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Review

Digital Twin Technology in Built Environment: A Review of Applications, Capabilities and Challenges

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Highlights:

What are the main findings?

- Digital Twin (DT) technology significantly enhances lifecycle energy optimisation and operational efficiency in the AEC industries.
- DTs enable predictive maintenance and improve user adaptability through real-time data integration and advanced analytics.

What are the implications of the main findings?

- Implementing DT technology can lead to substantial advancements in sustainable and efficient building management practices.
- Addressing the technological, data consistency, organisational, and cybersecurity challenges is crucial for the broader adoption of DT technology.

Abstract: Digital Twin (DT) technology is a pivotal innovation within the built environment industry, facilitating digital transformation through advanced data integration and analytics. DTs have demonstrated significant benefits in building design, construction, and asset management, including optimising lifecycle energy use, enhancing operational efficiency, enabling predictive maintenance, and improving user adaptability. By integrating real-time data from IoT sensors with advanced analytics, DTs provide dynamic and actionable insights for better decision-making and resource management. Despite these promising benefits, several challenges impede the widespread adoption of DT technology, such as technological integration, data consistency, organisational adaptation, and cybersecurity concerns. Addressing these challenges requires interdisciplinary collaboration, standardisation of data formats, and the development of universal design and development platforms for DTs. This paper provides a comprehensive review of DT definitions, applications, capabilities, and challenges within the Architecture, Engineering, and Construction (AEC) industries. This paper provides important insights for researchers and professionals, helping them gain a more comprehensive and detailed view of DT. The findings also demonstrate the significant impact that DTs can have on this sector, contributing to advancing DT implementations and promoting sustainable and efficient building management practices. Ultimately, DT technology is set to revolutionise the AEC industries by enabling autonomous, data-driven decision-making and optimising building operations for enhanced productivity and performance.

Keywords: building information model; digital twin; digitalisation; simulation; architecture; engineering; construction; sustainable building management; asset management; review

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1. Introduction

The rapid globalisation and urbanisation in the latter part of the 20th century has made it more difficult to optimise management of urban spaces and resources. Consequently, urban development has resulted in numerous environmental issues at local, regional, and global levels [1]. Therefore, it is critically important to manage both new and old infrastructure from an economic and environmental standpoint. Governments globally have acknowledged the inefficiencies in city and building management and have either suggested or mandated the adoption of new and advanced solutions to reverse the declining trend [2].

Most of a building's expenses during its lifecycle are incurred during the operation phase. It is estimated that these costs can range from five to seven times greater than the initial investment and three times higher than construction costs [2]. Traditional paradigms and approaches often prevail, impeding the potential improvements that could arise from adopting digital tools and methods. There is still limited progress in digitalisation, particularly during the asset's operational phase [3].

Greater importance is being given to the evolving demands of building occupants these days. By 2025, millennials, who are known for their adeptness with technology, are projected to make up 75% of the workforce in office spaces, with a similar tendency anticipated across various other building categories such as hospitals, airports, and hotels. This new generation of customers demands a heightened level of building functionality, adaptability, and versatility in both the design and utilisation aimed to improve user productivity [4].

In the past few decades, the advent of the latest generation of information technologies [5], such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and big data analytics, has accelerated the digitalisation of different systems and processes across various sectors including architecture, engineering, and construction [1].

Through digital transformation and integrated adoption of technologies, the entities and their conditions, behaviours, and interactions in the physical world are comprehensively digitised; thus, digitalisation is emerging as one of the primary forces behind innovation across AEC industries [5]. Such technologies lead to many IT-focused solutions, such as smart asset management, which is a promising approach that enhances performance and leads to greater economic profitability [3].

Geospatial information is fundamental in developing DTs for built environments, providing the detailed data necessary for accurate, real-time data modelling and analysis. Research highlights [6] that geospatial data, including topography, infrastructure details, and land use, are crucial for creating precise digital representations of physical spaces. These DTs support improved urban planning, resource management, and predictive analytics, leading to more efficient and resilient environments. Integrating geospatial data ensures that DTs remain aligned with the real-world environment [7].

DT, as a tool for smart asset management, offers the opportunity to integrate physical objects with their virtual counterparts throughout their life cycle to replicate their real-world behaviours [1]. A technology trend report identified DT as one of the top four emerging technologies among a selection of fifteen [8]. It is a revolutionary and innovative technology that enables a quicker and more efficient management, monitoring, and prediction of assets [9]. DT is drawing interest from both the academic and the industrial sectors [5] and has recently gained popularity in the AEC. It is increasingly becoming an essential tool for smart management and monitoring in the AEC sector [9] and was identified among the top 10 technological trends holding strategic significance for three years, spanning from 2017 to 2019 [5].

This paper is organised as follows. The article firstly studies the various definitions of the DT concept and briefly review its applications across different industries. Then, it examines DT from similar digital modelling techniques to provide a clear and precise understanding of what DT represents in the industry. Next the article analyses the digitalisation sophistication spectrum and categorise the levels of DT maturity, and then explores the capabilities of DT to determine ways it can transform traditional methods. Next, the challenges and obstacles to the full deployment of DT are discussed. Lastly, the research gaps and future possibilities for the application of DT in the AEC industries are explored.

2. Understanding Digital Twin Technology: Concepts, Applications, and Evolution

2.1. The Terminology and Core Concepts of Digital Twin

In recent years, there has been a significant increase in the number of publications focusing on DT research. The growing popularity of DTs reflects the inevitable trend that the virtual and physical worlds are becoming more interconnected and integrated as a whole [5]. Despite the lack of clear and formal definition of what DT really is or what it will evolve into in the future [8], it is essential to establish a comprehensive and unified definition of DT to mitigate the confusion and unrealistic expectation associated with this technology [10].

DT is founded on some current technologies, including, but not limited to, 3D modelling, system simulation, and functional and behavioural prototyping [5]. It has been used in aerospace and astronautics for implementation in as-built and next-generation aircrafts for years [11]. Since 1970, NASA and the Air Force Research Laboratory have been developing replicated systems to monitor inaccessible physical spaces (e.g., spacecrafts on mission) and, in turn, identify solutions to challenges [12]. While the concept of DT has remained stable over the years [11], its application has been expanded beyond its initial utilisation of military and aerospace domain into the civilian sectors, and DT encounters an increasing number of applications for various industries, users, and businesses [5].

In product lifecycle management, the concept of DT was initially defined in 2002 by Michael Grieves as "a virtual, digital counterpart to a physical product" [11]. Later, in 2014, Grieves defined the three primary components of a basic DT model in a whitepaper: (a) physical products in Real Space, (b) virtual products in Virtual Space, and (c) the data and information connections that bind the virtual and real products together [5]. A more thorough and widely accepted definition of a "Digital Twin" in research is offered by Glaessgen and Stargel, as "an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin" [13].

A DT can be the digital representation of a real-world entity, a concept, or a notion. Real-world entities are identified as having physical form, such as an aircraft engine, a bicycle, or a human heart. However, an entity represented by a DT can also be something abstract that is without traditional physical form such as a business or a manufacturing process [8].

2.2. Distinguishing Digital Twin Technology from Related Concepts

As a part of various digitalisation initiatives, DT's utilisation in literature often resembles conventional digital modelling techniques [10], sharing similarities that could lead to confusion due to their interconnected nature [1]. However, the scope of DT extends beyond these traditional methods of digital modelling techniques [9]. Often, the source of confusion arises because the concept is among the components of a DT [14]. In the construction context, DT represents a strategy that utilises various technological tools to drive improvement, including BIM [15], Computer-Aided Design (CAD) [14], and simulation [10]. Although there is no agreement regarding distinctions or similarities between these ideas, the evolution of DT is impacted by these technologies [16]. Additionally, identifying key components of the concept can aid in clearly categorising what qualifies as a DT, setting it apart from other analogous digital technologies [10].

The key and most fundamental distinction between DT and traditional digital models lie in the dynamic nature of DT. This characteristic is reflected in the real-time updates of the DT, which are linked to changes in the represented physical object, enabling the DT to evolve and age alongside it. This attribute is known as the real-time self-evolution of DT [17]. All CAD systems create files primarily consisting of vectors, associated line types, and layer identifications. As these systems were further developed, additional information was incorporated into the components. Subsequently, the aim shifted from drawings and 3D models to the data itself [18], resulting in Building Information Modelling.

Currently, BIM is the most widely used digital modelling technology in the construction sector [15], and although it is commonly perceived as intelligent 3D and 4D modelling techniques for construction, its primary focus is on fostering collaboration and eliminating data among various construction stakeholders [3]. Compared to BIM, DTs offer greater complexity and integration possibilities as they aim to establish a user-centric, functional platform. DT is primarily concerned with representing how individuals interact with the asset, whereas BIM focuses mostly on the asset [15]. Furthermore, the primary application of BIM is during the design and construction phases, whereas DT can monitor physical assets under construction or when constructed and evaluate the performance of installed equipment in real-time, aiming to enhance operational efficiency through enabling predictive maintenance of structures [16].

Simulation, on the other hand, involves utilising a digital prototype of a physical system. It is often used during the design process to determine how the system of interest would function under presumed conditions, such as operation, loads, and degradation mechanisms. Since simulation models mimic physical system behaviour, they can occasionally be confused with DTs. The primary distinction between a simulation model and a DT is that a simulation model forecasts the future states of a physical system by relying on basic assumptions whereas DT monitors the actual experience of a physical system, as well as the past and current states of a specific instance of the system [10].

Another aspect to highlight is that by enabling the implementation of what-if scenarios, DT enables more data-driven decision-making compared to other asset management methods [19]. Moreover, BIMs have limited self-learning capabilities and are unable to function autonomously or analyse data from external sources [16], unlike the self-evolving nature of DTs. DTs are in constant interaction with the physical assets, continuously enhancing and evolving by receiving, analysing, and applying the data obtained from the physical space [1].

In summary, as shown in Figure 1, DTs' characteristics can be outlined as follows:

1. Real-time reflection: In DTs, the physical and virtual space can maintain a high fidelity and synchronised connection.
2. Interaction and convergence: DTs are uniformed simulations of historical data and real-time data, where the physical and virtual worlds interact through an automatic bidirectional data flow.
3. Self-evolution: DTs are capable of real-time data updates, allowing for continuous enhancement of virtual models [13].

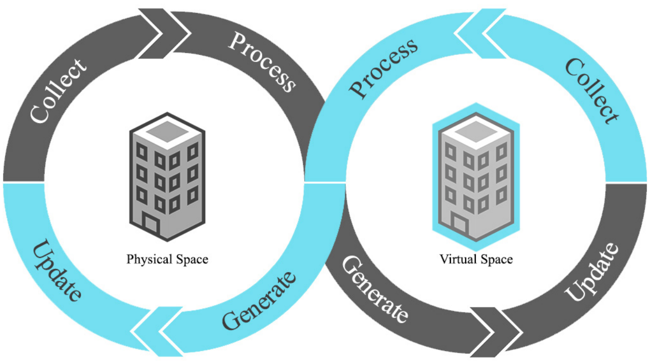

Figure 1. Digital Twin data flow conceptual model.

2.3. The Different Levels of Digital Twin Maturity

DT maturity is determined by how a developed DT compares to its full potential. The DT maturity model systematically outlines the conceptual scope, capability requirements, developmental process, and stage objectives, allowing for an effective assessment of its current development level and capabilities, as well as an understanding of the adoption and implementation of new technologies and approaches. There have been multiple efforts to define and develop a DT maturity model; however, a unified and thorough explanation of DT maturity is still lacking [9,17].

There are prior advancements in DT maturity based on its capabilities, enabling technologies, direction of data flow, levels of autonomy and intelligence, and cross-system integrations [17]. Combining these efforts with the key factors outlined in this paper, we propose five stages of DT maturity levels along its evolutionary spectrum, as depicted in Figure 2.

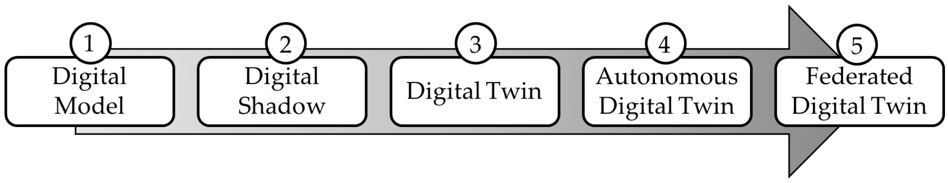

Figure 2. Digital Twin maturity spectrum.

Digital Model is the primary concept where automatic information flow is not present and the interaction between the physical object and the digital model are conducted through manual modification [20]. Working as an offline system, Digital Model captures the physical and geometric properties and characteristic data of physical objects [17], while aiding in decision-making during the early stages of design such as concept design. This system is usually developed prior to the construction of the physical prototypes [21].

Regarding Digital Shadow, data transfers automatically from the physical object to the digital counterpart, but not the other way around. This creates a one-way data flow, allowing virtual models to mirror the operating process, condition, and behaviour of the physical objects simultaneously and accurately [17]. This is best represented by a system in which sensors collect data from the physical model and send signals to the virtual model. Regardless of how the information is transferred, if the process is automatic, the integration level can be classified as a digital shadow [20].

In contrast, in the case of a DT, the interaction between the two objects is both automatic and bidirectional. The two-way communication forms a complete data loop. The virtual model receives historical and real-time data from the physical object and subsequently provides simulation results back to the physical object, influencing its behaviour [22] and facilitating real-time planning and decision-making in operations, maintenance, and support [21].

Autonomous DT as a self-governance system with comprehensive oversight and transparency [20] employs various unsupervised machine learning capability and AI algorithms to remain synchronised with the physical objects and identify objects and patterns in the environment [17,21]. At this level, the system exhibits a high degree of autonomy and can analyse detailed performance [21]. It can perform automatic prediction and operation under various unknown situations to ensure the safety of the physical entity [23]. This twin can autonomously develop decision suggestions to correct issues, provide feedback, or act on behalf of users [24].

On a larger scale, Autonomous DTs of different domains can be integrated to develop a Federated DT that empowers coordination, improves interoperability and secure communications, and enables seamless asset management [17,25]. For instance, Federated DTs can be used in developing smart cities, allowing for DT-enabled city management and contributing to the city's sustainability [26].

In the literature, most DT concepts are at the primary maturity levels of digital model and digital shadow, with few integrating real-time data streams to achieve DT. This is mainly due to the challenges of collecting, filtering, and processing data in real time, as well as the possibility of device malfunction and poor calibration which leads to anomalies or missing data [20]. It is important to remember that a higher level of maturity leads to greater technical complexity and increased functional requirements [17].

3. Digital Twin Applications in AEC Industries

DT technology has emerged as a transformative force across diverse industries, offering unparalleled opportunities for innovation and efficiency. From aerospace to healthcare, transportation to construction, DT applications are revolutionising operations by enabling real-time insights, predictive maintenance, and enhanced decision-making. This section explores the industries that lead the adoption of DT and studies its transformative influence on their processes, productivity, and prospects. In the AEC sector, digitalisation has been slow compared to other sectors despite the significant potential it holds for various stakeholders [3]. In the construction sector, digital innovations stand out as one of the most promising avenues for growth, with the potential to enhance global construction productivity by as much as 14% to 15% [3]. However, between the years of 2005 to 2014, digitalisation adoption in the construction industry had a rate of 1.4%, notably lower than the Information and Communications Technology industry [27].

3.1. Digital Twin in Building Lifecycle

The digitalisation of the construction industry and the implementation of smart technologies offer the potential to bring a building to life as well as allowing users to engage with it in more productive and efficient ways [4,27]. As Figure 3 shows, DT implementation has numerous applications across a building's life cycle [28], and depending on the demand, it can be utilised for design, construction, operation, maintenance, etc. [28].

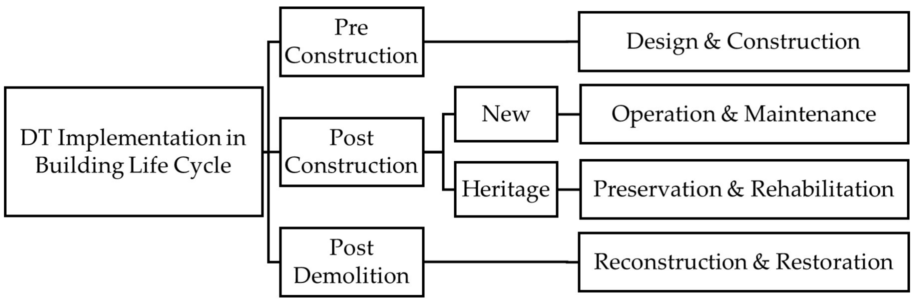

Figure 3. Digital Twin implementation in the building life cycle.

In the planning and design phase, various disciplines and consultants traditionally separately conduct their processes. This lack of coordination might lead to significant issues during the construction stage. Using a DT for planning across several disciplines enables the development of a coordinated multidisciplinary solution, which can help bridge the gap between people and urban design processes. DT can also assist stakeholders in analysing the feasibility of designs [4], selecting the best design for the project [29], and exploring different scenarios through simulation to conduct what-if analysis [27].

Despite its widespread application in design and construction, DT's potential within the Facility Management (FM) domain has received less attention [30]. This is noteworthy considering that Operation and Maintenance (O&M) accounts for more than 80% of the project's overall cost [31] and represents the longest phase of a building's life cycle—approximately 15 to 25 times longer than design and construction [32]. FM requires timely preventive maintenance and identification of any equipment malfunctions to maintain the facility's optimal state [33]. The traditional method of FM, which relies on manual labour, may encounter numerous shortcomings [32], such as low data quality, prolonged notification times, and delays in O&M activities [33]. These challenges present significant obstacles for facility managers in their efforts to maintain satisfactory building performance for both owners and occupants [32].

DT is increasingly being investigated as a means of decision-making support during the building maintenance phase [31]. DT models prove valuable for forecasting or back-casting, allowing the determination of an asset's future state and contrasting it against a planned, desirable state [29]. In contrast to the conventional facility management approach [32], DTs can be employed to analyse the building's dynamic response to changes, tackle operational challenges, suggest the necessity for building maintenance or upgrades [4], and reduce the time and cost associated with updating FM system databases [32].

Studies have also investigated the evolving applications of DT in historic buildings. The potential of digital technologies has been applied in the field of cultural heritage and archaeology [34], as well as in various areas such as health monitoring [35], disaster simulation [36], digital preservation, restoration, conservation management, and 3D visualisation for research, education, and engagement. In recent years, DT applications in the heritage sector have primarily centred around digital documentation of assets, driven by advancements in 3D data capture technologies such as photogrammetry and laser scanning [37]. As shown in Table 1, digital technologies have been used in a post-disaster context in the reconstruction process of Notre-Dame Cathedral in Paris and in the archaeology sector for semantic simulation of the ruins of the convent of the Paolotti in Italy [34].

Additionally, it is common to develop visually interactive platforms for management and virtual tours of historic buildings using 3D models and augmented reality. These approaches effectively explore the extensive application of digital methods in heritage conservation [36]. In a post-disaster context, such as the case of Notre-Dame Cathedral, the use of DT technology provides a framework to assess the value and resilience of heritage assets from their construction through to their destruction and subsequent restoration. It also helps ensure the authenticity and monitoring of archaeological remains for their future reuse during reconstruction [38].

Lastly, the adaptive nature of DT enables flexible application across diverse sectors [27], enhancing functionality and providing dynamic and real-time information for control and planning processes [29]. Certain types of projects can significantly benefit from the utilisation of digital models:

1. Large-scale projects such as buildings, bridges, and other complex structures that are subject to strict engineering regulations.
2. Projects with complex mechanical components such as jet turbines, automobiles, and aircraft.
3. Power-related equipment, including both the systems for power generation and transmission [39].

3.2. Digital Twin for Smart Cities

The term "smart city" originated in the 1990s and is associated with the concept of smart growth. The foundation for developing a smart city is a semantic data model that incorporates attributes of various city components, such as buildings, transportation, public utilities, energy, and the urban environment [40]. Initially, the concept focused on managing the physical growth of urban areas. However, it has since expanded to include a wide range of physical, social, and knowledge infrastructures due to the complexity of urban systems [41]. Despite its long history in public administration, there is no universally accepted definition that aligns with a global understanding of the concept [42]. Over the past two decades, the idea of smart cities has gained significant popularity, spurring interest in innovative development approaches. Many countries now view smart cities as a solution to challenges such as urbanisation, global warming, population growth, and resource depletion [43].

DTs hold significant potential for transforming the current urban governance model toward the development of smart cities [43], and the rapid advancement of DT technology within smart cities is making valuable contributions to their development [41]. As more smart cities are developed, communities become more interconnected, resulting in increased use of DT. This advancement helps to improve efficiency and sustainability while also enhancing both the quality of life and the experience of working in the city [26,43]. DTs in smart cities can be applied across various domains. By utilising data generated from smart cities, these DTs can model urban planning and policy decisions [44]. Moreover, they can support growth by providing a dynamic virtual testbed to test different scenarios and enable DTs to learn from their environment through the analysis of changes in collected data [26]. An example of an ongoing DT project for a city is Virtual Singapore, which is a 3D city model and data platform [44].

The urban DT is developed from a comprehensive 3D city model that utilises geographic data and information, such as a digital elevation models or digital building models, provided by regional authorities [42]. The DT of the city can be made available online, allowing the public to explore proposed changes in urban planning and policy. This facilitates greater transparency and communication with the public before implementing decisions. It also creates an additional virtual feedback loop where citizens can interact with the model and provide input on planned changes [44].

A typical smart city should feature technology-driven infrastructure, environmental initiatives, and innovative, efficient public transportation. It should also embrace progressive urban development and prioritise enhancing the quality of life for its residents [24]. However, as a model, the urban DT cannot encompass all information from the physical world. Its goal is to replicate real-world conditions with enough detail to effectively address complex issues. There is still a significant need for more social, economic, and environmental data. Therefore, future research should emphasise methodological advancements in handling socio-economic data [42].

3.3. Key Enabling Technologies for Urban Digital Twin Development

The development of a DT model requires the integration of diverse technologies, methods, and multidisciplinary knowledge. The foundation of DT is data, which encompasses a broad spectrum of information, including data collected from the physical world, such as sensor readings from equipment, materials, and workers, as well as data generated in the virtual space, including simulation models, algorithm outputs, and knowledge-based deductions [5,45]. In the following section, the technologies used in developing an urban DT are presented in three categories.

1. Collection of Static Data.

Surveying technology is essential for capturing static data from physical entities, allowing for the collection of 2D, 3D, aboveground, underground, indoor, and outdoor information [43,45]. Remote sensing systems, such as unmanned aerial vehicles (UAVs) and 3D laser scanning technologies, have improved the accuracy of digital models representing real-world objects [43,46]. For example, LiDAR technology, which generates point clouds consisting of 3D points that capture the surfaces of scanned areas, has played a crucial role in advancing remote measurement capabilities [46,47]. Recent advancements in these technologies have enabled real-time, precise acquisition of LiDAR data in urban settings, making the representation of 3D physical entities both efficient and accurate [43,48]. Moreover, UAVs have streamlined airborne scanning by overcoming the flying complexity issues [49].

2. Collection of Dynamic Data.

Physical entity data can be dynamic, encompassing entity states, environmental conditions, and unexpected disruptions. IoT technology is crucial for gathering this dynamic data and providing feedback. This data is collected in real-time through various means, including smart sensors, IoT devices, and embedded systems, [43,45,50]. Sensors, the core of IoT, measure environmental properties and convert them into electrical signals. They are classified by the type of energy they detect, such as location sensors (e.g., GPS), visual sensors (e.g., cameras, infrared), temperature sensors (e.g., thermometers), motion sensors (e.g., radar guns), and identification sensors (e.g., RFID). Moreover, simulations and AI, particularly machine learning, are essential for analysing this data, aiding in monitoring, diagnosis, prediction, and optimisation [51]. VR and AR tools provide immersive environments for these processes, while data-sharing technologies, blockchain-enabled IoT networks, and big data analytics are key to connecting virtual worlds in sustainable smart cities [52].

3. Building Information Modelling.

Developing a digital model that represents the physical world is the core technology for constructing a DT and the essence for real-time monitoring of physical assets and processes [5,53]. Traditional visualisation techniques are often inadequate for handling the vast and growing volumes of data, making it challenging to extract meaningful insights in a timely manner [54]. Two of the most widely used geometric modelling systems are point cloud technology and building information modelling (BIM). Point clouds, obtained from laser and photographic scanning, provide dense data collections, while BIM leverages object-oriented modelling to create detailed 3D models with embedded information. While GIS focuses on large-scale analysis, BIM operates at a finer scale. The combination of point cloud data with GIS's spatial capabilities enables BIM to support more advanced DT applications, including DT cities [48].

4. Case Studies of Digital Twin Development

Multiple efforts have been made in developing urban DT platforms, varying in scale, goals, target audience, and technologies used. Case studies highlight how this innovative technology is applied, providing a comprehensive understanding of the practical challenges and showcasing their potential and successes associated with the integration of DT in AEC projects. In the subsequent section, ten projects are discussed regarding their objectives, approaches, and maturity levels, as indicated in Table 1.

4.1. Sydney Opera House

The Sydney Opera House is one of the most well-documented examples of successful BIM implementation in FM. The Opera House is a complex and large building with a highly irregular configuration, making it a challenging case [55]. Since BIM was not derived from the design and construction process due to the building's age, it was specifically modelled for FM purposes [56]. The restoration team of the Sydney Opera House created a unified central data repository [57] as well as an accurate, reliable, and relevant integrated building model to support O&M, modifications and additions to building and service systems, and asset management. This was accomplished by the progressive incremental development of a model using master models and sub-models while complying with operational, logistical, and financial constraints. The master model for the Sydney Opera House is divided into various logical discipline-specific sub-models. Its aim is to incorporate data, such as Cadastre, Land Use, Terrain, Utilities, and Asset Register [55].

Table 1. Summary of selected DT case studies.

Selected Cases	Developed Approaches	Case Objectives	Data Collection	BIM Modelling	Application	Maturity Level	Ref.
Sydney Opera House	A BIM-based digital platform	Achieve collaboration across strategic, management and operation using BIM to support FM	Existing documents	ArchiCAD, GIS	Restoration, O&M	2	[55]
Institute for Manufacturing Building, University of Cambridge	A DT prototype based on Autodesk Forge and AI techniques	Develop a DT-enabled anomaly detection system for asset monitoring in O&M management	Vibration sensor, BMS data	Autodesk Revit	Operation and Maintenance	3	[57]
The Kerr Hall East Building, Ryerson University	A DT prototype based on Dynamo BIM	Automate information transfer between BIM models and FM systems	Simplified geometry and major equipment	Autodesk Revit	Operation and Maintenance	2	[58]
Leonardo Campus, Politecnico di Milano	A GeoBIM approach to improve digital AM	Support decision making on the operations, maintenance, and repair of digital built environment	Existing geometry models in 2D, geospatial data	Autodesk Revit	Operation and Maintenance	2	[3]
Manchester Town Hal	A BIM-supported map for reactive maintenance process	Document issues in BIM adoption for FM and identify its enablers and barriers	Archival documents	Autodesk Revit	Operation and Maintenance	2	[56]
Hong Kong University of Science and Technology	A data-driven predictive maintenance framework of MEP components	Predict maintenance of MEP components of buildings	IoT sensor network temperature, pressure, flow rate	Autodesk Revit	Operation and Maintenance	2	[59]
Northumbria University City Campus	A BIM-based platform for FM processes	Explore the value and challenges of BIM in FM for new and existing assets with a focus on enhancing space management	Existing plans in DWG, elevations and sections scans in JPEG	Autodesk Revit	Operation and Maintenance	1	[2]
Notre-Dame de Paris	A DT for post-disaster heritage building used for data acquisition and processing to develop a hybrid reconstruction hypothesis	Monitor and analyse collapsed arches of the Cathedral and propose a hybrid reconstruction hypothesis	Leica Geosystems laser scanner, existing photographs	N/A	Reconstruction & Restoration	1	[38]
The Engine House Paços Reais	An HBIM using scan-to-BIM approach, 3D laser scanning and photogrammetry	Produce the documentation for heritage assets rehabilitation	Digital photogrammetry and terrestrial laser scanning	Autodesk Revit	Preservation and Rehabilitation	1	[60]
The town of Herrenberg, Germany	An urban DT prototype	Support participative and collaborative planning and design processes, preserve smaller communities, visualise complex urban data	Faro Laser Scanner, particulate matter, temperature, humidity sensors	N/A	City Digital Twin	3	[42]

4.2. Institute for Manufacturing Building, University of Cambridge

The pilot evaluation study of the proposed building DT was carried out at the Institute for Manufacturing building at the University of Cambridge's West Cambridge campus. Based on the designed architecture, the developed DT features five layers, integrates multiple data sources, enables effective information search and decision-making, supports anomaly detection of building assets, and is essential for daily operations, maintenance, and management. The goal of this case study is to illustrate how the proposed data structure can facilitate data integration for a dynamic DT of existing buildings, enhancing its anomaly detection capabilities, and to further investigate the associated opportunities and challenges. To analyse and show the effectiveness of the proposed framework, a case study involving the pumps in the HVAC system was conducted. The results demonstrated that the system provided continuous condition monitoring of building assets (e.g., pumps) and enhanced efficient and automated asset monitoring in daily activities [57].

4.3. The Kerr Hall East Building, Ryerson University

Since 2014, Ryerson University has been developing a BIM for facility management to create a virtual campus model, beginning with the Kerr Hall building. This project focuses on the automation processes for data preparation and transfer, while concurrently discussing the FM information requirements used to develop and utilise the results of these investigations. The objectives of this project are as follows:

1. Create a virtual campus model with integrated BIM-FM models for all buildings within a site model.
2. Connect individual BIM models with FM data to provide a unified source of operations information.
3. Explore BIM applications in FM and evaluate their benefits in real operations.
4. Develop improved methods for FM–BIM data transfer, addressing barriers to BIM adoption in FM [58].

4.4. Leonardo Campus, Politecnico di Milano

The opportunity to apply the GeoBIM approach (integration of GIS and BIM) to asset management at the Leonardo Campus of the Politecnico di Milano, Italy, with a gross internal area of approximately 3700 sqm, led to a case study to evaluate the effectiveness of this approach. Preserving the functionality and overall quality of this urban environment involves not only maintaining the building and their equipment but also considering the surrounding infrastructure and services. This necessitates an operations, maintenance, and repair service at the built environment level that can address various management scales in an integrated manner. The BIM model of the existing building was developed with a low level of geometrical detail, aiming to support streamlined space assessment. Mechanical, electrical, and plumbing systems were modelled only when they were visible and accessible for visual inspection. This approach reduces the time required for BIM modelling. The focus of this project is on both the indoor and outdoor physical assets of the building and its surrounding neighbourhood to develop an integrated system for Condition Assessment [3].

4.5. Manchester Town Hall Complex

The study was conducted within the context of the UK Government's BIM effort. Gaining a deeper understanding of the key challenges involved in transitioning from traditional FM to BIM-FM is essential for development of guidelines. This study was undertaken to explore the use of BIM-FM in the Manchester City Council Town Hall Complex project in Manchester, UK. This study builds on a previous investigation conducted during the same project's design and construction phase in 2011. Based on the collected information, the research team created two process maps, an as-is map without BIM, which represents the current state of the reactive maintenance system, and a to-be map depicting the future state with BIM integrated into the routine process. Finally, a comparative analysis of these two scenarios was conducted. The research had four objectives:

1. Map both hard (building systems) and soft (catering, cleaning, health and safety) services to understand FM operations and organisation.
2. Investigate the benefits and drawbacks of using information models in FM, focusing on reactive maintenance.
3. Assess BIM-FM maturity levels to develop an application of the BIM maturity model for FM.
4. Identify enablers and barriers to BIM-based FM [56].

4.6. Hong Kong University of Science and Technology Campus

To enhance maintenance strategies for building facilities, a data-driven predictive maintenance planning framework for FM was developed, integrating BIM and IoT technologies. This framework consists of two layers: information and application. To test the proposed data-driven predictive maintenance planning system, three academic buildings on the Hong Kong University of Science and Technology campus were investigated and used as an example. Four chillers serve three campus buildings. To monitor the chillers, three types of sensors were installed: temperature sensors, pressure sensors, and flow rate sensors. The signals from these sensors were collected and transmitted through a sensor network to the BIM models [59].

4.7. Northumbria University City Campus

The case study was conducted on Northumbria University's city campus, located in Newcastle, UK, consisting of 32 non-residential buildings. The University engaged five developers to create building information models aimed at enhancing space management performance. The developers utilised existing floor plans from the estates department in DWG format, scans of original elevations and sections in JPEG format, and space information in Excel databases, and the models were completed within five weeks. Since the case study involved an existing asset, significant challenges had to be considered when applying BIM for FM purposes. These challenges pertain to the strategic considerations and the business case for transitioning from the traditional FM processes to BIM-based FM processes. The case study included individuals from the University's estates department, who participated in thorough discussions to evaluate the value and challenges of BIM for managing the spaces within the existing university campus [2].

4.8. Notre-Dame Cathedral de Paris

In the aftermath of the Notre-Dame Cathedral fire, ensuring the authenticity and monitoring of archaeological remains is essential for their possible reuse in reconstruction. Since the start of the scientific efforts on Notre-Dame, the digital data working group has been developing an innovative digital ecosystem. This system integrates data on the cathedral's current and past states. By utilising a DT framework, this paper examines the collapsed transverse arch from the nave of Notre-Dame as a reconstruction case study. A new type of DT was developed for the post-disaster reconstruction of heritage buildings, focusing on the collapsed transverse arch of Notre-Dame de Paris Cathedral. The findings show that the proposed modelling method aids in formalising and validating the reconstruction issue, thereby enhancing the effectiveness of the solutions [38].

4.9. The Engine House, Paços Reais

This research explores an architectural survey conducted using digital photogrammetry and terrestrial laser scanning. It discusses the process of generating and manipulating information and outlines the steps necessary to create a 3D model using BIM software for integration into an HBIM (Heritage BIM) workflow methodology. The Engine House of the Instituto Superior de Agronomia in Lisbon was used as a case study to illustrate the process. The aim of this project was to facilitate the building's rehabilitation. Although the initial requirements were traditional plans, sections, and elevations, the team opted for a scan-to-BIM approach due to its superior results [60].

4.10. The Town of Herrenberg, Germany

This urban DT was developed for the 30,000-people town of Herrenberg, Germany, allowing for seamless visualisation across scales and layers in virtual and augmented reality for urban planning, design, and decision support. The presented prototype includes a 3D model of the built environment, a street network model based on space syntax theory, an urban mobility simulation, a wind flow simulation, and various empirical data from volunteered geographic information [42]. The 3D scan was generated using a Faro Laser Scanner Focus 3D S 120, enabling quick and precise measurement of complex geometries in objects and buildings. A sensor network gathered real-life data on particulate matter, temperature, and humidity. Additionally, a mobile app was developed to collect volunteered geographic information, allowing users to track their routes, rate public spaces, log activities, capture images and sounds, and leave comments. The aim is also to visualise complex, often-invisible elements like urban data and simulations to support citizen participation and expert collaboration [42].

5. The Versatile Capabilities of Digital Twins

Digital technologies provide new ways of generating and securing value across the lifecycle of an asset, enabling widespread transformations in methodology. The advantages of employing technology such as enhancing efficiency and performance of assets can be attained through enabling and then maintaining the change [28]. As shown in Figure 4, DTs transform and enhance current methods in five categories:

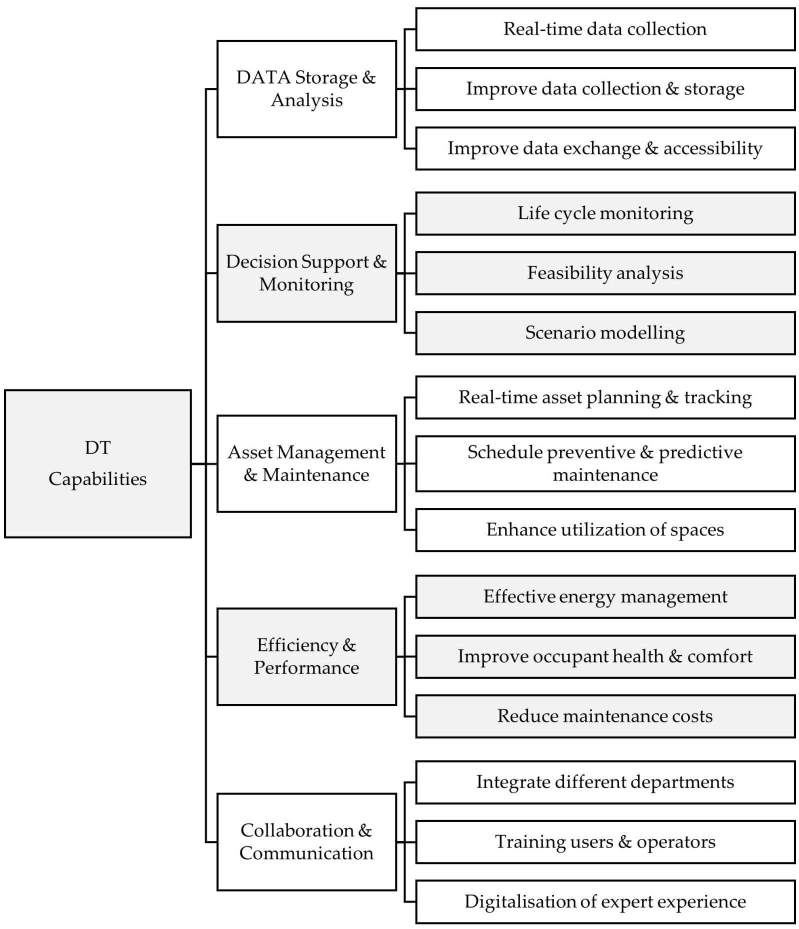

Figure 4. Digital Twin capabilities in AEC.

5.1. Data Storage and Analysis

Traditionally, Facility Management data transfer relies on paper records and Excel sheets, a method still widely used today [59]. However, with this approach, information may occasionally become lost or inaccessible [61], leading to delays in addressing service requests and a decrease in operational and maintenance efficiency [59]. To overcome these obstacles, a DT can be utilised. DT technology can collect and manage data in real time [32], providing a shared repository for all project-related data, past and present. This results in updated as-built models, minimises redundant data collection and re-entry, and improves information exchange and accessibility throughout the organisation's operational activities [61,62].

5.2. Decision Support and Monitoring

One advantage of implementing DT in the AEC industries is the ability to visualise the operations of physical assets in a virtual model [27]. By gathering both present and past data over time [21] and analysing current conditions and previous issues [5], DT can be employed for automated progress monitoring [27], diagnostics, prognostics, and optimisation [5]. This results in statistically based decision making and enhanced management of the system [63]. Another potential advantage of DT is design feasibility analysis before construction. It serves as a crucial tool in the planning and coordinating of multi-disciplinary solutions, allowing for early verification and validation of design choices [4].

5.3. Asset Management and Maintenance

The application of DT in asset management offers several benefits, such as resource planning, logistics optimisation, and efficient equipment usage [27]. DT serves as a central information repository and aids in keeping track of equipment locations and conditions [64]. It also manages repair part inventories [27] and provides information about the required parts at the appropriate time and location, minimising inventory during facility construction or operation [27] and enabling efficient utilisation and planning of resources [33].

Furthermore, in traditional asset inspections or maintenance, a technician examines the equipment, investigates the causes, make numerous notes, and offer specific solutions. This may result in errors or imprecise results [64]. By utilising smart sensors [32], DT can schedule preventive and predictive maintenance tasks [27] by assessing the current state of assets, analysing their behaviour, and predicting the degradation of components [1], leading to more accurate work, better results, and reduced downtime [64]. On top of that, DT assists in tracking real-time locations of people and utilisation of spaces across the facility [4], as well as planning orders, activities, schedules, and labour [65].

5.4. Efficiency and Performance

One major challenge that organisations face during digitalisation is effectively demonstrating the benefits and value of investing in developing digital technologies. With decreasing storage and computation costs, the number of use cases and possibilities for enabling a DT has increased dramatically [4]. Based on a cost–benefit analysis, despite requiring a substantial initial investment, DT provides significant returns in the long run [21].

Building energy efficiency stands out as one of the foremost research areas, given that buildings contribute to 40% of the global energy consumption [33]. DT can assist in illustrating the problems and limitations to stakeholders, such as estimating energy consumptions [29]. Furthermore, by integrating operational data with advanced control strategies, the energy management process can be enhanced through offering insights into operational status of buildings and optimisation of equipment operation via user behaviour analysis, indoor environment condition monitoring, and building performance analysis [66].

A key factor contributing to the business value of a DT is its scalability. The data generated by the DT can be used to develop new applications with minimal effort and cost. For example, real-time data from the HVAC sensors can also be used to determine room occupancy, enhancing energy efficiency by automatically turning off the HVAC or switching to economy mode when the room is unoccupied [4].

Another benefit of Efficient FM is the ability to improve occupant health and comfort. Given that people spend around 80% of their lives in buildings, maintaining a healthy and comfortable indoor environment is crucial for their well-being and productivity. Implementing a real-time interior condition monitoring system can improve the overall quality of facility services and reduce repair costs and building energy use [33].

5.5. Collaboration and Communication

One of the primary goals of establishing an asset management system is to integrate disparate systems, such as backend business operations [27], to eliminate the organisational silo effect and enhance collaboration between departments [65]. DT can also be used for training users, operators, maintainers, and service providers. Additionally, DT facilitates the digitalisation of expert experience, allowing it to be documented, shared, and adapted across the organisation to reduce knowledge gaps [5].

6. Challenges in Implementing Digital Twins for AEC Projects

Although IoT has brought benefits and advancements to the building industry, there are still challenges and issues in various domains that need to be addressed [33]. Significant efforts have been made by numerous organisations and researchers to accelerate the advancement of DT applications [65]. The obstacles that create setbacks in DT adoption in the AEC industries are classified in five groups as shown in Figure 5. To address these challenges more effectively, they have been prioritised based on their fundamental importance and impact on the successful implementation of DTs. This prioritisation is informed by existing literature and is presented as follows:

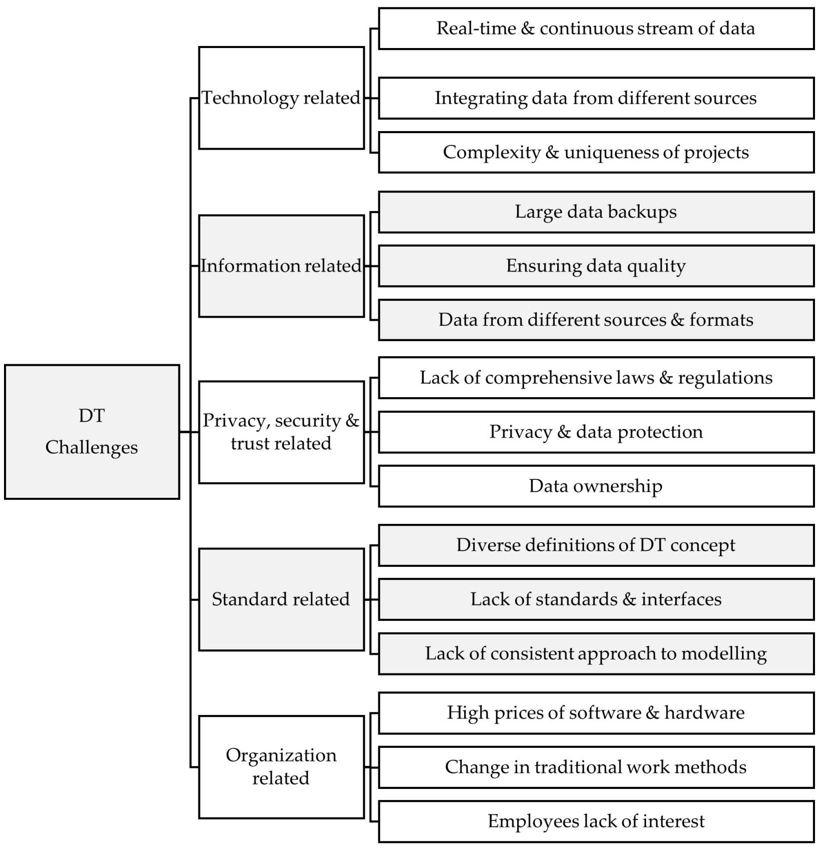

Figure 5. Digital Twin challenges in AEC.

6.1. Technology Related Issues

The primary challenge lies in the overall IT infrastructure. To execute the algorithms, the latest technologies with high-performance infrastructure are required and the infrastructure needs regular updates in both software and hardware to support the successful operation of such systems [26]. To develop a DT environment, it is also necessary to re-evaluate and alter the foundational software platform, along with the hardware of production machines and their cloud/physical interface [4], which may potentially limit the widespread adoption of DT technologies [12].

For the DT to function effectively, data must be transmitted from the physical asset to the digital model in real-time. Ensuring the system has a continuous feedback loop without any interruptions is essential. Above that, the data required for DT models is stored in separate systems, making it challenging to ensure data consistency across the system. Therefore, the major challenge in the construction sector remains the integration of data from various stakeholders and multiple technology sources in different formats. Standardising and developing the formats of BIMs and the semantic web data of IoT devices are necessary to facilitate seamless data integration [29].

The complexities of the construction sector and the dynamic and unstable nature of the industry contribute to the delayed adoption of digitalisation in this field [27]. Implementing DT within a large owner organisation, which encompasses numerous departments, processes, cultures, networks of systems and databases, and individuals from diverse backgrounds [62], poses a highly complex task that might take a considerable amount of time [29]. Furthermore, every project in the construction industry is unique. In contrast to construction, in manufacturing and other industries, DT implementation requires straightforward replications for all manufactured products. However, the construction industry requires different DT demands for various construction projects [27].

6.2. Information Related Issues

Given that IoT systems gather massive amounts of data [33], a large number of hardware devices are required for the data backup, posing financial risks, particularly in large-scale buildings [32]. Hence, it is crucial to optimise the design of the storage architecture to ensure that data is consistently accessible for retrieval and can be easily recovered from backup [33].

The utilised sensors and other devices generate large amounts of data of various types, and this information also varies among different types of buildings [33]. The collected data must meet the quality standards for its intended use, but its quality can degrade during extraction from the source or during transformation [29]. To ensure that meaningful data is collected, thus guaranteeing the best quality of data input into the AI algorithms [26], the system must be able to perform the following steps:

- Data transition, which enables robust data transfer from raw sensors to repository.
- Data cleaning, which involves removing corrupted and null data.
- Data consistency checking, which ensures that the data is neither duplicated nor contradictory [33].

Data formatting is a challenge after the data collection step since data from various sources sometimes exists in different formats. Asset, operational, historical maintenance activity, and historical asset evolution data are some examples of these data sources. For instance, data from humans may be in the form of voice recordings and images, while data from appliances might consist of textual content. Reformatting this data in a consistent and timely manner, while integrating it from multiple sources [1], to ensure that the output of the formatted data is ready to be utilised by potential solutions is a complex task [33].

6.3. Privacy, Security and Trust Related Issues

Cybersecurity poses a significant concern in the adoption of DTs, particularly in web-based environments [16]. Addressing cybersecurity and building trust should be prioritised early on for any new digital technology. Since the field of DT technology is still in its infancy [8], comprehensive laws and regulations have yet to be fully established [26]. The vulnerabilities and security risks inherent in IoT systems span various components, including web interfaces, network services, and software [33], exposing DTs to cyber threats [26] and potentially jeopardising the physical entities being twinned [12].

From the users' perspective [33], privacy and data protection are key priorities [29]. Since many applications include [33] users' private, confidential, or valuable data [12], an insecure system not only raises concerns about unauthorised access to individuals' confidential information [16] but also diminishes their willingness to adopt the technology. For instance, the utilisation of cameras in office buildings for safety monitoring and GPS for localisation purposes can lead to discomfort among individuals [33].

Data ownership, involving the establishment of access levels and permissions, is another critical and unresolved issue for DTs. Regulation, privacy policies, legal constraints [12], and data accessibility limitations are necessary for involved stakeholders [16] to safeguard personal data [26]. This is particularly crucial for government-owned assets or DTs at the city level [16].

6.4. Standard-Related Issues

The diverse definitions of DT concept [26], some created by researchers, some by industry, and some by standards committees, result in an absence of any agreed-upon definition [8]. This broad scope extends to managing information throughout the entire lifespan of an asset and involves multiple stakeholders in the process [65], contributing to the setback in DT adoption [27].

Another barrier to the development of DT technology is the lack of standards and interfaces [4]. The AEC sector demands tailored DT standards for each unique project, which can results in inconsistencies among DT projects [26]. In contrast, the manufacturing industry requires a uniform standard across all products, for instance, in the case of implementing DT technology in the design and production of a particular model of a vehicle [27].

In the existing standards, there is a fundamental absence of a framework to facilitate the development of DT within O&M and asset management contexts and support the alignment of technical standards and specifications [65]. Furthermore, a small number of manufacturers in the construction sector have been able to supply BIM-compatible data for their components [4], and the existing standards are developed for individual lifecycles and disciplines [65].

Another contributing factor is that there is no standardised approach to modelling. From the initial design phase to the simulation of DT, there is a need for a standard method and a consistent approach that ensures domain and user comprehension while facilitating information flow across each stage of development [26].

6.5. Organisation Related Issues

The comparatively high prices of purchasing appropriate software tools [4], along with the increased costs of technology initiation due to the complexity of technologies and the demanding fidelity, accuracy, and computational requirements, pose significant obstacles to adopting smart FM [66]. Furthermore, the exclusion of "digital" planning and simulation from budget considerations and project fee structures creates a barrier to DT adoption in the construction industry [4].

Transitioning from traditional facilities management practices to BIM-based practices necessitates changes in work methods [62]. Since computerisation technology is advancing rapidly, training personnel to stay updated on the latest knowledge and developments can be challenging for industries [67]. Additionally, another potential obstacle is employees' and workers' lack of interest due to fear of losing their jobs [27]. Therefore, to prevent redundancy of tacit knowledge within the workforce and embrace the concept of lifelong higher education, institutes must collaborate more closely with practitioners [67].

7. Research Gaps and Future Potentials

This research classifies and prioritizes the challenges associated with the adoption of urban Digital Twins (DT) based on a comprehensive literature review, as detailed in Section 6. These challenges span various domains, including software, cloud interface, legal frameworks, and standardization, necessitating coordinated efforts from diverse stakeholders. An important avenue for future research involves conducting surveys across organizations and companies of different scales and sectors to identify the specific challenges they encounter in real-world contexts and to understand their priorities in addressing these issues.

Implementing DT is a complex and lengthy process that involves integration and collaboration of multiple technologies developed by different companies [5]. In many current research and industry applications, a lack of collaboration has prevented the full utilisation of IoT in the building industry. Therefore, there is a need to increase collaboration between technical teams with civil engineering and building technology researchers to further advance IoT's application in building industry. Effective collaboration allows IoT developers to revise and optimise the system [33]. Another beneficial approach can be a comparative analysis of DT applications in the AEC sector with those in more technologically advanced industries such as aerospace and automotive. Such analyses could facilitate the transfer existing solutions to AEC industries. The challenges require innovative solutions to transform industry practices, which can be enhanced by stronger interdisciplinary research and collaborations [67].

As was previously discussed, in the construction industry, no two projects are the same; they consist of wide ranges of activities with social, economic, and environmental dimensions [68], and the maturity level of a DT platform largely depends on the asset to which it is applied [15]. Therefore, there are notable differences in model size, operational rules, data management, etc. For instance, city DTs and shop-floor DTs are entirely distinct projects [5]. Hence, a potential research area can be to develop DT platforms for diverse real-world projects through scientific testing and validation [15,67]. Additionally, most DT development studies have typically been conducted in lab environments, depending on controlled variables and simulated data and overlooking numerous practical issues that could arise in practical settings. To date, only a few studies have tested their platform on in-use buildings. Therefore, multi-disciplinary teams should focus on the full integration of complex and dynamic environments. The potential benefits of DTs can be substantiated by employing real world case-studies [33,67,69].

DT goes beyond just a collection of new technologies; it also represents a new approach to conducting business activities and a different mindset. While different stakeholders may have varying expectations regarding the extent of connectivity and digitalisation they require [15], the goal of DTs is to achieve the highest possible level of digital maturity. As no existing example of a DT has fully realised its capabilities, the concept of DT remains somewhat undefined, making it challenging to determine when a DT has reached its full potential [70].

8. Conclusions

The transition from traditional asset management to DT technology in the AEC industries marks a significant leap in productivity and performance. This paper has provided an in-depth review of DT definitions, applications, capabilities, and challenges, emphasising the profound impact DTs can have in this field. The comprehensive literature review and case studies illustrate the notable benefits of DTs in enhancing data storage, decision support, asset management, and collaboration.

DT technology offers numerous advantages, such as optimising lifecycle energy use, facilitating predictive maintenance, and improving user adaptability. By merging real-time data from IoT sensors with advanced analytics, DTs generate dynamic and actionable insights that enhance decision-making and resource management. These capabilities are crucial for building design, construction, and facility management, driving operational efficiency and sustainability.

However, several challenges hinder the widespread adoption of DT technology. Key obstacles include technological integration, data consistency, organisational adaptation, and cybersecurity concerns. Overcoming these challenges necessitates interdisciplinary collaboration, standardisation of data formats, and the creation of universal DT design and development platforms. Additionally, the high initial costs and the need for specialised skills to manage and operate DT systems present further barriers.

Future research should priorities real-world case studies to validate the practical applications and benefits of DT technology in the AEC sector. Encouraging interdisciplinary collaboration among researchers, industry practitioners, and policymakers is essential to developing holistic solutions that address the diverse challenges of DT adoption. Standardising DT platforms will aid in the integration and scalability of DT applications across various projects and sectors.

Furthermore, comparing DT applications in the AEC industries with those in more technologically advanced industries, such as aerospace and automotive, can provide valuable insights for adapting existing solutions to the construction sector. Exploring DT technology's potential in areas such as smart cities and heritage building preservation can also pave the way for new research and application opportunities.

In conclusion, DT technology is set to revolutionise the AEC industries by enabling autonomous, data-driven decision-making and optimising building operations for enhanced productivity and performance. As the industry progresses, embracing DT technology will be vital for achieving sustainable and efficient building management practices, fostering innovation, and maintaining a competitive edge. By addressing the current challenges and utilising the full potential of DTs, the AEC industries can look forward to a future characterised by smarter, more resilient, and more efficient built environments.

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