated | Ensemble learning algorithms for occupancy prediction | Trend graphs | Occupancy monitoring and occupancy detection |
| Antonino, et al. [71] | Microsoft Azure SQL cloud database | Not stated | Visibility analysis | Occupancy values | Occupancy monitoring |

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Table 4 (*continued*)

| Reference | Data/model integration layer | | | | Service layer |
|---|---|---|---|---|---|
| | *Data storage* | *Data/model integration and fusion* | *Data processing and analysis* | *Data visualisation* | *Functionality* |
| Khajavi, et al. [72] | Not stated | Not stated | Matching lux values to the defined colour spectrum | Colour coding, lux values | Visualise the real-time state of a façade brightness |
| Rashid, et al. [73] | Not stated | Unity 3D | Positioning algorithm | Unity 3D. Colour coding | Detect interactions between a user and appliance of interest to control the appliance |
| Li, et al. [74] | Cloud server | Not stated | Visibility analysis | Colour coding | Progress visualisation and monitoring, Error alerts |
| Chang, et al. [75] | Not stated | Dynamo plug-in into Revit. Firefly suite to link Dynamo and Arduino sensor microcontroller | Numerical models to integrate values of sensor data into a colourful 3D fashion | Dynamo in Autodesk Revit. Time series graphs, Colour coding in a 3D schematic | Visualisation of sensor data for indoor temperature and humidity |
| Kang, et al. [76] | Data storage for BIM in Mongo database and monitoring data in Influx database | Revit plug-in written in C# language | Data analysis using Python and Chronograf tool | Revit. Time series graphs and colour coding in 2D schematic | Visualisation of data in the BIM model |
| Cheng, et al. [77] | Cloud database and SQL server | Autodesk Revit API plug in | Algorithms for planning rescue paths | Colour-coded agents in a 3D schematic, Colour coding on the 3D schematic, Colour coded arrows on the 3D schematic | Early detection of fires and planning of rescue paths |
| Yuan, et al. [78] | Amazon Elastic Compute Cloud (Amazon EC2) service using Heidi SQL | Autodesk Navisworks add-in tool using Microsoft Visio studio | Comparisons to user-defined thresholds | Autodesk Navisworks management and mobile application. Colour coding. | Warning alerts for potential failures |

frameworks respectively [90]. The most commonly used transmission protocol was MQTT (Message Queuing Telemetry Transport) [42,44–46,48,52,66,68,76]. MQTT is a lightweight publish/subscribe messaging transmission protocol that connects remote sensors to other software layers of an application [91]. It is characterised by high latency and suitable for restricted equipment, unreliable networks and low bandwidth. It uses a client-server architecture whereby the MQTT client publishes messages to an MQTT broker to be subscribed to by other clients or retained for future use [92]. The HTTP (Hypertext Transfer Protocol) was the other mostly used transmission protocol [37,50,61,63,64]. The HTTP is a web messaging protocol that supports request/response RESTful web architecture [92]. It uses the Universal Resource Identifier (URI) to send data from the servers to the client who receives the data through a specific URI. In Hosamo, et al. [47] study, a specific URL from the sensor data API was used for data transfer to the BIM model. Jiang, et al. [63] used both the HTTP and socket protocols for their study. A socket protocol is a standard protocol for transferring data from one machine to another [93]. On the other hand, Lee, et al. [54] applied an Azure blockchain platform to provide an IoT hub for receiving the GPS data from the IoT sensors which was then later sent to the as-built BIM model. Seghezzi, et al. [59] stored sensor data in an online database and downloaded it as CSV files which was then visualised in the SophyAI online platform. The gazebo_ros_pkgs, a set of robot operating software, was used to create a communication interface between the Gazebo platform with sensor data and the ROS (Robot Operating Software) [67].

### 5.2.3. *Digital modelling layer*

This layer involves the development of the corresponding virtual model of the physical entity. This process is generally done by modelling the digital model. Modelling is the process of "representing a physical entity in digital forms that can be processed, analysed, and managed by computers" [24]. Through modelling, the physical entity and related information are represented in a digital environment. To be able to model the physical entity, the parameters of the physical environment such as the geometric structure, functionality, state, time, location, process, performance [25] etc. are measured to produce a virtual replica that mirrors the physical environment. From the analysis, laser scanning was used to obtain the 3D point cloud model of the physical assets [37,53,56,61]. Other measurement methods included laser tape measurement [73], Mixed Reality (MR) [61] and photogrammetry [37]. Modelling parametric design software is used to develop the virtual model that mirrors the features of the physical entity. Most of the studies used a 3D model (BIM model) to represent the virtual equivalent of the physical entity. Autodesk Revit was the most used software for 3D modelling of buildings as indicated in these studies [43,47,50,52,60,62,71,75,77].Other 3D geometric software tools that were applied include Autodesk Navisworks [78], Solidworks and 3D Max [45], Sketchup 3D [49] and Rhinoceros 6 software [66].To create a BIM model of a road, Autodesk Civil 3D and Autodesk Revit were used [57]. The former was used to generate the road model while the latter was used to model sensors to create the BIM model. Autodesk Revit and AECOsim building designer were used to develop geometry models at the system, building and city levels Lu, et al. [37]. On the other hand, game development software is also used to develop the virtual entity of the digital twin application. A human avatar was modelled using the Unity game engine and Autodesk 3D Max [65]. Four studies imported geometric data into Unity 3D to develop 3D models [48,54,58,73]. A Virtual Reality (VR) environment was created using the Unity 3D platform, Oculus Rift S VR headset and the Oculus touch controllers [67].To create a human-robot construction system, the Robot arm model was developed using the Unified Robotics Description Format (UDRF) and sent to Robot Operating Software (ROS) to be loaded as a game object in VR. Moreover, BIM components for the construction site were also loaded into the VR environment. Other 3D modelling platforms that were used include Three.js program [46] and Midas Gen software [42].

### 5.2.4. *Data/model integration and fusion layer*

*5.2.4.1. Data storage.* In the data/model integration layer, the digital twin data undergoes a series of stages that include data storage, data/model integration and fusion, data processing and analysis and data visualisation to produce useful information. Digital twin data is multi-source and of high volume requiring big data storage technologies [24]. The selection of a storage database depends on the accessibility, scalability, high-performance and management capability of massive data. The studies mostly used cloud-based computing platforms for data storage. Cloud databases provide adaptable and exceptional backend access for computing applications [94]. Examples of the cloud-databases from the studies include Internet my openHAB cloud [44], Google cloud platform [50], web database [45], BIM cloud database [53], Azure Microsoft for cloud storage [54], cloud servers [55,59,66,74], Alibaba cloud server [69], Microsoft Azure SQL cloud database [71], Cloud database and SQL server [77], Heidi SQL [78], Amazon Web service (AWS) DynamoDB [60,64], MSSQL [47,77], MySQL [43,46,52,61], ArangoDB database [68] and influx database [76]. To collect data from already existing building systems like the BMS (Building Management System) with security firewalls, a mirrored database was used to store all data sets in the protected BMS into DynamoDB NoSQL schema [37]. Data was also stored on-premise in Mongo database [76] and using a PHP interpreter server and Apache web service [52].

*5.2.4.2. Data/model integration and fusion.* The various digital twin data from the physical and virtual spaces are integrated through data fusion techniques to provide human-understandable inferences [35]. This involves integrating sensor data like environmental data, mechanical data, and image and video data into the BIM models to reflect the real-time status of the physical entity in the virtual model. This requires the use of technologies to provide a platform for hosting the digital twin with both sensor and model data. To enable this data integration, customised APIs are built into the 3D model software platforms. Therefore, API add-in plug-ins were developed for Autodesk Revit [47,62,77], Midas Gen software [42], Bexel Manager [57], Dynamo into Revit [75], Autodesk Navisworks [78], Autodesk forge [37,52,60] and Three.js program [43,46]. The Unity game engine platform by Unity technologies was used by eight studies as the data/model platform [45,48,49,54,58,65,73]. Shahinmoghadam, et al. [50] used the Datasmith tool to import geometric data for building spaces into an Unreal Engine 4 game engine using Oculus Rift S headsets. Other platforms used for data/model integration and fusion included the 'Processing' development environment [66] and SophyAI online platform [59]. Peng, et al. [61] used data processing frameworks that include Apache Kafka and Flink and Scheduled ETL (Extract, Transform and Load) to integrate sensor data from 13 subsystems into a virtual environment. To integrate the multi-form sensor data and data from other systems into the BIM model, the data can be modelled into formal data structures to allow for seamless fusion of the data into the model. Four studies provided details on the data structures for the integration of the sensor data and 3D models. Hosamo, et al. [47] used the Brick schema for the semantic description of the metadata. Three studies used semantic data description to map the BIM model data in the IFC schema with the sensor systems and asset management systems [37,60,62].

*5.2.4.3. Data processing and analysis.* The digital twin data is processed and analysed using advanced technologies to obtain useful information. Table 4 analysis consists of both simple and advanced data analysis techniques. Examples of simple data analysis techniques include the comparison of measured values against target values/thresholds [42,46,50,54,66,68,72,78], visibility analysis [49,59,69,71,74], numerical models [48,75] and rule-based reasoning [44,45,52,65]. The other studies applied artificial intelligence techniques that include machine learning, deep learning and artificial intelligence algorithms for data analysis. Artificial intelligence (AI) involves programming a machine to behave in an intelligent manner [95]. Machine learning was the most used technique in the studies. Various machine learning techniques that include the analysis of variance (ANOVA) and support vector machine (SVM) [47,62], Markov model preparation and ANN (artificial neural network) training [51], Apriori algorithms and complex network analysis [55], Markov chain [55], Cumulative sum charts and machine learning [37] and ensemble learning algorithms [70] were applied. Tan, et al. [43] applied deep learning to convert video stream data into text data to analyse the pedestrian trend, time and determine the most saving energy saving option. Artificial intelligence models using popular frameworks like TensorFlow, Keras and Pytorch deep learning were used for event identification, fault diagnosis and automated decision making [61]. Algorithms were developed for face recognition, personnel positioning and mechanical attitude positioning [63], anomaly detection [64], Bayesian online change point detection [60], planning rescue paths [77] and positioning [73]. Pan and Zhang [53] applied data mining techniques to produce process models, diagnose bottlenecks, and predict progress of works. Other studies analysed data using Python and Chronograf tool [76], Bexel manager [57], computation mechanical analysis [69], Robot Operating Software (ROS) [67] and 3D simulations [58].

*5.2.4.4. Data visualisation.* The visualisation of temporal sensor data in a virtual environment is one of the powerful aspects of digital twins. From the analysis, the 3D modelling software platforms are used for data visualisation. Examples of these include Autodesk Revit [47,56,62,75–77], Midas Gen software [42], Autodesk Navisworks [78], and Autodesk Civil 3D [57]. Some studies used Autodesk forge [37,52,60] for visualising the sensor data in the BIM model. Gaming environment platforms like Unity 3D game engine, which possess powerful visualisation capabilities are also used for visualisation [45,48,54,58,67,68,73]. Furthermore, game engine platforms can be used to create VR (Virtual Reality) environments as indicated by Akanmu, et al. [65] Wang, et al. [67] and Shahinmoghadam, et al. [50]. Akanmu, et al. [65] applied a VR environment using the Unity game engine. Wang, et al. [67] created a Virtual Reality (VR) environment in Unity 3D and Oculus Rift S VR headset that was connected to the ROS (Robot Operating Software). Similarly, Shahinmoghadam, et al. [50] used Unreal Engine 4 game engine with Oculus Rift S headsets for the VR environment. On the other hand, AR (Augmented Reality) was used for visualisation [49,64]. An AR mobile-based application was applied to allow the users to interact with the application for remotely operating of construction machinery [49]. This was developed using Unity3D in the form of a server with AR interfaces and marker images that were uploaded as assets. Other software that were used for visualisation include the Three.js program [43,46], SophyAI online platform [59] and a Node-RED dashboard in the 'Processing development' [66].

The processed digital twin data is finally availed to the end users straightforwardly in various visualisation forms. The two most used methods of visualisation for the digital twin data were colour coding in 2D and 3D schematics, performance dashboards, and time series graphs supported by the visualisation platforms. Other forms of visualisation included trend graphs [43,59,61,70], pie charts [43], line graphs [48,55,56,61], real-time status Kanban [48], thermal comfort charts [50], S curves [37] and cumulative sum control charts [60]. In many studies, the values for monitored parameters like pedestrian count and sensor readings for ambient temperature and humidity were indicated on the visualisation platforms. Other forms of visualisation involved the use of anonymous virtual agents [59,67,77] and real-time animations [61]. Most studies had more than one form of visualisation of the data.

### 5.2.5. Service layer

The last layer represents the service that digital twin offers to the users. Digital twin offers a diverse range of service depending on the context within which it is applied. The most common service offered in the studies was real-time monitoring of assets and activities. This included monitoring a suspension bridge [42], building façade [66], façade brightness [72], pedestrian trends and time [43], construction site activities [48], compaction progress and quality [46], smart objects [45], machine and worker operations [49,63], construction progress [53,54,74], structural health [55], the safety of materials [57], occupancy trends and movements [59], ambient environment monitoring [37], working conditions [60], energy consumption [61], chiller condition [62], workers' postures during operations [65], tunnel operations [69] and room occupancy [70,71]. Another functionality of the digital twin involved early detection: of potential failures in a scaffolding system [78], faults in building AHUs [47,61], bottlenecks in on-site construction [53], anomalies in a pump's operations [37] and indoor environment [64], and fires in a building [77]. Moreover, digital twins were applied for the prediction of faults in building systems [37,47], the condition of a chiller system [62], and comfort and $CO_2$ levels in spaces [51]. Also, some applications used digital twins to provide early warnings about potential accidents [69] and alarm signals when thresholds are exceeded [52]. Some studies showed that digital twin enabled the visualisation of environmental and thermal comfort levels [50], fan coil status [52], space use [61], construction progress [74] and indoor ambient conditions [75,76]. Other studies showed that digital twins can be used for simulations [44,53,56,58,68], real-time control of robotic operations [45,67] and home appliances [73].

### 5.3. Summary of findings

The existence of the three components of a physical entity, its virtual model and the data connection between both entities highlights a shift away from static BIM models to the emerging technology of digital twins in construction. The studies show the diverse application of digital twins to various entities in the physical environment from building components, buildings, workers, machinery, site resources, civil engineering structures, and even at the city level. This implies that digital twins can be applied at different levels of granularity of the construction industry ecosystem. Data from the physical environment was mainly acquired using IoT sensor technologies. Other technologies that include vision and component-based sensing devices, RFID and UWB tags were also used. In some cases, sensor data was acquired from already existing monitoring systems like the BMS. For the transmission of the data, the applications mostly relied on wireless technology. MQTT protocol was most used standard communication protocol followed by the HTTP protocol. MQTT protocol is favoured for IoT networks because it is designed for use in low bandwidth and high latency networks. Moreover, its publish-subscribe strategy that allows for one-to-one and one-to-many connections makes it useful for digital twin development as it allows for several subscriptions to the sensor data. Also, it is considered to be faster than other transmission protocols [91]. On the other hand, the HTTP protocol uses a specific Universal Resource Identifier (URI) to send data from the servers to the client [92]. However, there was lack of emphasis on the technologies for networking, communication and transmission protocols under the data transmission layer as over 18 studies did not provide these details in their system architectures. For the digital modelling layer, most of the studies used a 3D model, mostly a BIM model and four studies used 3D point cloud models. Various parametric design software was used to generate the 3D models, with Autodesk Revit being the most used modelling software. Four studies imported geometric data into the Unity 3D software. One study used a VR environment. For the storage of digital twin data, studies mostly used cloud-based computing platforms that exist on the market. Customised plug-ins were added to the geometric software platforms for data integration and fusion. The Unity cross-platform by Unity technologies was the most used platform for data/model integration. However, most of the studies did not provide the details of the integration of the sensor, model and other digital twin data in the data/model layer. Only four studies provided some details on their data structures for the sensor and model data integration. Both simple and advanced data analysis techniques were used in the processing and analysis of data, with machine learning being the most applied technique for data processing. The visualisation of the data was done using the data/model integration platforms. Four studies used VR/AR technologies for visualisation and interaction with the users. The presentation of the digital twin data was done using 2D graphical methods mostly in form of performance dashboards, colour-coding and time-series graphs.

## 6. Research gaps and future research

Through the analysis, some challenges and opportunities were identified in three areas namely 1) data transmission 2) interoperability and data integration and 3) data processing and visualisation, as discussed in this section.

### 6.1. Data transmission

The use of wireless technology for creating the network was the most commonly used approach in the studies. However, the focus was on the use of short-range wireless technologies that included Wi-Fi, Bluetooth and UWB. The use of long-distance wireless transmission technologies like digital radio and satellite communication needs to be investigated. This is essential for the future of digital twins to be expanded to city digital twins, country digital twins and the worldwide scale. The most applied standard transmission protocols for data transfer in the studies were the MQTT and HTTP protocols. These two protocols are popular in IoT technologies [91].However, over 20 studies did not state the details of their communication protocols for their applications. It is also the case that the acquisition of digital twin data from heterogeneous systems, networks and devices increases the complexity of data transmission. Transmission protocols create mediums for data transmission using standardised formats. This is essential for achieving a two-way data synchronous transmission channel in a digital twin application and enabling machine to machine communication. Therefore, the use of standard communication protocols for data transmission in digital twins of varying complexity should be further investigated.

It is the case that digital twins use a diverse range of data, some of which is confidential in nature to people and organisations. The transmission of such data is prone to cyber-attacks which can essentially become a security threat to people's lives and the infrastructure that is monitored. Therefore, it is necessary to consider security requirements and secure transmission protocols for the network and communication layer. From the analysis of the studies, three studies considered the security and privacy aspects in their digital twin monitoring systems. In their proposed digital twin for management of a hospital facility, Peng, et al. [61] used only private HTTP APIs inside hospital firewalls to address the safety issues about the use of security monitoring videos and visiting records of patients. Shahinmoghadam, et al. [50] opted to use a marker-based registration method to obtain orthogonal thermal image mosaics taken by a FLIR lepton thermal camera instead of using visual cameras to avoid undermining the privacy-preserving aspect of their system. Smart contract and block chain technology were integrated in a digital twin prototype to increase network security and traceability of data [59]. Thus, the issues of privacy-preserving networks and context-aware privacy policies are some of the areas that need to be researched [96].

### 6.2. Interoperability and data integration in digital twins

The integration and fusion of the virtual model and IoT sensor data are core to the functioning of a digital twin. As indicated from the studies, digital twin data is diverse and is collected using different types of sensors resulting in heterogeneous data sets like image data, video data, positioning data, environmental data, mechanical data, etc. that have to be integrated with the BIM model. This data is obtained from disparate and heterogeneous systems like the BMS and Asset management system. These systems operate on different software platforms with different syntax and schematics. This increases the complexity of digital twin models creating integration and interoperability issues at both syntax and semantic levels. From the analysis of the studies, most of the studies did not provide the details pertaining to the structure of the digital twin data for the purpose of data integration. Only four studies provided details for the data architecture for integrating the various digital twin data. To integrate BIM and FM data, the IFC data of the AHU was mapped onto the relevant COBie and FM using an ontology-based strategy in GraphDB [47]. Moreover, a single Brick schema model describing the metadata for the AHU, its components and sensor data points was developed. Cheng, et al. [62] imported BIM data into COBie spreadsheets and then the COBie data was mapped onto the facility data in FM systems. The attribute names of COBie data were matched to the attribute names in the FM database table. Furthermore, a sensor data model was proposed and used as a basis to extend the the Ifcsensor entity to enable sensor entities and attributes to be visualised in a BIM model. An IfcObject matching table was used to describe the link between the BIM object Globally Unique Identifier (GUID) and corresponding item ID from different data sources like the BMS and sensor system [37,60]. These studies use semantic data modelling to enable data integration from various sources.

The use of semantic models and ontologies [97,98] has been proposed for data integration and interoperability in digital twin models. Semantic modelling involves the use of semantic web-based methods to map data streams, active sensing data and proprietary relational data sets and combine them with user preferences to a dynamic structure of things [24]. On the other hand, ontologies provide a formal and explicit representation of domain concepts that can be shared [99]. Therefore, there is a need to investigate semantic data modelling of sensor data, BIM model data and data from other systems to aid in moving towards standardising digital twin data by enabling data integration and interoperability. The development of rich data models for various applications, data sets, different assets and processes is a ripe area of research. Through the use of web-based ontologies, the IFC schema, which is the standard format for interoperability within the built environment can be extended and linked to other domains. Semantic web technologies can help overcome the limitations of the IFC standard models by providing flexible methods of data integration across various domains and scales to facilitate interoperability among data and systems [100]. Therefore, the use of web-based semantic ontologies for digital twin data integration should be explored.

### *6.3. Data processing and visualisation of digital twin data*

Both simple and advanced data analysis techniques were used in the processing and analysis of data such as the comparison of measured values against target values/thresholds and machine learning respectively. The introduction of artificial intelligence techniques such as machine learning offers opportunities for analysing the heterogenous and voluminous data of the built environment. Artificial intelligence methods attempt to recreate the problem-solving and reasoning abilities of the human brain [101]. AI uses machine learning or deep learning models for reasoning about the real world [102]. From the analysis, machine learning was the most used AI technique in the studies. It involves the use of algorithms that learn from the data by automatically extracting patterns within a defined context [103]. Thus, machine learning algorithms can be applied to a diverse range of functions to solve complex problems in the real world. The advent of digital twins in the construction industry has led to an increase in dynamic data which creates challenges in storing, and processing of this big data and situations of 'garbage' data. There is a need to explore the use of advanced technologies for storing and processing this smart big data as well as managing 'garbage' data in the digital twins. The use of AI techniques like machine learning and deep learning enables the automatic processing of large data sets into useful knowledge for various applications [104]. Research should be conducted on developing AI models for processing big data to tackle various challenges in the industry. For example, expert systems for various functions in the different phases of a project lifecycle can be developed. Moreover, there is a need to consider realistic practical applications of these systems to improve the accuracy and intelligence levels of the applications. This will provide more advanced data models and richer data sets that are useful for decision-making in various project and asset management functions.

The visualisation of the digital twin data involved the use of common 3D modelling software platforms and gaming environment platforms. There was also the use of more powerful visualisation technologies that include Virtual Reality [49,50] and Augmented Reality [64]. Virtual Reality (VR) can be defined as the simulation of 3D objects in a virtual world to enable real-time interactions in pseudo-natural immersion via sensorimotor channels [105] while Augmented Reality involves the use of an interface to overlay digital information onto a user's view, which is often a camera image of the physical environment [106]. VR/AR technologies are capable of providing interactive and immersive experiences for users in various functions in the built environment [107]. This is achieved by the support of devices that can be stationary-based displays, head-based displays and hand-held displays. Within digital twin applications, the VR/AR technologies enable the user to visualise, engage and also control selected components in the physical environment as required. Therefore, future research on the use of VR/AR environments for digital twin applications is recommended. Another key aspect in the visualisation of digital twin data is the presentation of the data in meaningful ways to the users. From the analysis, most of the studies used 2D graphical methods to present the digital twin data to the users. However, this diminishes the use of a 3D virtual model and environment to reflect the three-dimensional world that humans exist in. It is therefore worth exploring alternative approaches to visualising temporal data in a BIM model and 3D environments. It is also the case that the IoT sensors for digital twins collect data on various parameters in the physical environment such as temperature, humidity, pressure, etc. These are abstract parameters that cannot be seen but can be measured. With the advanced technologies of digital twins, it could be possible to explore various methods of visualising such abstract parameters within a digital model.

## 7. Conclusions

The concept of digital twins has the potential to improve performance and productivity in the construction industry through effective decision-making enabled by real-time condition monitoring, predictions, simulations and optimization of processes. The study conducts a systematic review of digital twin studies with demonstrative case studies or experimental setups to identify the current technologies used in the development of digital twins, the research gaps and future focus. The first contribution of the paper is the identification of current technologies that have been used in existing research literature in the five digital twin conceptual layers by [37] that include data acquisition, data transmission, digital modelling, data/model integration and services. This has provided a state of the art for the technologies in the development of digital twins in the existing research literature. The digital twins in the applications have been created using state-of-the-art and off-the-shelf technologies and tools that are developed independently and integrated to form digital twin platforms. The second contribution of the paper is the identification of the research gaps and potential areas for future research from a technological perspective. Future research is required on the technologies for data transmission in the application layers, interoperability and data integration and advanced data processing and data visualisation to generate high-performance digital twins with effective bi-directional data exchange capabilities, interoperable and semantic data/model integration, advanced data processing and enhanced visualisation and navigation by the users. The application of digital twins is still in its nascent stages within the construction industry. Most of the identified studies used small-scale experiments and case studies to demonstrate the application of digital twins. Mature practical applications from industry are missing in the research literature. This study was limited to the technologies of digital twins, but the successful implementation of digital technologies in practice requires both technological and organisational factors to work together. Thus, research on the organisational aspects of digital twin applications is recommended. This study is limited to the publications obtained from using the seven keywords that were used for searching for records in the ScienceDirect database and other additional databases that included Web of Science and Google Scholar. The search might have missed out on records that were very specific to certain aspects of the AEC industry and those that did not use similar keywords. It is therefore recommended to undertake the study in specific domains and activities of the construction industry using different search terms.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

## Acknowledgements

Valerian Vanessa Tuhaise acknowledges the PhD scholarship support from the Commonwealth Scholarship Commission in the UK.

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