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Review

Digital Twin and Industry 4.0 Enablers in Building and Construction: A Survey

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Abstract: With increasing interest in automatic and intelligent systems to enhance the building and construction industry, digital twins (DT) are gaining popularity as cost-effective solutions to meet stakeholder requirements. Comprising real-time multi-asset connectivity, simulation, and decision support functionalities, many recent studies have utilised Industry 4.0 technologies with DT systems to fulfil construction-specific applications. However, there is no comprehensive review to our knowledge, holistically examining the benefits of using DT as a platform from the angles of Industry 4.0 technologies, project management, and building lifecycle. To bridge this gap, a systematic literature review of 182 papers on DT-in-construction works over the past 6 years is conducted to address the three perspectives. In this review, a unified framework is first modelled to incorporate Industry 4.0 technologies within the DT structure. Next, a Six M methodology (comprising of Machine, Manpower, Material, Measurement, Milieu, and Method) based on Ishikawa's Diagram with building lifecycle considerations is proposed to highlight the advantages of DT in ensuring successful construction projects. Lastly, through the identification of 11 future directions, this work aims to serve as a reference for both industry and academia towards the use of DT systems as a fundamental enabler to realise the Construction 4.0 paradigm.

Keywords: industry 4.0; construction industry; digital twin; cyber-physical system; building information modelling

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1. Introduction

In a bid to enhance productivity and performance through machine-to-machine interconnectivity [1], Industry 4.0 leverages recent internet and communication technologies (ICT) advances to spur breakthroughs in many domains [2]. Digital twins (DT), as a prevailing Industry 4.0 manufacturing technology, is often regarded as a "high fidelity virtual replica of the physical asset with real-ff time two-way communication for simulation purposes and decision-aiding features for product service enhancement" [3]. Often considered to be a versatile and scalable solution [4–6], DT offers a cost-effective approach towards resource tracking, scenario simulation, and solution generation. In recent years, there has been a growing interest from both academia and industry alike towards the use of DT systems in construction.

The construction industry is often touted as inefficient and unproductive due to the lack of cyber-physical interconnectivity [7], with commonly cited improvement areas in design and engineering processes, logistics management, on-site execution, digital technology integration, and workforce management. As advanced building and construction solutions require advanced representation and computational models to provide valuable insights and wisdom, DT has emerged as a core enabler for Construction 4.0 developments [8]. While capable of multiple lifecycle considerations, DT in construction differs from other industries through its utilisation of building information modelling (BIM) and other domain-specific protocols to meet unique stakeholder requirements. Hence, there is a need to explore the role of DT as a platform to integrate other industry 4.0 technologies holistically to form a foundation for Construction 4.0, defined as "a means of finding a coherent complementarity between the main emerging technological approaches in the construction industry" [8].

In our opinion, the establishment and application of DT systems in the building and construction area are two main concerns. This work tries to address the abovementioned concerns and challenges with two objectives: (1) providing a practical guide towards incorporating Industry 4.0 technologies and deploying feasible DT-enabled solutions in the building and construction industry; and (2) investigating the role of DT in complex building and construction projections with the consideration of essential factors and lifecycle perspectives. In this review, recent DT studies utilising Industry 4.0 enabling technologies are analysed systematically and mapped onto a DT-oriented technology stack to realise novel construction functionalities. Furthermore, these developments are consolidated within a Six M (Machine, Manpower, Material, Measurement, Milieu, and Method) methodology, which is essential for any successful building and construction project.

The rest of this article is organised as follows: Section 2 illustrates the article search process and analyses research trends. Section 3 consolidates the tools and techniques within a unified technological architecture. Section 4 categorises these studies from a Six M and lifecycle perspective, whereas Section 5 discusses the future of DT-enabled solutions in Construction 4.0. Lastly, Section 6 concludes the contributions of the work done.

2. Literature Review

This systematic survey focuses on reviews and articles from the past 6 years featuring DT-related technologies, frameworks, and industrial applications in the building and construction domain. This section identifies general trends and patterns for DT applications in construction.

2.1. Research Compilation Methodology

The literature search is conducted through Scopus, the largest peer-reviewed research database. Following an approach by [9], a three-step process flow is used to distinguish relevant articles, as shown in Figure 1. To avoid overlooking relevant studies, keywords related to DT paradigms and resembling construction terminologies are used. As such, the search can be repeated via the following pseudo-code: Topic = ("Digital Twin" OR "Cyber Physical" OR "Cyber Twin" OR "Virtual Twin" AND "Architecture, Engineering, and Construction" OR "Civil Engineering" OR "Building" OR "Construction"); Time Span: 2016–2022; Language: English; Type = "Article" OR "Review"; Source = "Journal" (searched on 5 September 2022). Following that, the abstract of each article is examined and benchmarked to further filter out studies that are irrelevant to the scope of this review.

The selection criteria consist of (1) Cyber-physical systems (CPS) and DT-related implementations in construction applications; (2) System framework and architectures to establish smart systems; (3) Enabling technologies to enhance existing practices; and (4) Other appropriate references relevant to this study. As a result, the literature search yielded 182 articles in which discussions in the following sections were based upon. Furthermore, 12 additional articles are referenced to boost the reliability of the survey.

2.2. Trends and Analysis

As DT systems and applications gain popularity throughout industry and academia, an increasing number of DT-related studies are directed towards the construction sector in a drive to enhance industry productivity and site efficiency, as showcased in Figure 2. With two-thirds of the collated studies published under Q1 journals, *Automation in Construction* is the most established source, as highlighted in Table 1. Construction is often viewed as a strategic national interest centered on many government-led research strategies and roadmaps [10,11]. Following this, Figure 3 highlights countries with the highest publication count. Publications in related fields exponentially increased in 2019 before slowing down in 2020. The predicted count for 2022 is based on the extrapolation of actual journal records as of September 2022.

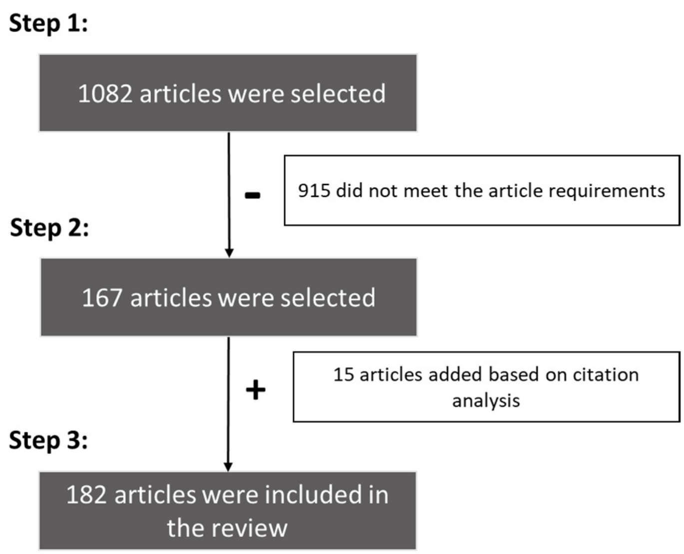

Figure 1. Flowchart of article selection.

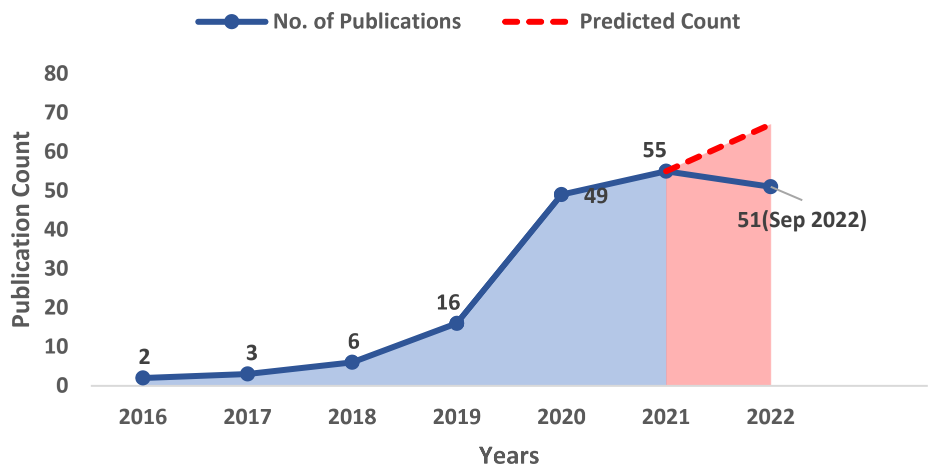

Figure 2. Publications count over the past 6 years (September 2016—2022).

Table 1. Top Journals Presented in the Review.

Journal	No. of Publications
Automation in Construction	32
Sustainability Switzerland	12
Applied Sciences Switzerland	8
Energies	7
Journal of Cleaner Production	7
Buildings	5
Energy and Buildings	5
Journal of Management in Engineering	5
Advances in Civil Engineering	4
Journal of Construction Engineering and Management	4
Sensors Switzerland	4

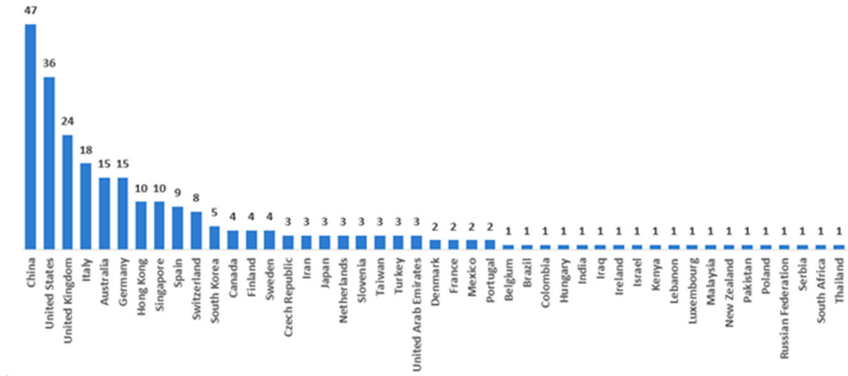

Figure 3. Publication counts categorised by countries.

3. Enabling Construction 4.0 through DT and Other Emerging Technologies

3.1. State-of-the-Art Technological Developments in Construction 4.0

Whereas DT solutions are increasingly adopted to boost efficiency and competitiveness, a diverse mix of Industry 4.0 technologies are used to fulfil applications specific for construction contexts [12,13]. This sub-section classifies the use of Industry 4.0 technologies within four fundamental DT aspects, namely data acquisition, data processing, simulation and modelling, and decision support enablers.

Data acquisition. The data acquisition process starts with raw data extraction and ends with the information being passed on to a cloud-based server or database. These technologies are highlighted in Table 2 with their corresponding construction applications and enabling tools.

Wireless sensor networks (WSN) provide a constant input of raw data for tracking and monitoring applications, which are fundamental towards the creation of DT systems in construction projects. **(1)** For SHM applications, Bhuiyan et al. [14] showcased a WSN-to-CPS design transition approach, highlighting design requirements, deployment hurdles, and networking guidelines, whereas Loubert et al. [15] facilitated long-distance communications within reinforced precast concrete. Yang et al. [16] developed mobile robots detection systems to perform data collection in dangerous environments. **(2)** For building performance applications, Zhang et al. [17] integrated heterogeneous data from different buildings into a CPS, whereas Lin and Cheung [18] established an environmental monitoring management system. **(3)** For building cost efficiency applications, Khajavi et al. [19] established an office building façade DT based on more than 25,000 sensor reading instances, whereas Grübel et al. [20] developed an indoor sensor network for building performance analysis. Abrol et al. [21] showcased an economical and noninvasive energy-efficient approach. **(4)** For sustainability applications, González et al. [22] proposed a calibration methodology to reduce the number of sensors required for building energy monitoring, whereas Keskin and Mengüç [23] implemented an adaptive vent system to localise and customise building thermal conditions. Liu et al. [24,25] implemented a CPS for greenhouse gas emission monitoring to enhance sustainability efforts in prefabricated construction.

As IoT is often utilised to establish cloud-enabled systems, and the critical difference between IoT and WSN lies in the use of IP-enabled connectivity (aka internet connectivity) such as IPv6-based low-power wireless personal area network (6LoWPAN) [26]. **(1)** For building performance optimisation, Tagliabue et al. [27] and Liu et al. [28] proposed BIM-IoT-DT integrated frameworks to support building comfort and indoor safety management. **(2)** For project management, Niu et al. [29] proposed a deployment framework to improve the synergies between construction entities based on a knowledge-based taxonomy. **(3)** For SHM applications, Zonzini et al. [30] utilised an IoT-based architecture to improve vibration engineering techniques, emphasising damage detection and task prediction.

Social media technology offers a unique approach towards enhancing data acquisition and communication techniques while incorporating social science theorems as part of sociotechnical systems. Turk and Klinc [31] proposed a three-tier information service framework that encompasses physical structure, DT, and a social network to facilitate construction activities.

Data processing. With the huge amount of real-time heterogeneous data collected, there is a need to facilitate raw data conversion and treatment to derive meaningful information for modelling and analysis. Table 3 highlights existing enabling technologies and tools used in existing studies to tackle industry-related challenges.

Semantic modelling allows for intricate relations between construction entities to be mapped and represented before storage. As such, the collected data can be processed into useful information essential to aid decision making and transparency for value chain enhancement [32]. **(1)** For equipment design and optimisation, Wei and Akinci [33] introduced a novel image-based registration method for panoramic images through minimizing semantic segmentation errors, whereas Haoyu et al. [34] proposed a linear segmentation method for the tunnel representation to support asset dynamic updates.

Blockchain is a distributed ledger or decentralised database of transactions recorded by a network of computers [35], which increases user confidence and trust in information reliability in construction projects. **(1)** For project management, Lee et al. [36] utilised DT to provide secure and reliable data communications between stakeholders, whereas Hunhevicz et al. [37] proposed the performance-based smart contract through the integration of digital building twin and blockchain. Jiang et al. [38] developed a blockchain-enabled platform to facilitate cross-enterprise information sharing during modular integrated construction. **(2)** For sustainable practices, Li et al. [39] developed an intelligent service platform to incorporate ICT to achieve sustainable prefabricated housing construction through a smart product-service system (Smart PSS) approach.

Data mining serves as an extraction and pattern discovery process within large datasets and involves ML approaches, statistics, and database systems [40]. **(1)** For building performance optimisation, Schmidt et al. [41] integrated CPS and cross-industry standard processes for data mining through a generic model-based design methodology. **(2)** For project management applications, Pan and Zhang et al. [42] deployed a data mining-driven DT system using fuzzy miner and ARIMAX to identify potential bottlenecks and reallocate resources dynamically.

Modelling and Simulation. DT technologies rely on 3D high fidelity models and simulations to provide comprehensive visualisation for evaluating specific scenarios and verifying automatically computed solutions while complimenting other construction-related enabling technologies highlighted in Table 4.

Utilising BIM technology, stakeholders can model building designs with dynamic optimisation and lifecycle consideration based on the various parameters setting [43]. This portion maps various BIM-DT solutions to core construction aspects and highlights enabling techniques used. **(1)** For facility management, Desogus et al. [44] and Wernerová et al. [45] utilised cloud-based BIM to enable building management capabilities. Adibfar and Costin [46] developed a dynamic DT for bridge through integrating real-time traffic data. Emphasising as-built models, Nicola Moretti et al. [47] and Rausch and Haas [48] automated asset management processes to support cognitive buildings throughout various lifecycle aspects, whereas Huynh and Nguyen-Ky [49] proposed a cross-platform system to visualise data and manage comfort levels. Wang et al. [50] achieved the interaction and virtualisation of various processes during building construction. Torrecilla-García et al. [51] proposed a BIM-enhanced decision support approach for safety management in the building industry. **(2)** For structural health monitoring, Lei et al. [52] developed a disaster prevention platform which identifies the building structural state, whereas Yuan et al. [53] evaluated the integrity of temporary structures. Taraben and Morgenthal [54] used voxel-based methods to discretise acquired 3D geometries for building damage propagation. **(3)** For asset design and optimisation applications, Al-Saeed et al. [55] and Schimanski et al. [56] implemented automation solutions within the construction manufacturing domain based on lean manufacturing paradigms and configure-to-order services. Kosse et al. [57] and Huang et al. [58] developed a DT framework to optimize the modularized construction of precast concrete. **(4)** For sustainability applications, Agostinelli et al. [59], Kaewunruen et al. [60], Zhao et al. [61], and Banfi et al. [62] achieved the visualisation and assessment of Net Zero Energy Building (NZEB) solutions. Xing et al. [63] applied the product-service relationship to manage stakeholders involved in the various lifecycle stages to derive higher eco-efficiency with reduced material consumption and waste generation. Kaewunruen and Lian [64] established a 6D BIM for railway turnout system, which enables assessing schedule, cost, and sustainability, and achieving a balance.

Simulation provides core functionalities, including but not limited to scenario visualisation and solution verification. **(1)** For structure design optimisation, Lydon et al. [65] presented a coupled simulation approach to optimise the thermal design of a lightweight roof, whereas Kyvelou et al. [66] described the numerical simulation method for the verification and assessment of a bridge structure. **(2)** For building performance optimisation, Lilis et al. [67] proposed a discrete event simulation (DES)-based system to virtualise intelligent buildings via a scalable architecture.

Following that, the point cloud offers an efficient approach to map these virtual models via 3D scanning and photogrammetry software. **(1)** For structural health monitoring, Omer et al. [68] digitised a typical masonry bridge in VR space as an alternative to traditional inspection methods, whereas Maroc et al. [69] proposed a novel method to transfer point cloud into parametric models for historic masonry buildings detection. **(2)** For asset design and visualisation, Xue et al. [70] processed urban LiDAR point clouds based on the object cross-sections, whereas Pantoja-Rosero et al. [71] automatically reconstructed the LOD3 models for existing buildings through a ML-based segmentation method. To model assets and structures, Jiang et al. [72] established the DT model of existing highway assets from map data, whereas Münzinger et al. [73] reconstructed tree models in the 3D city view.

Virtual/Augmented reality (VR/AR) offers an immersive and interactive approach to engage with new tools and explore high-risk environments. **(1)** For human-robot collaborative work, Wang et al. [74] established a remote collaborative system with an intuitive VR interface, which enables real-time bidirectional communication and supervision between workers and construction robots. **(2)** For urban planning and design, Kikuchi et al. [75] integrated AR and drones into a detailed 3D model to achieve city landscape visualization, which allows non-expert users to understand and participate in the construction project.

Decision support enablers. To enable disruption management capabilities and facilitate lifecycle transition, construction systems rely on decision support functionalities such as semantic solution generation, which are established using tools and techniques highlighted in Table 5. As AI-related techniques for decision support implementation can cover a broad area, key AI domains are highlighted below.

Computer vision (CV) enables the derivation of meaningful information from visual inputs to facilitate solution generation. **(1)** For the bridge maintenance system, Shim et al. [76] combined both maintenance information and digital inspection systems to generate reliable decision-making to enhance the bridge maintenance process. **(2)** For facility management, Antonino et al. [77] utilised an image recognition module to detect user's movements. Lu et al. [78] proposed an image processing approach to reconstruct 3D models from CAD drawings, whereas Pang and Biljecki [79] achieved the 3D reconstruction through the proposed image-to-mesh approach and street view images.

Machine learning (ML) involves the use of algorithms that utilise historical data and experience input to perform predictions and solution optimisations for decision support systems [80]. **(1)** For urban management, Döllner [81] developed an ML/DL Geospatial analytics engine to derive domain or application-specific semantics. **(2)** For improving energy efficiency, Alanne and Sierla [82] concluded that ML equipped building-integrated energy systems with adaptability for unpredicted changes, and Konstantakopoulos et al. [83] encouraged energy-efficient behaviour through facilitating the human–building interaction. Austin et al. [84] proposed the DT-based energy saving architecture for a smart city. **(3)** For safety management, Kamari and Ham [85] and Liu et al. [86] presented risk assessment frameworks for disaster preparedness and risk control through the DT system, whereas Gichane et al. [87] developed an elevator security DT system utilising a YOLOV3 algorithm. Pan et al. [88] proposed an AI-based segmentation method to capture and recognise important electrical and fire-safety entities. **(4)** For construction equipment monitoring, Zhang et al. [89] developed a construction equipment recognition algorithm to facilitate asset performance evaluation. **(5)** For building performance optimisation, Lv et al. [90] designed an AI-driven CPS to support indoor environment management via temperature response and control. **(6)** For on-site construction optimisation, Saini et al. [91] proposed an action planning system to optimize and automate the operation for well construction, whereas Tariq et al. [92] optimised the design of solar chimney considering energy efficiency and environmental factors. **(7)** For structure design optimisation, Fernández-Cabán et al. [93] utilised a stochastic optimisation algorithm to support sustainable tall building design based on occupant comfort and building drift, and Abdelaziz and Hobeck [94] developed an optimal controller to reduce the vibration caused by wind.

3.2. Integration of Technologies Using a DT-Adapted Framework

The range of core enabling tools and techniques presented earlier varies in technological advancement and implementation difficulty. To frame these co-construction entities within a Construction 4.0 context, a unified DT-adapted architecture is proposed. Through the five-layered technology stack, as shown in Figure 4, each entity fits into the overall structure towards enabling smart construction applications. This architecture leverages previously featured layered DT hierarchies [18,24] to provide an overview of the technological landscape for enhancing the building and construction environment.

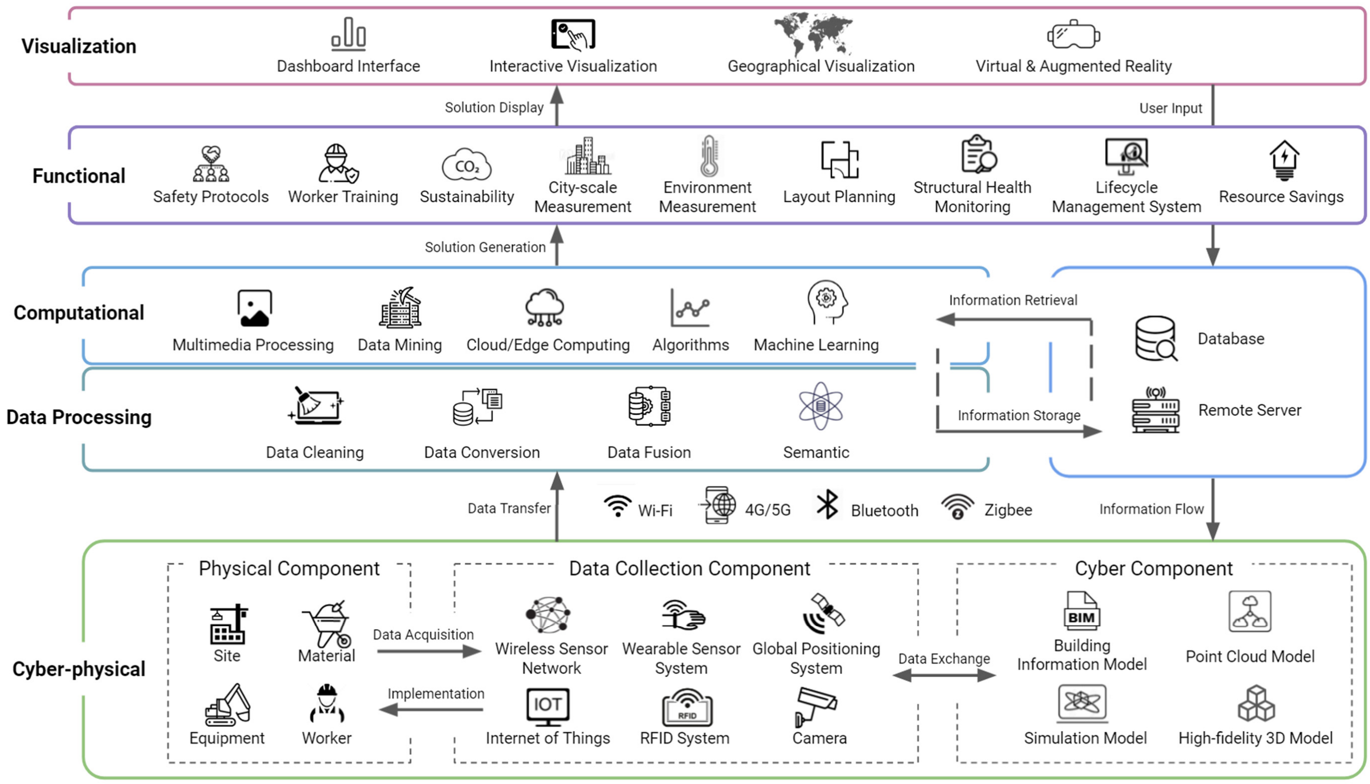

Figure 4. A unified technological architecture featuring co-construction elements to achieve Construction 4.04. DT perspectives on construction lifecycle aspects based on a Six M methodology.

Table 2. Data acquisition in Construction 4.0.

Technology	References	Construction Applications	Tools/Techniques
Wireless Sensor Network (WSN)	[14–16]	Enhance structural health monitoring (SHM) via cyber-physical systems.	*Connectivity*: Zigbee; LoRaWAN; Bluetooth *Controller*: Raspberry Pi; Arm; Arduino *Sensors for*: (*Structural health monitoring*) Acceleration; Piezoelectric; Ultrasonic; Radar; Laser; Strain gages; Optical fibre; Vision; Corrosion; Linear voltage displacement transducers; Inclinometers; Footprint accelerometer; Inertial Measurement Unit; Meteorological (*Building performance*) Gas concentration; Temperature; Humidity; Hazard detecting; Cloud-Oriented Radiation; Radiological measurement device; CORSAIR; Occupancy (*Building cost efficiency*) Temperature; Passive infrared (PIR) (*Sustainability*) Electrical power; Airspeed; Heat flux; Humidity; Wind speed; Wind direction; Radiation; Temperature; Acceleration; Barometric; GPS; Inductive displacement; Soil moisture; Asphalt strain; Horizontal inclinometer; RFID
	[17,18]	Building performance evaluation. Include evacuation planning, monitoring energy usage, emissions (CO, radiological), and temperature.	
	[19–21]	Improve building cost efficiency through lifecycle management and energy conservation.	
	[22–25]	Develop sustainability practices. Include applications in HVAC systems, reduce energy usage, carbon emission monitoring, equipment, and raw material tracking.	
Internet of Things (IoT)	[27,28]	Building performance optimisation. Include energy efficiency, sustainability assessment, indoor safety management, and enhanced FM system in the BLM process.	*Connectivity*: Cellular networks (GSM/3G/4G); Wi-Fi; Universal mobile telecommunications system; Low-power wide-area network (LPWAB) *Controller*: Arduino; Programmable logic controller (PLC) *IoT Sensor for*: (*Building performance*) Temperature; Humidity; Smoke; Oxygen Concentration; Carbon monoxide concentration; Gate magnetic; Infrared (*Project management*) Ultrasonic, RFID tag, Inertial measurement unit (IMU), GPS, Load cells, Switch, Barometers, Accelerometer (*Structural health monitoring*) Accelerometer, Inertial measurement unit (IMU) Auxiliary tools: NodeJS; TICK stack; Grafana; Blockchain
	[29]	Project management. Integrate CPS/DT technologies to enhance efficiency and synergy.	
	[30]	Enhance structural health monitoring (SHM). Include predictive maintenance of infrastructure.	
Social Media	[31]	Enhance construction lifecycle management. Include plan, design, build, usage aspects.	*Auxiliary milieu*: Log files; Emails; Social media messages; Building models

Table 3. Data processing in Construction 4.0.

Technology	References	Construction Applications	Tools/Techniques
Semantic Modeling	[33,34]	Asset design and optimisation. Enable equipment re-/configurations for disruption management. Localize a panorama with sub-meter localization error. Improve asset representation.	*Software*: Apache Jena, Protégé, Revit, Unreal Engine 4, Datasmith *Language*: XML, OWL, SPARQL, C++ *Library*: OpenCascade, OpenVDB *Algorithm*: CNN, ResNet101, PSPNet

Table 3. *Cont.*

Technology	References	Construction Applications	Tools/Techniques
Blockchain	[36–38]	Project management. Improve efficiency via contract implementation, stakeholder collaboration with increased reliability and service. Enhance information sharing and continuity for Modular Integrated Construction.	*Cloud platform*: Microsoft Azure *Database*: Distributed ledger *Mechanism*: Consensus mechanism, Encryption mechanism *Platform*: Ethereum blockchain
	[39]	Develop sustainable practices. Develop an intelligent platform integrating with blockchain to improve the sustainability of prefabricated housing construction.	
Data Mining	[41]	Building performance optimisation. Improve the energy efficiency of both legacy and modern buildings.	*Algorithm*: Inductive miner, fuzzy miner, ARIMAX mode *Modelling languages*: Petri net, business process modelling notation (BPMN) *Standard*: Cross-industry standard process for data mining (CRISP-DM) *Model*: CRISP-DM reference model
	[42]	Project management. Achieve a higher degree of intelligence and automation.	

Table 4. Modelling & simulation in Construction 4.0.

Technology	References	Construction Applications	Tools/Techniques
Building Information Modelling (BIM)	[44–51]	Facility management, improve comfort, energy efficiency, and building lifecycle management (BLM). Include anomaly detection, maintenance work, and decision support systems.	*BIM authoring tools*: Autodesk Revit, ArchiCAD, Allplan, AECOsim, Tekla structures *BIM auxiliary tools*: BIMserver, Autodesk Navisworks, Revit DB Link, Dynamo *BEM authoring tools*: Green Building Studio, EnergyPlus, Design Builder, Open Studio, CYPETHERM HE;
	[52–54]	Enhance structural health monitoring (SHM). Include disaster planning and damage inspection.	
	[55–58]	Asset design and optimisation. Incorporate lean manufacturing and configure-to-order business approaches to automate construction-related productions. Optimize precast elements production.	
	[59–61,63,64]	Develop sustainability practices. To realise net or nearly zero energy building (NZEB) solutions, circular economy, carbon cost estimation, and other green initiatives via product-service paradigms, lifecycle considerations, building energy models (BEM), and 6D BIM adoption.	

Table 4. *Cont.*

Technology	References	Construction Applications	Tools/Techniques
Simulation	[65,66]	Structure design optimisation. To reduce prototype development time and cost through high-resolution analysis, parametric geometric modelling.	*Coupled simulation*: ANSYS Fluent, TRNSYS, MATLAB *Numerical simulation*: ABAQUS *DES simulation*: coroutines, open BMS, ZeroMQ library
	[67]	Building performance optimisation. Enable infrastructure visualisations for power and environment monitoring.	
Point cloud	[68,69]	Structure health monitoring. Inspection services for digitised structures in a VR environment, future damage validation for historic masonry structures.	*Software*: Cyclone register 360, Cloud Compare, Civil 3D *Hardware*: Stationary/Airborne/terrestrial Laser scanner, Leica ScanStation P40, Leica ScanStation P20 *Library*: Point cloud library, ODAS library
	[70–73]	Asset design and visualisation. Generates building and city models using LiDAR, gestalt design principles, and as-built reconstruction approaches. Include ML/DL-based interpretation of point clouds to classify models.	
Virtual/Augmented Reality (VR/AR)	[74]	Human-robot collaboration. Facilitates task planning and supervision through bidirectional communication and asset control.	
	[75]	Urban planning and design. Multiple viewpoints and usability testing from nonexpert stakeholders involved in the building project.	

Table 5. Decision support enablers in Construction 4.0.

Technology	References	Construction Applications	Tools/Techniques
Computer Vision	[76]	Bridge maintenance system. Includes image recognition to enhance inspection processes.	*Algorithm*: Mask R-CNN, DeepSORT, Self-designed localisation, Fuzzy Logic, Edge detection, Neuro-fuzzy system, Optical Character Recognition, DeepLabv3 *Software*: Self-designed Revit, Blender
	[77–79]	Facility management. Includes movement recognition for maintenance operations, 3D structure reconstruction from CAD drawings and street view images.	

Table 5. *Cont.*

Technology	References	Construction Applications	Tools/Techniques
Machine Learning	[81]	Urban management. Contribute to building and maintaining base data for geospatial DT efficiently, including virtual 3D city, building indoor models, or BIM.	*Algorithm*: Tree-based classification, Clustering, Association, Categorizing, YOLOV3, Support vector machine (SVM) models, genetic algorithms *Network structure*: PointNet neural network (PNN), convolutional neural network (CNN), Deep bi-directional Recurrent Neural Networks (DBRNN), long short-term memory (LSTM), Back-propagation neural network (BPNN), Deep Residual Networks (DRN), Iterative Closest Point (ICP), Random sample consensus (RANSAC), KPConv, Monte Carlo tree search (MCTS), Multivariate regression mode, Non-dominated sorting genetic algorithm
	[82–84]	Improve energy efficiency. Include energy management through interacting with occupants, smart building design, and integrating semantic model.	
	[85,87,88]	Safety management. Develop a security system for a three-floor elevator in a commercial building setting and an indoor safety management system based on DT. Propose a threat assessment framework for construction site. Identifying essential entities from the electrical and fire-safety domain.	
	[89]	Construction equipment monitoring. Evaluate asset performance in various conditions.	
	[90]	Building performance optimisation. Integrate with CPS in a building environment and provide theoretical information and practical reference for developing the indoor environmental control system.	
	[91,92]	On-site construction optimisation. Improve construction workflow schedule and optimise the structure of building components.	
	[93,94]	Structure design optimisation. Support structure evaluation dynamically and minimise wind-induced vibration.	

Starting with the cyber-physical layer, assets and resources are digitalised through a systematic approach onto a virtual space, emphasising multi-source data acquisition, real-time two-way connectivity for asset monitoring and control, and cyber-physical information exchange. Within the physical component, raw data is acquired from construction assets and resources (e.g., working site, materials, equipment, and workforce) via a range of spatially dispersed sensors and communication devices, as shown in the data collection component. Following industrial communication protocols such as the OSI standard, site activity monitoring and resource tracking can provide additional value to stakeholders regarding safety, productivity, and quality assurance. Additionally, instructions can be passed down to the physical entities using remote controls and actuators to implement solutions under user supervision. Meanwhile, updated contextual heterogeneous data is mapped onto respective cyber entities through techniques such as point cloud mapping and BIM modelling. In the cyber component, common tools to facilitate data representation include BIM, simulation, point cloud, and high-fidelity 3D models. Depending on stakeholder/project requirements, the type of simulation technology selected may vary between dynamic, discrete event, and agent-based to reflect construction activities accurately [95], whereas the use of point cloud models often requires a LiDAR system setup for real-time mapping. With mobile robots being increasingly utilised in detection systems, information from dangerous environments can be safely collected, whereas structural and health monitoring activities can be automated through sensor networks and IoT systems [16].

Next, the data processing and computational layer comprise data treatment, storage and retrieval, and analytical processing modules to convert raw data into useful information and, subsequently, knowledge based on a systematic approach. Whereas high-frequency data collection enables accurate analysis e because of lower estimation variance, data cleaning and filtering processes are crucial towards ensuring quality input due to the higher probability of data redundancy and inaccurate recordings. Data conversion ensures format compatibility and standardises information flow into the subsequent computational modules, whereas data fusion enables multiple data sources to be integrated to generate consistent, useful, and accurate information. Semantic modelling refers to the method in which information is organised and allows for reasoning models to infer useful knowledge based on the networks and relationships established between data nodes [32]. Following that, the processed data are stored in remote servers which host the databases and data lake. The selection of database types depends on the intended application and was previously highlighted in Section 3.1. To derive meaningful knowledge, the computation layer draws on multimedia processing, data mining, cloud/edge computing, algorithms, and ML approaches to generate insights and analysis for use in the functional layer.

Subsequently, the functional layer identifies core construction applications featured in existing studies and contains domain-specific knowledge such as the various ISO protocols for safety and sustainability, government regulations and guidelines, and stakeholder-centric preferences and requirements. Relevant knowledge obtained from the computational layer will be further refined to provide wisdom to end-users, who can view the recommended solutions and current situation through the visualisation layer. Through the various interfaces and mixed reality displays, users can interact and control the physical assets, as well as implement system-generated solutions. The modules showcased within each layer can be integrated to fulfil specific use cases [81], and as such, potential technology combinations can be deployed to overcome advanced construction pain points.

4. DT Perspectives on Construction Lifecycle Aspects Based on a Six M Methodology

This section presents a Six M methodology based on Ishikawa's diagram [96] to represent the essential factors required for successful construction projects and elaborated in Table 6. Adapted from established reliability engineering paradigms with lifecycle consideration [97], this methodology consists of Machine, Manpower, Material, Measurement, Milieu, and Method (Six M) and is closely associated with the building lifecycle management approach [98]. Based on both the Six M and building lifecycle perspective as illustrated in Figure 5, the benefits of DT are categorized accordingly. It is noted that DT technologies did not prominently support the 'requirements identification' and 'project planning' stages.

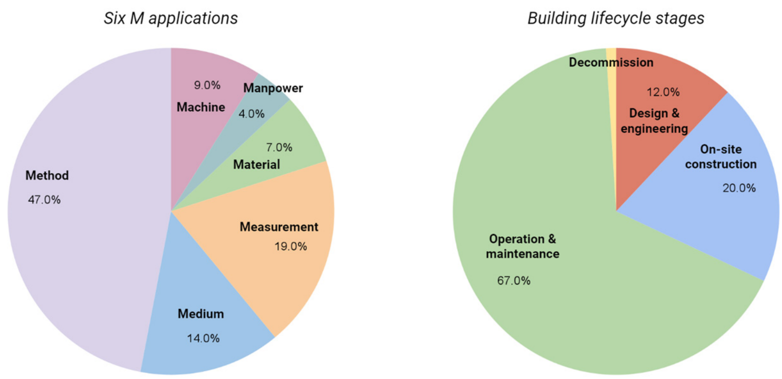

Figure 5. Distribution of existing applications on Six M and building lifecycle management aspects.

4.1. Machine

The Machine aspect represents all physical assets related to equipment and machinery (e.g., Truck, crane) used within the construction industry. DT technologies are often deployed on high-value assets to enhance efficiency and reduce breakdowns throughout the usage phase. Within the on-site construction phase, Zhang et al. [99] proposed a multi-system coupling mechanism to support a CPS-based hierarchical autonomous control of a tunnel boring machine, whereas Li et al. [100] developed a DT-driven virtual sensor structure for trailing suction hopper dredger to support pre-warning and safe operations. Zhang et al. [101] proposed a unified robot-oriented framework for building automation and robotics, whereas Cai et al. [102] developed an automatic path planning method for Crane lifting in construction environment. Liang et al. [103] established a robot control policy to handle repetitive tasks, whereas Zhang et al. [104] developed a dynamic data-driven modelling mechanism to allow robots to handle automatic pavilion constructions. Furthermorea, Lee et al. [105] proposed a DL approach to enhance the task allocation performance during robotic construction. In the operations and maintenance phase, Jiang et al. [106] simulated hoisting behaviours to avoid the potential safety accident for the tower crane and Liu et al. [107] utilised an SVM approach to predict risk in advance for prefabricated elements hoisting. Moreover, Kan et al. [108] proposed a layered CPS approach to plan and monitor mobile crane operations.

4.2. Manpower

The Manpower aspect involves the working force engaged throughout the construction stage and ranges from designers to equipment operators. Current DT studies in this aspect only focus on the on-site construction phase. For worker safety, Wu et al. [109] introduced a real-time visual warning system to proactively avoid dangerous entities for construction workers based on deep learning and mixed reality. For worker training, Akanmu et al. [110] showcased a CPS-driven postural training platform for workers to practice construction operations via a VR environment, whereas Sepasgozar [111] integrated VR/AR and DT technologies to educate stakeholders in the design, development, and implementation of a tunnel boring project as part of an education pedagogy.

4.3. Material

The Material aspect includes raw materials and intermediate products such as precast models, and recent studies mainly focus on material performance and tracking. In the design and engineering phase, He et al. [112] utilised a BIM-enabled fabrication methodology with material configurations to advance 3D printing capabilities in construction. In addition, Orozco-Messana et al. [113] presented a novel solution for building envelop regeneration through leveraging Phase Change Materials elements. In the on-site construction phase, Marini et al. [114] presented a CPS-based method to improve the traceability and radiological detection of construction material. In the operations and maintenance phase, Meža et al. [115] explored the use of secondary raw materials in terms of feasibility, suitability, and sustainability in the long run. In the decommissioning phase, Züst et al. [116] enhanced construction sustainability by evaluating excavation and demolition material flows via economic and circular economy perspectives.

4.4. Measurement

The Measurement aspect refers to the transformation of drawn information into descriptions and quantities and can be extended to include the value, cost, and price of construction work. Moving towards a digitalised landscape, data acquisition and status monitoring of both physical objects and target environments are essential for the development of infrastructures in a speedy, dependable, and sustainable manner. In the on-site construction phase, Hao et al. [117] reduced carbon emissions through a BIM-based approach. In the operations and maintenance phase, Chiachío et al. [118] proposed a DT framework for structural monitoring tasks within the civil engineering domain, and many researchers implemented practical health monitoring systems for different structures and scenarios [119], including beam string structures [120], large-scale structures [121], timber buildings [122], bridges [123,124], underpasses [125], and roads [126]. For non-destructive asset evaluations, Angjeliu et al. [127] developed an expedited modelling method for dynamic reconstruction simulations, whereas Kong et al. [128] presented an ML approach based on percussive diagnostic techniques to determine conditions of bolted joints. To assist in failure avoidance, Mahmoodian et al. [129] developed CPS-enabled monitoring systems to provide early warning capabilities and corrective instructions.

4.5. Milieu

The Milieu aspect represents the physical environment in which work is carried out and includes ambient information, terrain type, and surrounding layout. In the on-site construction phase, Zhang et al. [130] integrated DT and the extension of level of details in BIM into a framework to support construction site monitoring and management. Jiang et al. [131,132] proposed a DT-enable system to achieve the real-time management of on-site assembling during modular integrated construction. In the operations and maintenance phase, both building and city environments are targeted as potential optimisation areas. For indoor environment management, CPS-enabled systems were deployed to boost thermal comfort for both homes and offices based on user preferences and energy efficiency [133–136]. Meanwhile, Zhao et al. [137] visualised indoor conditions and energy consumption parameters, whereas Shahinmoghadam et al. [138] developed a VR platform to monitor thermal comfort conditions. Zhang et al. [139] developed an automatic humidity control system for heritages sites via computational fluid dynamics simulation and Bonci et al. [140] developed a BIM-based CPS platform to evaluate and optimise building performance. For building occupancy monitoring, Gomes et al. [141] proposed a context-aware recommendation system for co-working environments, whereas Seghezzi et al. [142] presented an occupancy-oriented building management system to optimise cleaning operations. For smart city development, Schrotter, Hürzeler [143], White et al. [144], Cho and Kim [145], and Wu et al. [146] developed DT cities to enhance transparency, transport efficiency, and urban planning.

4.6. Method

The Method aspect covers the approaches used to improve building and construction efficiency throughout the lifecycle. In the design and engineering phase, building shape optimisation can allow planners and architects to minimise environment influence when designing buildings. Wei et al. [147] proposed an assessment approach for the wood panelised components during off-site construction to progress next construction step. Böke et al. [148] demonstrated the CPS-enabled automation of adaptive façade functions ranging from solar shading to sound insulation, whereas Ding and Kareem [149] utilised building shape morphing and evaluation techniques to reduce wind load significance to satisfy building drift and comfort requirements. For Building Energy Modelling (BEM), Porsani et al. [150] and Demianenko et al. [151] proposed workflow and framework for automating energy analyse based on BIM. For indoor environment design, Jia et al. [152] developed a platform-based method for rapid prototyping and explored design spaces to improve design performance. In the on-site construction phase, for safety management, Jiang et al. [153] established CPS-based risk data synchronisations with warning and scene reconstruction mechanisms, whereas Liu et al. [154] proposed a hoisting safety risk management framework for prefabricated buildings with considerations to relations between risk factors. To improve construction logistics, Greif et al. [155] implemented a decision support system for silo dispatch and replenishment via fill level monitoring. As for quality assessment, Tran et al. [156] ensured the 3D geometric quality of as-built prefabricated façades through comparisons between the as-designed and as-built digital models. To enhance sustainability, Yang et al. [157] contributed to the long-term city development through summarising publications considering DT integrated with the intelligent green building. Çetin et al. [158] explored how to apply circular principles during the construction lifecycle.

In the operation and maintenance phase, asset management organises resources through structured and competent means [159]. To enhance the operation and management flow of buildings, Zhao et al. [160] and Quirk et al. [161] proposed conceptual frameworks for DT-based FM systems while detailed solutions for specific assets including pumps [162], tunnel [163], bridge [164], and airport [165,166] have also been explored. To lower energy consumption, Francisco et al. [167] benchmarked daily electricity usage according to strategic period while innovative approaches including activity monitoring [168,169] and resilient buildings achievement [170,171] were proposed. Bass et al. [172] and Huang et al. [173] achieved the regional energy saving system through urban-scale energy modelling to achieve NZEB [174]. Hosseini Haghighi [175] enhanced the interoperability between urban building data and energy consumption evaluation. To enhance lifecycle management, Yitmen et al. [176] analysed the impacts of using cognitive DT systems in various lifecycle aspects based on applicability, interoperability, and integrability. Furthermore, several studies have illustrated DT-enabled decision support capabilities in infrastructure projects [177–179] with emphasis on sustainability and vulnerability. Lastly, Zu and Dai [180] highlighted a distributed path planning strategy to reduce crowd-induced casualties during building evacuation.

5. Discussion and Future Directions

5.1. Strengths and Limitations of DT in Construction

This section analyses the potential strengths and limitations of DT implementation in the building and construction industry. For building and construction, by enhancing an automatic data acquisition and variation system, DT first provides opportunities to simulate and improve the design and production-related activities, such as the visualisation of blueprints, prefab units' production schedules, and materials logistics optimisation. Secondly, DT realises automatic and intelligence during the operation and maintenance (O and M) stages in the building industry through the establishment of as-built models for construction projects and related facilities. Real-time conditions updates from the physical side can achieve a basic level of O and M functions, such as monitoring and assessing buildings, facilities, and inner structures. With the help of data analytics and decision support techniques, some advanced applications, including energy saving, predictive maintenance, and maintenance schedule optimisation, are able to be implemented. Therefore, DT contribution can cover the whole life cycle of building and construction in the improvement of operating and cost efficiency.

Most DT-related publications are about virtual model generation. Making the virtual part accurate and efficient is a major issue because of the limitations of real-time information interaction in the construction industry caused by the harsh data collection environment and complex equipment types. Moreover, the higher initial investment is another important consideration during DT implementation, and the cost varies according to the level of services provided. Furthermore, unlike manufacturing cases, data collection equipment on construction sites is mostly temporary, and they will be withdrawn after the construction mission is completed, which also increases the investment. Therefore, developing reused DT system contributes to a significant improvement in cost efficiency.

5.2. Future Directions for Construction 4.0

This section reviews potential trends highlighted from existing studies and outlines 11 directions to advance DT-enhanced systems in construction. These future directions are categorised from technical, application, environmental, and management perspectives, as shown in Table 7.

Starting with system and technology enhancement, the development of diverse and multi-function sensor systems would facilitate data collection in complex and harsh environments through intelligent, miniaturisation, and integrative functionalities to support cellular networking, GPS, and robotics. AI-enhanced functionalities such as ML, CV, and optimisation algorithms can significantly improve process efficiency and provide better analysis and solutions. Multi-function and integrated DT systems aim to incorporate functionalities with higher operation performance to include additional project considerations within the same platform, such as environment monitoring, safety management, and building evacuation.

Next, a wider scope of implementation would provide more industrial relevance as DT systems can take on increased functional roles and alleviate pain points based on a holistic outlook. Multi-asset servitisation requires multi-source datasets to manage high quantity assets and leverage resource data to enhance overall building and construction operations. City-scale DT systems highlight the shift from building-oriented DT systems towards the mapping and management of virtual cities for mass administration and urban planning cases. Broad industry implementations will provide a wider sense of realism to enterprises and industry stakeholders by implementing DT-enabled solutions with an emphasis on industrial protocols and guidelines to resolve real-life situations feasibly. Encompassing the entire lifecycle refers to the expansion of DT solutions to include knowledge from design to demolition stages to better manage bottlenecks economically and efficiently.

The circular economy promotes sustainability and is emerging as a crucial factor in the modern construction environment. Sustainable construction mainly targets resource savings, emission reduction, and waste management in the on-site, operation, and decommissioning stages. Meanwhile, lean concept integration ensures the efficiency and environment footprint of prefabricated production operations through reduced material and energy consumption in the design and manufacturing stages.

Lastly, DT has the potential to improve project management from both a time and cost perspective. The Time-based analysis utilises DT-enabled solutions to optimise project timelines, mitigate disruptions, and reduce the risk of delays. Economic considerations factor in the financial perspectives and ensure that the recommended solutions are feasible while operating within the preferred business model.

With these directions to enhance DT capabilities, other functional techniques derived from previous work such as complex environment path planning [181], BIM-enabled detection methods [43], and other construction enablers can leverage DT systems to enhance construction robustness and resilience.

Table 6. Benefits of digital twin applications categorised by Six M aspects based on building and construction lifecycle stages.

Six M	Lifecycle Stage	Construction Function	Reference	DT-Enabled Benefits
Machine	On-site construction	Intelligent equipment control	[99,100]	Reduce steady-state errors and safety risks.
		Automatic robot construction	[101–105]	Improve context observation to implement robot control policy, enhance the generative design and robotic construction through real-time perception-modelling, achieve real-time bidirectional communication and supervision remote collaboration between workers and robots.
	Operations and maintenance	Safety management	[106,107]	Improve object detection confidence level in the digital triplet security system.
		Asset management	[108]	Enhance bidirectional coordination between virtual and physical assets and establish context-aware capabilities for configuration and workflow efficiency.
Manpower	On-site construction	Worker safety	[109]	Synchronise information in dynamic and complex environments to process hazards.
		Worker training	[110,111]	Decrease training risk by virtual practice platform and improve learning effects of construction practitioners.
Material	Design and engineering	Structure design optimisation	[112]	Provide more accurate models to support the design validation of 3D-printed modules.
		Reuse and recycling	[113]	Reduce material consumption and waste generation through building component reuse.
	On-site construction	Material information tracking	[114]	Improve traceability and radiological detection of construction material.
	Operations and maintenance	Durability and response monitoring	[115]	Facilitate material circularity by exploring properties and responses of secondary raw materials (SRM).
	Decommissioning	Reuse and recycling	[116]	Guide material flows towards a sustainable material flow through quantitative assessment.
Measurement	On-site construction	Greenhouse gas emissions tracking	[117]	Improve the potential for establishing energy conservation and emission reduction strategy through real-time GHG emissions monitoring.
	Operations and maintenance	Structural health monitoring	[118–129]	Provide promising paradigms for real-time and continuous SHM application, including structural damage detection, safety assessment, failure avoidance, and maintenance operations assistance.
Milieu	On-site construction	Construction site monitoring	[130–132]	Improve construction digitalisation through automatic detection and monitoring of construction site and assembly progress.
	Operations and maintenance	Indoor environment management	[133–140]	Benefit visually dynamic common platforms for intelligent indoor management functions, including real-time monitoring, safety maintenance, thermal comfort, and reducing resource consumption.

Table 6. *Cont.*

Six M	Lifecycle Stage	Construction Function	Reference	DT-Enabled Benefits
		Building occupancy monitoring	[141,142]	Improve space utilisation and sensor system efficiency and accuracy through real-time building occupancy monitoring and intelligent algorithm.
		Smart city development	[143–146]	Easier demonstration and transparency of administration tasks, urban planning, and policy to the public through visualisation and analysis of digital prototypes.
Method	Design and engineering	Building shape/profile optimisation	[147–149]	Automate façade functions development, minimise the influence of wind load through dynamic façade and provide a cost-effective method to satisfy serviceability limits, optimise the shape of the concrete roof structure with complex geometry for energy saving.
		Building energy modelling	[150,151]	Enhance the interoperability between BIM and Building Energy Model (BEM) in the building design phase.
		Indoor environment design	[152]	Enable rapid prototyping of applications to improve design performance by reusing hardware and software on shared infrastructures.
	On-site construction	Safety management	[153,154]	Enhance safety management in construction sites through risk factors analysis, proactive risk control, and threat assessment.
		Construction logistic	[155]	Support decision-making during silo dispatch and replenishment activities.
		Quality assessment	[156]	Facilitate the visual quality assessment of as-built prefabricated façades during the construction process.
		Sustainability enhancement	[157,158]	Support data synchronisation, blockchain integration for traceability, and incorporate the smart product-service paradigm.
	Operations and maintenance	Asset management	[160–166]	Better access to siloed data and support the development of asset management applications such as real-time monitoring and more intelligent decision-making for cognitive buildings.
		Energy reduction	[167–173,175]	Promote energy-saving construction to achieve energy-reduction goals through accurate energy simulation analysis, encourage energy-efficient behaviours, and intelligent matching of residents and activities.
		Lifecycle management	[176–179]	Enable cognitive features in assets to support sustainability, vulnerability assessments, and maintain quality throughout the construction lifecycle.
		Building evacuation	[180]	Provide guidance information for efficient building evacuation in emergencies.

Table 7. Future Directions for DT in Construction 4.0.

Category	Reference	Future Direction	Description
Technology enhancement	[16,19,30,95]	Diverse and multi-function sensor systems	Develop advanced miniature sensors with intelligent and integrative features to support GPS, 4/5G, and robotics for performance improvements.
	[18,81,84,87,90,182]	AI-enhanced functionalities	Automate and accelerate learning, reasoning, and perceiving from extensive datasets to tackle higher-order tasks such as detection, prediction, optimisation, and planning.
	[28,39,161,183,184]	Multi-function and integrated DT systems	Enhance computation capabilities to include higher quality simulation and solution accuracy as well as faster processing time to support visualisations and evaluations.
Application scope	[78,89,185]	Multi-asset servitization	Integrated solutions using assets and resources to enhance recognition, tracking, and management operations.
	[143,144,186–188]	City-scale DT systems	Validate current DT architecture to a broader scale and expand DT application from building to community and city level to provide the foundation to optimise city services.
	[29,42,47,52,108]	Broad industry implementations	Incorporate complex multi-asset scenarios based on real-life practices to suit industrial needs with an information-rich digital twin model.
Circular economy	[117,189]	Encompass full lifecycle	Achieve an efficient DT system that can be used to plan, design, operate maintenance and demolition economically and environmentally throughout the whole lifecycle of the construction project.
	[24,25,167]	Sustainable construction	Improve resource efficiency, tracking, and reduce emissions, extend asset lifespans, and enhance waste management through functional component monitoring and analysis in each lifecycle stage.
	[55,56,190]	Lean concept integration	Integrate lean concepts within digital solutions to enhance resource sustainable infrastructure projects or implement lean manufacturing approaches for PPVC production.
Benefits analysis	[191]	Time-based analysis	Explore the influence of DT solutions on project timelines with comprehensive dataset analysis.
	[192–194]	Economic considerations	Ascertain the financial viability of DT adoption and the use of DT solutions to achieve cost savings.

6. Conclusions

The versatility and scalability of DT solutions are evident in many industries stretching from aerospace to healthcare. With growing awareness of DT capabilities in Construction 4.0, there is a need to review this emerging technology and provide an overview of the various application methodologies and trends. This article is a comprehensive state-of-the-art review with 182 related studies selected from 61 journals over the past 6 years to derive an architecture showcasing the integration of Industry 4.0 technologies as functional modules within DT systems. Ishikawa's diagram originally proposed for quality control is extended to a Six M methodology for in-depth analysis with an outlook on the advantages brought forth by DT-enabled systems for various construction functional roles. Horizontal technological perspective (scalability of DT applications): most existing studies focus on enhancing the Method, Milieu, and Measurement aspects. Meanwhile, Machine, Manpower, and Material aspects are less emphasized because of the environmental and resource complexity as well as the lack of data reliability. As DT systems are primarily deployed for environmental monitoring and resource tracking roles within specific use cases, there is a need to investigate the role of DT in handling multi-asset integration and complex scenarios. To overcome this challenge, the Six M methodology is highlighted to ensure the scalability of construction DT systems. Consisting of essential factors for successful project outcomes, the Machine, Manpower, Material, Measurement, Milieu, and Method aspects provide a reference model for academics and industries in the implementation of future DT models.

Vertical technological perspective (advancement of DT systems): current research is mostly used for monitoring, management, and functional applications but rarely for decision support and automatic solution generation systems. To further refine the role of DT systems in distinct operations, a five-layer DT-oriented architecture consisting of cyber-physical, data processing, computational, functional, and visualization layers highlights how Industry 4.0 technologies can be incorporated. Furthermore, the breakdown of specific tools and techniques previously utilized provides a practical guide towards identifying research gaps and deploying feasible DT-enabled solutions.

Complex resource relations, fluctuating environmental conditions, and the lack of high-quality datasets are challenges resulting in fewer automatic decision support and recommendation systems within the Machine, Manpower, and Material aspects. Thus, 11 future directions are identified, including diverse and multi-function sensors systems, AI-enhanced functionalities, multi-function and integrated DT systems, multi-asset servitization, city-scale DT systems, broad industry implementations, full lifecycle encompassment, construction sustainability, lean concept integration, time-based analysis, and economic considerations. Hopefully, this survey can be regarded as a useful resource for more DT-related research and discussions towards innovative construction applications and Construction 4.0.

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