www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

A REVIEW OF DRIVERS AND BARRIERS OF DIGITAL TWIN ADOPTION IN BUILDING PROJECT DEVELOPMENT PROCESSES

SUBMITTED: November 2023
REVISED: March 2024
PUBLISHED: March 2024
EDITOR: Robert Amor
DOI: 10.36680/j.itcon.2024.008

Muhammad Farhan Jahangir, PhD candidate
DIGIT, Department of Civil and Architecture Engineering, Aarhus University, Denmark
mfj@cae.au.dk

Carl Peter Leslie Schultz, Associate Professor
DIGIT, Department of Software Engineering & Computing, Aarhus University, Denmark
ORCID: 0000-0001-7334-6617
cschultz@ece.au.dk

Aliakbar Kamari, Associate Professor
DIGIT, Department of Civil and Architecture Engineering, Aarhus University, Denmark
ORCID: 0000-0003-2566-9520
ak@cae.au.dk

SUMMARY: *Over the past few years, the AECO Industry has undergone a shift toward digital transformation, with a growing trend towards adopting innovative technologies such as Digital Twin (DT). DT offers a wide range of applications throughout the building development process. However, some specific factors impede its widespread adoption in the building industry. This study aims to systematically review the available literature on the building project development process from the perspective of DT, with a particular focus on predictive simulations, i.e., co-sims. The review provides a comprehensive overview of drivers and barriers to DT adoption through an analysis of 147 studies between 2013 and 2023. The research identifies seven external and 41 internal drivers, including efficient project management and monitoring, predictive maintenance, and the collection and visualization of real-time data, all of which contribute to improved decision-making processes and reduced operational expenses. Further, the study identifies nine external and 31 internal barriers that impede the adoption of DT in the building development process. These barriers encompass challenges such as a high initial investment cost, a scarcity of a skilled workforce, difficulties in data interoperability, and resistance to change within the organization. A key outcome of the literature review is having identified the opportunity to exploit technologies developed in the automotive sector that enable a seamless integration of specialized simulator models in building development processes, resulting in collaborative simulations. Thus, we propose the concept of a Building Simulation Identity Card (BSIC) to be pursued in future research that would enable stakeholders to address the challenges of collaboration, cooperation, coordination, and communication by creating a common vocabulary to effectively facilitate the adoption of DT in the building's development process.*

KEYWORDS: *Digital Twin, Model Identity Card, Building Information Modeling, Lifecycle Data, Building Simulation Identity Card (BSIC), Simulators, Collaborative Simulations.*

REFERENCE: *Muhammad Farhan Jahangir, Carl Peter Leslie Schultz, Aliakbar Kamari (2024). A review of drivers and barriers of Digital Twin adoption in building project development processes. Journal of Information Technology in Construction (ITcon), Vol. 29, pg. 141-178, DOI: 10.36680/j.itcon.2024.008*

COPYRIGHT: *© 2024 The author(s). This is an open access article distributed under the terms of the Creative Commons Attribution 4.0 International (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.*

1. INTRODUCTION

The design of future sustainable and smart buildings is growing in complexity, coupled with growing environmental and economic concerns. This underscores the crucial need for substantial innovation in the AECO (Architecture, Engineering, Construction, and Operation) (Vial 2019) industry in terms of digital transformation (Ebert and Duarte 2018) and technologies such as Information and Communication Technologies (ICT) (Kaware and Sain 2015), Artificial Intelligence (AI) (Winston 1984; Baduge et al. 2022) Industry 4.0 (Ghobakhloo 2020), the Internet of Things (IoT) (Madakam et al. 2015; Shishehgarkhaneh et al. 2022), Big Data (Sagiroglu and Sinanc 2013), Blockchain Technologies (Liu, Han, and Zhu 2023), and Building Information Modeling (BIM) (Eastman et al. 2011; Smith 2014).

The incorporation of the aforementioned technologies has increased the performance complexity of buildings and their development processes (Kim and Nevatia 2004). To understand these complexities, it is necessary to decompose the various systems involved. The AECO industry typically develops models at various abstraction levels, encompassing high-level decompositions of building systems and detailed specifications of individual components. Engineering disciplines use domain-specific languages (Fowler 2010), tools, and methodologies to represent and simulate the concerned building. This process involves creating, reusing, and exchanging domain-level simulation models to construct a complete building model, forming a system of systems. The building project sector encompasses disciplines such as structural, mechanical, and electrical. For instance, a building may be divided into a Structural Frame System (SFS), HVAC (Heating, Ventilation, and Air Conditioning), Lighting, Electrical Power, and Security sub-systems. This approach allows design consultancies to delegate tasks, roles, and simulation model creation between related engineering disciplines.

The integration of Digital Twin (DT) simulation models has become essential in this context, providing a comprehensive solution to manage the challenges of modern building projects. DT facilites the digital transformation of physical buildings by integrating their digital models with analytical simulation engines, i.e., specialized simulators with their real-world data, maximizing the value of data and creating beneficial synergies across their development stages (Lu et al. 2022). Simulators are used in building DT to predict the behaviour of a building, allowing architects and engineers to test different design scenarios and optimize the system's performance. DT can also be exploited to monitor the system's performance in real-time, allowing facility management teams to detect and diagnose problems before they become critical. In addition, DT can help to ensure the availability of digital building information throughout the entire development process of a building. DT technology elevates BIM models (e.g., for clash detection, cost analysis, project efficiency, etc.) to a new tier of sophistication, allowing stakeholders to visualize data in real-time.

The advancements and growing research in DT within the AECO industry represent significant progress, they also highlight a range of challenges that prevent its widespread adoption for predictive simulations. Researcher like (Opoku et al. 2023) and (Naderi and Shojaei 2023) have been examining the applications and implementation requirements of DT, contributing to the growing body of knowledge through scientific articles and reports. Addressing these challenges is crucial for the successful implementation of these technologies. The critical challenges are (a) to identify potential inconsistencies and errors that may hinder the creation and combination of accurate simulation models and their associated outcomes, and (b) to properly coordinate the different specialized simulators in a unified *collaborative simulation* (co-sim).

In light of the identified challenges, it has become important to understand the complex nature of building simulations. Simulation model for buildings draws data from a variety of sources, including building digital model data (e.g., concerning construction material information, occupancy levels, and cost analysis), building monitoring data (e.g., IoT solutions and multi-view data analysis), user preferences (e.g. regarding comfort, safety, and energy efficiency), environmental conditions (e.g., environmental impact, biodiversity), etc., which must be reconciled before the configuration of a simulation model can be initiated. Moreover, depending on the overall aim and function of a DT, there is a need to perform multiple computations and simulations for different purposes and with different characteristics, features, requirements, degrees of complexity, etc. The problem becomes yet more complicated when the simulation outcomes of each specialized simulator need to be merged or used as input for other specialized simulators, thereby creating an intricate and complex network of dependencies between specialized simulators where initiating one simulation entails completing one or multiple prior operations.

For example, consider a prediction scenario of an emergency evacuation of a building during an earthquake, conducted within the design or operational phase of a building. Running simulations that model critical details about many facets of the scenario is essential. Necessary aspects that require simulation include the propagation of the earthquake within the building, occupant and emergency services communication during the event, densities and flows of dynamic occupant crowds during egress, the establishment of safe evacuation routes, geometric modelling of the building structure, assessment of structural integrity under seismic conditions, identification of potential evacuation challenges through physical simulations, estimation of evacuation time, monitoring temperature changes within the building to prevent casualties, and analyzing occupant movement patterns. These simulations are essential to ensuring an efficient exit strategy in emergency situations and maintaining personal safety. Effectively integrating different criteria and attributes of simulation models is a persistent challenge in the building industry (Ozturk 2021). This limits our ability to fully exploit the potential of these simulations and compromises analysis efficiency and accuracy.

1.1 Reseach aims and contributions

This paper aims to provide a thorough review of the drivers and barriers influencing the adoption of DT in the AECO industry, with a focus on integrating advanced, specialized simulators for making holistic, comprehensive, and accurate predictions in the context of building DT.

In this framework, the present study will address the following research questions:

- RQ1. What are the key internal and external factors that influence the drivers and barriers to the adoption of DT in the building industry? How do these factors contribute to the overall integration of DT?
- RQ2. What are the phase-specific drivers and barriers for integrating DT across various stages of a building's development process? How can stakeholders leverage this understanding to optimize decision-making, efficiency, and sustainability throughout the building's development process?

Building upon the research questions mentioned above, this paper's contributions are as follows:

- C 1. To adress RQ1, this study provides a comprehensive analysis for integrating DT technology into the building industry. It examines internal organizational factors as well as external market and regulatory influences. This approach enables the identification of various drivers and barriers associated with the adoption of DT technology in the building industry.
- C 2. In the response to RQ2, a framework is proposed that identifies corresponding drivers and barriers for each phase in a building's development process, including design, construction, operation and maintenance, and demolition. Within this framework, we have identified a total of 48 drivers and 40 barriers across all phases. With the aim to adapt DT, this phase-specific approach will enable stakeholders to integrate DT technologies more effectively at each stage, thereby ensuring optimized decision-making, enhanced efficiency, and improved sustainability.

Reviewing existing literature on drivers and barriers to DT reveals a need to identify specific strategies to effectively enhance the integration and interoperability of specialized simulation models in the development of DT. From this background, our exploration of existing solutions for the identified barriers gives an introduction to a cutting-edge classifying analysis modeling knowledge from the automative industry called Model Identity Card (MIC) to formally integrate simulators into collaborative simulations. Inspired by this, and to be developed in future research, we propose the concept of a novel framework, the Building Simulation Identity Card (BSIC), specifically designed to address the integration of specialized building simulators.

1.2 Research structure

The remaining sections of this paper are structured as follows: Section 2 provides a background, defining DT and discussing key concepts such as collaborative simulations, the Functional Mockup Interface (FMI), and the Model Identity Card (MIC). Section 3 outlines our research methodology, including the selection of databases and search queries. Section 4 categorizes the drivers and barriers to DT adoption in the building industry, dividing them into four phases: design, construction, operation and maintenance, and demolition. Furthermore, each section builds upon the findings and discussions of the preceding ones, creating a comprehensive and interconnected analysis of the topic. Section 5 discusses the implications of these drivers and barriers and introduces the BSIC concept. Section 6 presents the study's key insights and offers concluding remarks, while Section 7 identifies the research's

cc BY

limitations and proposes directions for future investigations. Figure 1 represents the overview of the research structure followed in the paper.

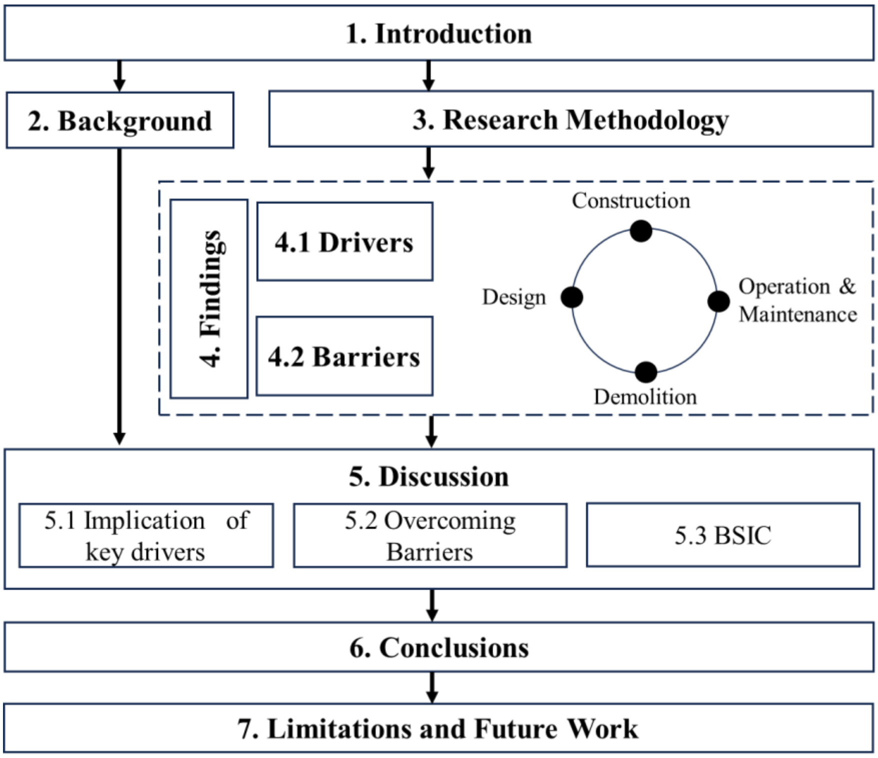

Figure 1: Overview of research structure followed in paper.

2. BACKGROUND

This section provides a compilation of DT definitions used for various applications in several industries. Additionally, it elucidates the fundamental principles and concepts crucial for comprehending DT essence.

2.1 Definition of Digital Twin (DT)

A DT integrates data from multiple sources to accurately replicate the behaviour and dynamics of a physical entity, system, or process, e.g., a building's development process. It establishes real-time connectivity for data exchange between the physical and digital worlds (Khajavi et al. 2019; Rafsanjani and Nabizadeh 2023). In the last decade, DT has started gaining more attention in the AECO industry as a tool for virtually replicating numerous aspects of a building product, process, or service. This growing focus on DT enables companies to detect and resolve physical problems, design and build improved models, and achieve value and benefits more efficiently (Zhang, Yang, and Wang 2023; Tuhaise, Tah, and Abanda 2023; Opoku et al. 2021). The origin of DT can be traced back to the aerospace industry, specifically when the National Aeronautics and Space Administration (NASA) published a roadmap for modeling and simulation (Schroeder et al. 2016). While DT is gaining recognition in academic literature and industrial practice, there is no universally accepted definition. A literature review reveals that while specific definitions of DT may differ, the general idea or focus remains consistent. Table 1 provides an overview of a few definitions of DT from the perspective of their applications in various industries.

The transition from BIM to DT within the building and construction sector signifies a paradigm shift towards more dynamic and interconnected digital representations of built assets. While BIM (see section 2.2.8) has been useful in creating detailed digital models of buildings (BuildingSMART), the emergence of DT introduces a deeper layer of digitalization by not only replicating the physical building but also by capturing real-time data and interactions, thus forming a DT that mirrors its physical counterpart throughout its entire lifecycle.

Table 1: Definitions of DT in various related industries and academic publications.

No	Definitions	Applications	References
1	"Integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."	NASA's Integrated simulations	(Glaessgen and Stargel 2012; Knapp et al. 2017; Rafsanjani and Nabizadeh 2023)
2	"In the context of Centre for Digital Built Britain a DT is a realistic digital representation of assets, processes, or systems in the built or natural environment."	Information Management	(Bolton et al. 2018)
3	"The DT is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its DT"	Complex systems	(Grieves and Vickers 2017)
4	"The concept of connecting a physical system to its virtual representation via bidirectional communication (with or without a human in the loop) allowing for the exploitation of Artificial Intelligence and Big Data Analytics to unlock value."	Big Data Analytics	(Al-Sehrawy and Kumar 2021)
5	"A model of the physical object or system, which connects digital and physical assets, transmits data in at least one direction, and monitors the physical system in real-time. In addition, it also should support analytics, control, and simulation functions."	Manufacturing systems	(Catapult 2018)
6	"A DT is a real mapping of all components in the product life cycle using physical, virtual, and interaction data between them."	Cyber-physical data	(Tao et al. 2018)
7	"Digital entity that reflects physical entity's behavior rule and keeps updating throughout the lifecycle."	Industrial Applications	(Liu et al. 2021)
8	"A dynamic digital representation of an industrial asset that enables companies to better understand and predict the performance of their machines find new revenue streams and change how their business operates."	Industrial Equipment	(Digital 2017)
9	"DT can be regarded as a paradigm by means of which selected online are dynamically assimilated into the simulation world, with the running simulation model guiding the real world adaptively in reverse."	Anti-Submarine	(Wang, Yang, et al. 2019)
10	"DT is defined as a digital copy of a physical asset, collecting real-time data from the asset and deriving information not being measured directly in the hardware."	Offshore vessels with cranes	(Fotland, Haskins, and Rølvåg 2020)
11	"The new technology, accessing realistic models of the current state of the process and their behaviors in interaction with their environment in the real world is called the DT."	Machining Process Planning	(Liu et al. 2019)
12	"DT is essentially a unique living model of the physical system with the support of enabling technologies including multi-physics simulation, machine learning, AR/VR and cloud service, etc."	Machinery fault diagnosis	(Wang, Ye, et al. 2019)
14	"Faster optimization algorithms, increased computer power and amount of available data can leverage the area of simulation toward real-time control and optimization of products and production systems – a concept often referred to as a DT."	Real-time control and optimization	(Söderberg et al. 2017)
15	"The real-time digital representation of the physical building or infrastructure. Usually, data is gathered by on-site sensors that continuously monitor changes in the building and the environment and update the BIM model with the most recent data and measurements."	Construction Industry	(Ammar et al. 2022b)

In the building and construction sector context, DT can be stratified into three layers: the physical building, the digital replica of the building, and the way the two are interconnected (Qian et al. 2022).

Based on the flow of information, the physical-digital system that is the outcome of a building digitalization process can be classified into three types: Digital Model, Digital Shadow, and DT (Madni, Madni, and Lucero 2019; Naderi and Shojaei 2023). Figure 2 illustrates this architectural representation.

a) Digital Model

Digital models are simplified digital representation of buildings. It may include static information, such as the geometry of building components and other properties. Still, it doesn't contain real-time data nor information about how the building behaves in the real world. A change in the physical building does not automatically affect the digital representation of that building, and vice versa (Kritzinger et al. 2018).

b) Digital Shadow

A digital shadow is an advanced type of digital model that incorporates real-time data from sensors, cameras, and other sources to accurately represent an object or system. It can monitor, analyze, and optimize data but cannot interact with a physical object or system. A change in the physical building leads to an automatic change in the digital model of the building. However, a change in the digital model does not automatically result in a change to the physical building, i.e. the flow of information is uni-directional from the physical building to the digital building model (Sepasgozar 2021).

c) Digital Twin

A DT represents the most advanced type of digital model that replicates a physical building in a virtual environment. It incorporates real-time data and information about the building's behaviour, performance, and interactions with its surrounding environment (Ladj et al. 2021). IoT devices link DT to physical buildings, enabling both virtual and physical entities to interact automatically. DT allows bi-directional data exchange between the physical and digital model of the building.

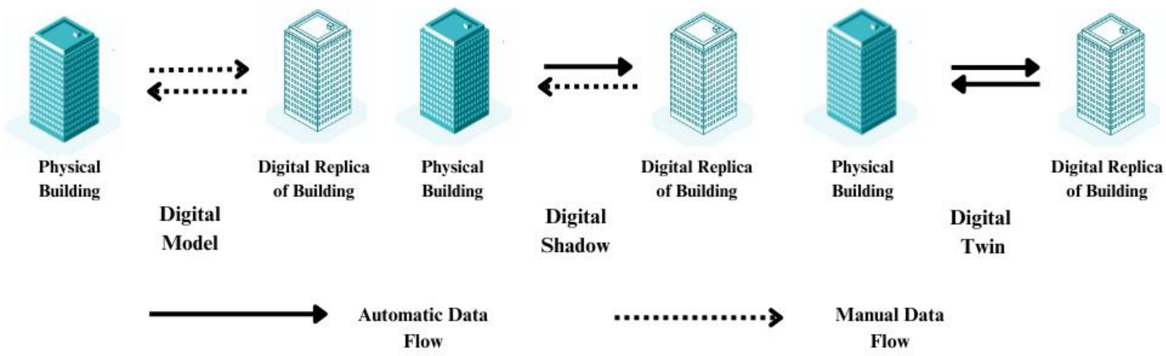

Figure 2: Level of Integration for DT.

2.2 Key Concepts

2.2.1 Significance of DT in Industry 4.0

Industry 4.0 is based on core design ideas, which includes decentralization, virtualization, interoperability, service orientation, real-time capabilities, and modularity. These principles serve as guidance for its implementation (Pires et al. 2019). Among these concepts, virtualization can be defined as the capability of the cyber-physical system (CPS) to create a digital replica of the physical model and establish a connection between the physical and digital model to gather information that will affect the model's simulation. Eventually, this idea developed into the concept of the DT (Hermann, Pentek, and Otto 2016). DT plays a key role in Industry 4.0 development, according to the Gartner hype cycle, which sets the DT as an innovation trigger of emerging technologies in 2017 (Panetta 2017) and at the pinnacle of inflated expectations in 2018 (Panetta 2018; Pires et al. 2019).

2.2.2 Collaborative Simulations

Collaborative simulation, also known as co-simulation and co-sim, is a sophisticated process that involves running multiple specialized simulations simultaneously to model an entire system. This approach is particularly significant

CC BY

in the realm of DT, addressing the intricate interactions and dependencies within building systems that isolated simulations cannot capture accurately. It combines individual models or simulations, each representing specific aspect of the larger system despite being developed using different simulation tools, programming languages, or platforms. This diversity introduces additional complexity in the analysis of interconnected heterogeneous systems (Hansen et al. 2024) within the realm of digital twins.. By leveraging the Functional Mock-up Interface (FMI), model interoperability is facilitated, allowing the seamless exchange of simulation models among various simulation tools (Schwan, Unger, and Pipiorke 2017). As a result, the co-simulation process generates a comprehensive output that represents the behaviour and performance of the complete system.

To enable this seamless integration and communication between diverse simulations, a software component called the Collaborative Simulation Orchestration Engine (COE) is employed (Larsen et al. 2016). The COE serves as the central control unit, managing interactions between different simulation instances. It synchronizes their behaviours and facilitates communication among users involved in co-simulation by running a so-called master algorithm.

2.2.3 Functional Mockup Interface (FMI)

DT facilitates the monitoring and predicting various scenarios for buildings and the systems installed in them. In the AECO sector, DT is critical due to its ability to accurately and dynamically model interconnected systems, which is key to predictive analysis and informed decision-making. Integrating multi-domain models is critical for developing a comprehensive building model. The FMI interface is a standardized interface that allows for model exchange and co-simulation within system simulations (Gomes et al. 2021). While FMI has gained widespread recognition in automotive engineering (Ravi et al. 2023), its potential and application in the AECO industry have received little attention. T. Schwan et al. (Schwan, Unger, and Pipiorke 2017) investigated four different applications of FMI in building simulations that went beyond simple model exchange. They first demonstrated FMI's role in developing an advanced, high-level building control system. Secondly, FMI facilitates smooth communication between a real-world HVAC component and a complex model of a virtually connected building. Thirdly, it integrates a fast-calculation simulation model into a complex virtual power plant controller. Lastly, FMI allows the combination of various simulation platforms, incorporating individually optimized numerical solvers. These applications highlight FMI's effectiveness in handling complex simulation needs within the AECO industry, particularly in the development and operation of DT.

2.2.4 Model Identity Card

Simulation models are virtual entities that reproduce and mimic real-world scenarios, systems, or processes. They represent and simulate complex systems or events, providing valuable insights, analysis, and predictions (Angjeliu, Coronelli, and Cardani 2020). Simulating full systems requires a multidisciplinary approach, and different teams of domain experts must use the same strategies. DT creates simulation models of a building by integrating data from different sources. They employ an integrated multi-physics model to simulate the behavior of the physical twin, system, and process (Boyes and Watson 2022). A significant reduction in inconsistencies resulting from miscommunications or misinformation can be achieved by implementing measures that restrict large groups of users to a uniform vocabulary and standardized options. The aim is to create a universally accepted lexicon titled "Model Identity Card (MIC)" that seeks to simplify the procedure of specifying and exchanging simulation models while mitigating ambiguity (Sirin et al. 2015). MIC implementation facilitates collaboration among stakeholders and reduces model development complexity. MIC allows users to reduce the time it takes to get a correct model by checking the completeness and consistency of their models throughout the modelling process.

The method of developing a MIC for simulation models involves two key steps. In the initial step, the principal classes and attributes of the model are identified. Once the classes and attributes are identified, they are grouped in a logical manner. This helps in structuring the simulation model and organizing the different elements. Assuming each numerical model is treated as an object, possessing distinct attributes that define its nature, the majority of these objects will exist within a physical system. They will engage in interactions with other objects to form a larger object. To comprehend and extract individual objects within a system, including their interfaces, it becomes imperative to ascertain and leverage the qualities and interconnections of an object and its role within the system. Table 2 highlights the most significant classes and attributes that play a major role in the development of the simulation model (Sirin et al. 2015; Blattnig et al. 2008). This table serves as a visual representation to emphasize the key components and their contributions to the overall model.

Table 2: MIC Development Procedure (inspired from Sirin et al. 2015).

Main Classes and Attributes	**Attributes Grouping**
Physical Object	**Physical Object**
Method	*Object Physics*
• Model Dimension • Chosen Method • Precision • Solver • Time step • Linearity • Continuity	• Tool Name • Developer name • Scalability • Time Computation • Hardware Requirements
Usage	*Method*
• Compilability • Time Computation • Scalability • Software Name • Software and Hardware Version	• Model Dimension • Chosen Method • Time step • Linearity • Physical Equations
Verification and Validation	*Verification and Validation*
• Accuracy • Code Verification • Level of technical review • process control	• Accuracy • Code Verification • Level of technical review • process control
Interface	**Object Interface**
Control	*Attributes*
• Signal • Human • Monitor	• Nature • Domain • Sub-domain • Variable • Unit
Physics	*Assumptions*
• Geometry • Mechanics • Boundary Condition • Material Property • Energy Transfer	• Closed System • Uniformity • Stability • Rationality • Complete Information
Parameters	*Dependence*
	Object Context
	• Historical Information • Usage • Software Use

2.2.5 Internet of Things (IoT)

Kevin Ashton, a British technology pioneer, coined the term "Internet of Things" (IoT) in 1999 to refer to a network where sensors connect physical objects to the Internet (Li, Xu, and Zhao 2015). The term was created by Ashton to highlight the potential of using the Internet to link Radio-Frequency Identification (RFID) tags used in corporate supply chains to count and monitor things without the assistance of humans (Li, Xu, and Zhao 2015; Attaran 2017). By continuously updating data, IoT enables DT applications to create a real-time virtual representation of a physical object. Therefore, IoT is the primary technology used in all DT applications (Attaran and Celik 2023). For example, real-time gathered from smart infrastructure enables the authorities to monitor and manage the structures more efficiently. This can lead to improved building efficiency, reduced traffic congestion, better management of natural resources, and enhanced public safety.

2.2.6 Data Analytics

Data analytics refers to the process of collecting, analyzing, and interpreting data generated by the DT (Erikstad 2017). It involves using advanced technologies and algorithms to extract insights and predict outcomes based on the captured data. DT technology enables the collection of large amounts of data from sensors and other connected devices. Data analytics allows this data to be processed and analyzed in real time, enabling organizations to identify trends, anomalies, and potential problems before they occur (Datta 2016).

Data analytics helps the AECO industry make informed decisions, optimize operations, and reduce costs. For example, it can be used in the building industry to simulate the performance of buildings or infrastructure, identify potential issues, and devise strategies to resolve them (Ram, Afridi, and Khan 2019).

2.2.7 Block Chain

A blockchain can be defined as "a distributed ledger of transactions implemented as data batched into blocks that use cryptographic validation to link the blocks together. Each block references and identifies the previous block using a hashing function which forms an unbroken

chain (i.e., blockchain)" (Bambara and Allen 2018). In the context of DT, blockchain technology can be used to securely store and share data, such as sensor readings, machine performance metrics, and maintenance logs, between the physical asset and its digital representation (Hasan et al. 2020). This ensures that the DT reflects the current state of the physical asset and that the data being used to make decisions is accurate and reliable, along with a record of the predicative simulation results. By recording and tracking both the predictions and the actual sensor data collected in reality, the prediction *error* made by simulations can also be carefully tracked and exploited to improve predictive accuracy over time. This would enhance decision traceability, accountability, and (computational) reproducibility of the simulations. Figure 3 presents the benefits of using blockchain for DT (Yaqoob et al. 2020).

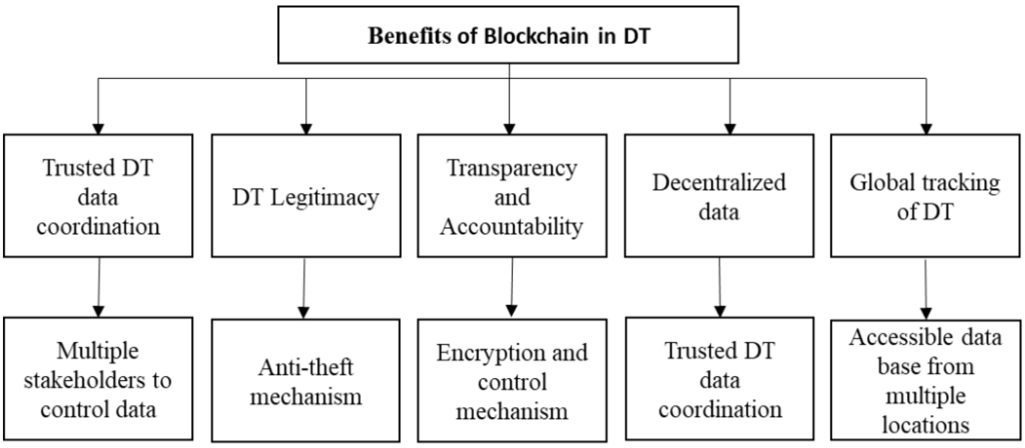

Figure 3: Benefits of Blockchain for DT.

2.2.8 Building Information Modelling (BIM)

Building Information Modelling (BIM) is a tool which enables the physical and functional aspects of a building to be digitally represented in one shared platform using 3D objects (ISO_29481-1 2016; Jung, Häkkinen, and Rekola 2018). However, BIM alone may not be sufficient for asset management throughout the entire development process in the AECO industry due to its reliance on fixed information regarding the built environment. BIM is unable to automatically incorporate real-time data updates into the models unless supplemented with additional data sources (Deng, Menassa, and Kamat 2021; Pishdad-Bozorgi et al. 2018). An object that does not exist or has not yet been constructed may be represented by a BIM model, but a DT must promptly reflect the physical counterpart's current state (Jiang et al. 2021). Therefore, a proposed approach to the advancement of smart asset management integrates the principle of DT (Lu, Xie, Heaton, et al. 2020).

CC BY

3. RESEARCH METHODOLOGY

3.1 Database and Search Query

This section gives an overview of the methodology used to systematically review the literature and prior research on drivers and barriers to DT applications for buildings. This systematic review adheres to the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-analyses) (Moher et al. 2010). This is crucial when the systematic review concerns an important subject, like DT. Combining data from several sources, such as the Scopus, Web of Science, and Google Scholar, allows us to search for more DT data for building-related studies (Kugley et al. 2016). However, Google Scholar is not considered a suitable platform for systematic reviews; thus, to identify studies related to DT for buildings, we combined Scopus and WoS (Gusenbauer and Haddaway 2020; Naderi and Shojaei 2023).

In identifying relevant articles in the field of study, query-based searches are used. It is, however, challenging to formulate a search query that is appropriate for including DT studies in the building industry, because "Digital Twins" is used in different fields of study. Therefore, a comprehensive search query was formulated. The search query was constructed using the keywords family (Digital Twin, and Building). It is important to note that this method of constructing a search query allows for a targeted and specific search.

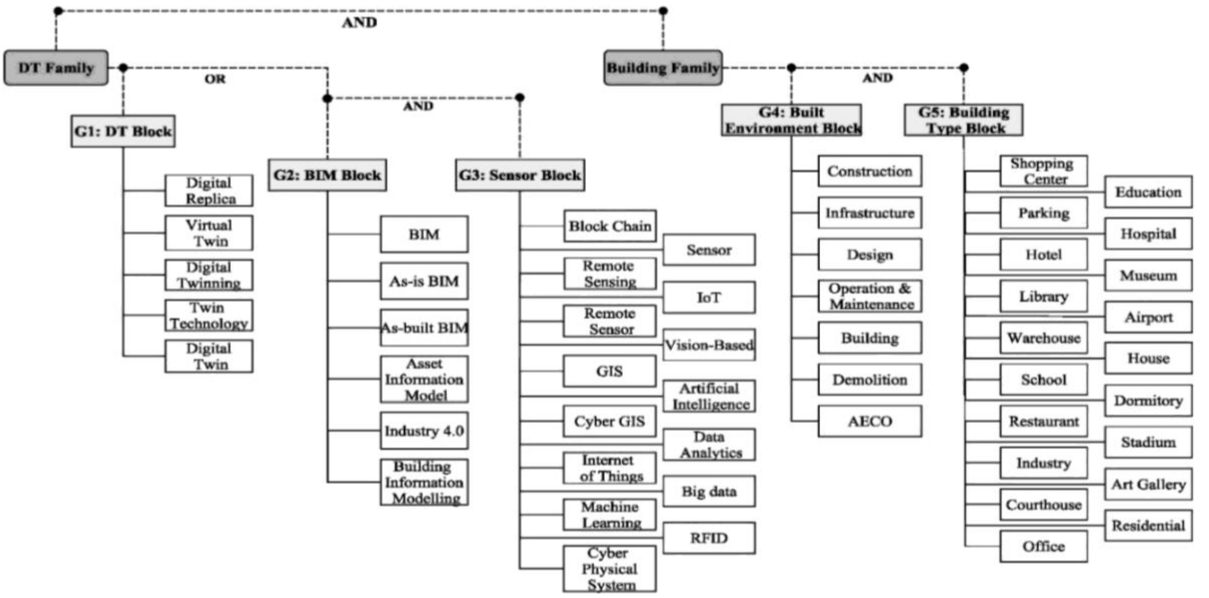

Figure 4: The list of search keywords and how they were logically combined for the literature survey.

To commence the identification of relevant studies for this review, we initiated the formulation of appropriate search queries and then determined potential databases that may contain pertinent information. The keywords depicted in Figure 4 are linked through the logical OR operator within their respective groups, and the combination between the groups is represented by the following expression: (G1 OR (G2 AND G3)) AND (G4 AND G5). Here, G1 identifies the DT block, G2 represents the BIM block, G3 refers to the sensor block, G4 indicates the built environment block, and G5 corresponds to the building type block. Research on Digital Twin-based predictive co-simulations is encompassed by the phrases “Digital Twin”, “Machine Learning”, “Big Data”, “Data Analytics”, and “Cyber-Physical Systems”. The review is conducted in three sequential steps: study identification, exclusion criteria, and screening process.

As per our search query, Figure 5 illustrates annual publication trends related to DT. This graphical representation delineates the volume of scholarly articles in journals and conference papers over the last ten years. This information is sourced from databases of Scopus and Web of Science. The data we have is up to December 31st.

CC BY

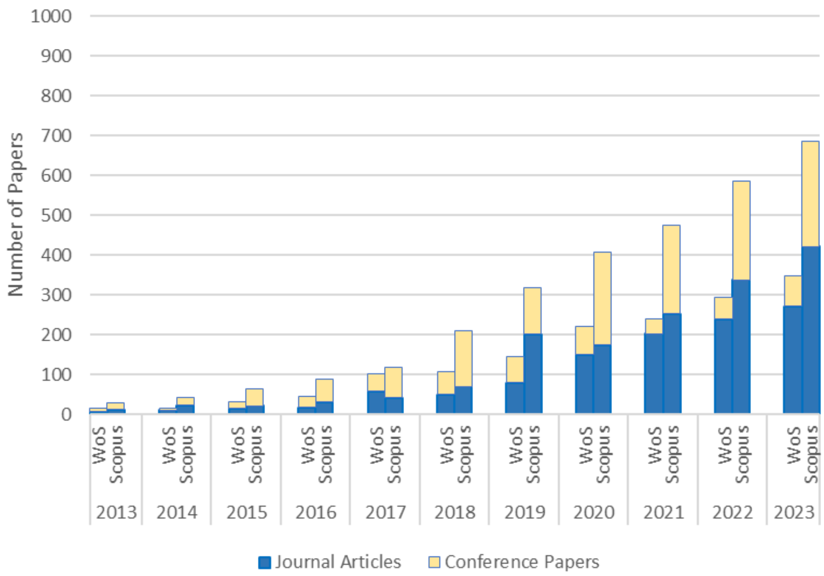

Figure 5: Yearly Publications on DT from Scopus and WOS.

3.1.1 Step 1: Study Identification

Firstly, we utilized the OR and AND commands to apply the search query to both the "Title" and "Abstract" fields of the selected platforms. This process ensures that any studies contained within the Scopus and WOS and Scopus databases that include search keywords in their abstracts or titles are captured. Moreover, our methodology permits researchers to concentrate on studies within their area of interest. By applying the OR command, the search query's scope is broadened to encompass any studies with one or more of the query keywords in their title or abstract, while the AND command ensures relevance to the field of study. This methodology guarantees that all relevant studies are identified and included in the review. As of December 31st, 2023, we identified 1612 and 3775 records in the WoS and Scopus databases, respectively.

3.1.2 Step 2: Exclusion Criteria

We limited the search to articles published in English in the last ten years between 2013 and 2023. Systematic reviews (Santos, Costa, and Grilo 2017) are considerably influenced by journal articles, which enhance the quality of research studies. Moreover, several DT-enabling technologies are derived from computer science, whose research findings are often published in conference papers. (Vardi 2009). Consequently, we have restricted the selected document types to journal and conference proceedings articles. As a result of these limitations and the removal of 1483 duplicate studies from Scopus and WOS, the number of records has been reduced to 3904.

3.1.3 Step 3: Screening

We identified the studies based on the following criteria after narrowing our search and removing duplicate articles:

- Identified studies must be within the AECO industry context.
- The selected articles should involve the DT or a combination of a static model with real-time data that allows the flow of information.
- There must be relevance to the buildings in the developed DT.

A preliminary screening of the articles was conducted based on their titles, resulting in the removal of 1326 articles that were unrelated to the AECO industry. Subsequently, 767 articles were eliminated after reading their abstracts as they did not pertain to the building industry. Upon further screening according to our research questions and criteria, we identified 138 articles that were inclined toward other research areas, such as computer science, and subsequently excluded them from our study. This resulted in 147 articles that served as the basis for further analysis. Figure 6 represents the PRISMA diagram of systematic review.

CC BY

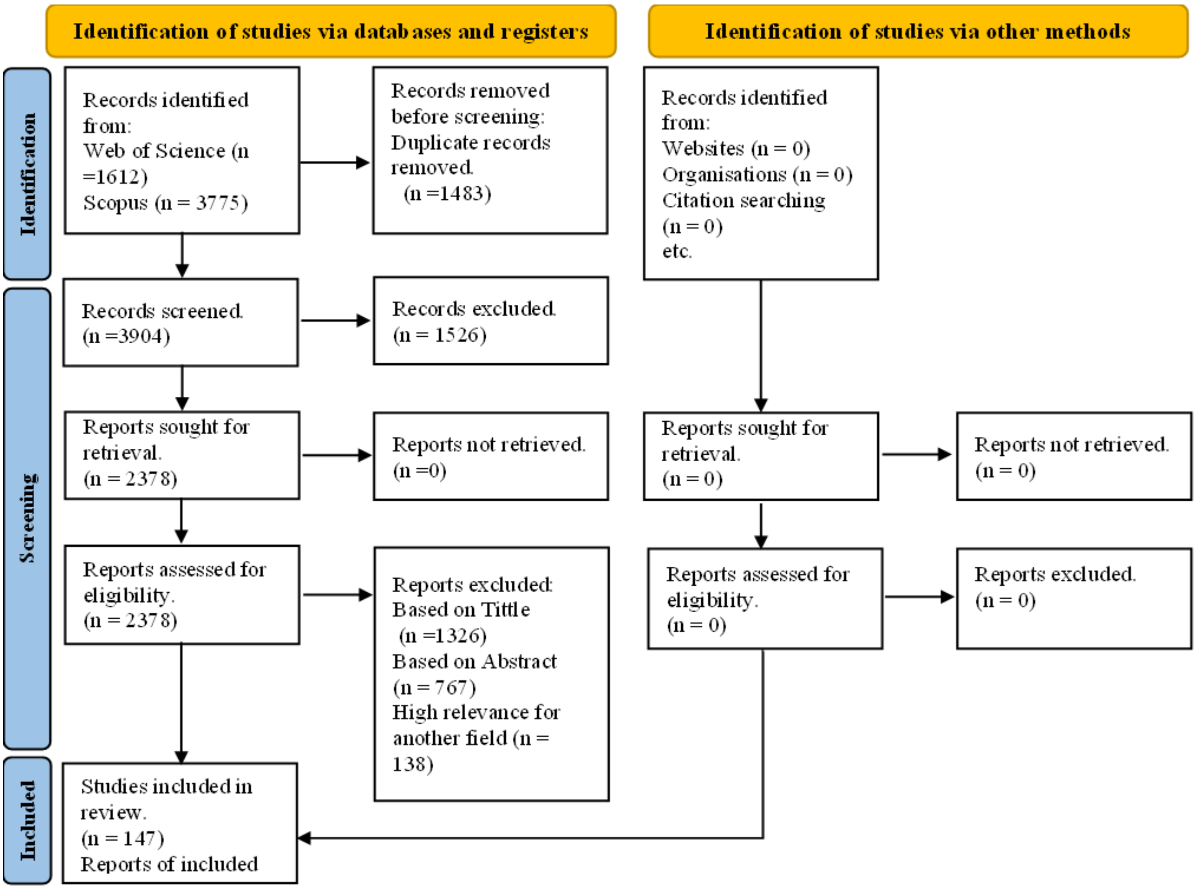

Figure 6: PRISMA Diagram for the systematic review of DT for Buildings.

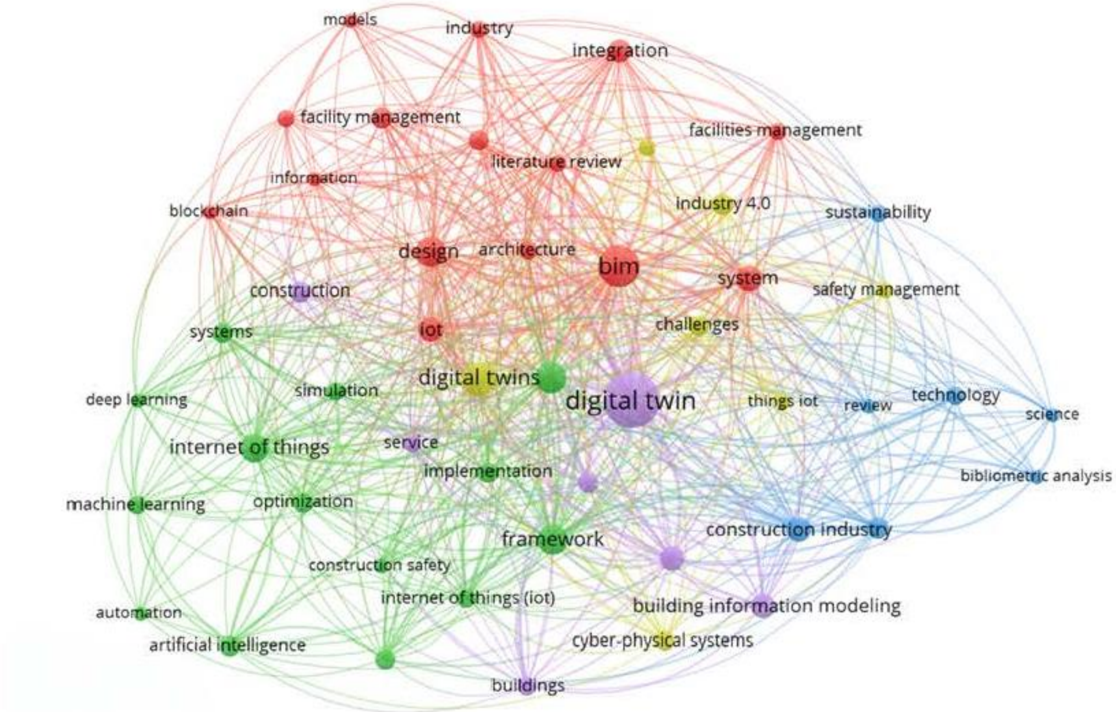

Figure 7: Visualization of co-occurrence network of keywords (generated by using VoSViewer).

CC BY

3.1.4 Co-Occurrence Network of Keywords of DT in Building Industry Research

The keywords used in a research study convey its theme, help identify the article through indexing and contribute to understanding a specific field of study by mapping out all the relevant keywords (Wuni, Shen, and Osei-Kyei 2019). It is imperative to note that the strength of the association between two keywords in a keyword co-occurrence network depends on how often they appear together in research papers (Nees Jan van Eck 2019). The software tool VOS viewer was employed to generate the keyword co-occurrence network. A "minimum number of occurrences" criterion was established to achieve an optimal network, requiring a keyword to appear at least four times before inclusion in the network. Out of the initial pool of 572, we selected 51 keywords. This ensured an optimal and easily reproducible network while maintaining readability.

Figure 7 illustrates the co-occurrence network of keywords. It highlights the interconnected nature of key drivers and barriers to DT adoption within the building industry. It provides a visual validation of the analytical analysis presented, showing clusters that represent critical areas of focus such as integration, sustainability, and collaboration, which are essential for understanding the motivation behind DT adoption and the complexities involved in its implementation.

4. FINDINGS

This section presents the research findings and descriptive analysis, as well as the categorization of the drivers and barriers to DT adoption in building construction identified through content analysis. Also, it introduces the idea of MIC as a way to overcome those barriers.

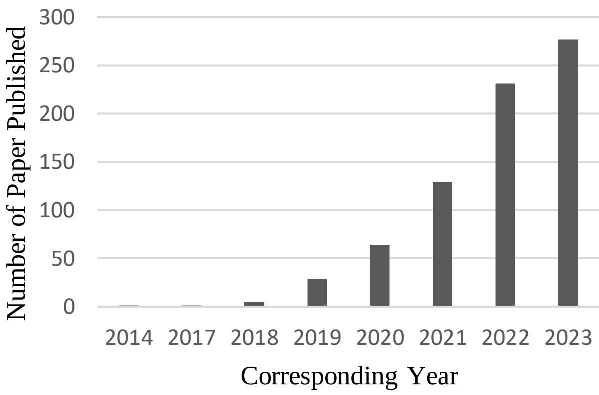

Figure 8: DT related publications over the last ten years from WoS.

The search term was "Digital Twin", and the database used was the Web of Science in the category of Engineering Civil and Construction Building Technology. Consequently, an annual publication on DT in the AECO industry was generated for the last ten years, as portrayed in Figure 8. Figure 8 was intended to thoroughly explore the publication of DT in the AECO industry, utilizing a single, high-quality data source for a more precise examination. The years 2015 and 2016 were excluded from the study as no papers were published in those years in the Web of Science (WoS) database for the aforementioned field of study.

4.1 Drivers to the Adoption of DT in the Building Development Process

External and internal factors influence DT adoption throughout a building's development process. External drivers are those related to the market or the industry at large. They include demand for sustainable building practices, regulatory changes, and technological advancements. Internal drivers, on the other hand, are those specific to a given organization or project. These can include the desire to improve collaboration between stakeholders, increase construction efficiency, or reduce costs. While external drivers may influence the decision to adopt DT, internal factors are crucial in determining how they are implemented and utilized. Ultimately, the successful adoption of DT requires a balance between external and internal drivers.

Table 3: Internal and External drivers for the adoption of DT in Building Construction.

	Drivers	Description	Internal/ External	References
(a)	**Design Phase**			
D1	Improve the efficiency of the overall design process	DT enhances the overall design process by allowing real-time data monitoring and analysis, resulting in faster problem identification and resolution.	Internal	(Opoku et al. 2022; Pan and Zhang 2023; Rafsanjani and Nabizadeh 2023; Sepasgozar et al. 2021; Xia et al. 2022; Osadcha, Jurelionis, and Fokaides 2023)
D2	Visualization of real-time data	DT creates a virtual representation of physical assets or systems, allowing users to easily comprehend and interpret complex data. It improves the ability to monitor, analyze, and predict real-world scenarios, resulting in better decision-making and problem-solving abilities.	Internal	(Aleksandrova, Vinogradova, and Tokunova 2019; Antonino et al. 2019; Belaroussi et al. 2023; Kor, Yitmen, and Alizadehsalehi 2023; Mavrokapnidis et al. 2021)
D3	Popularity of the Term DT	In literature, the popularity of the term DT has also been discussed as one of the factors driving its implementation, since organizations often implement DT to follow what appears to be a global trend	External	(Neto et al. 2020)
D4	Incoorporation of social sustainability	DT analyzes different design options, enabling stakeholders to evaluate social impact and make informed decisions for creating more inclusive spaces.	Internal	(Boje et al. 2020; Evangelou, Gkeli, and Potsiou 2022; Naderi and Shojaei 2022; Tagliabue et al. 2021)
D5	Maintenance of occupant comfort	It enables real-time monitoring and analysis of building systems and occupant behavior for proactive maintenance interventions, maximizing comfort and ensuring a pleasant indoor environment.	Internal	(Almusaed and Yitmen 2023; Opoku et al. 2021; Banfi et al. 2022; Bortolini et al. 2022; Clausen et al. 2021)
D6	Optimizing building design	DT enables real-time simulations and predictive analytics to optimize building design.	Internal	(Gopinath et al. 2018; Zhou et al. 2021; Kaewunruen, Rungskunroch, and Welsh 2019)
D7	Installation of a secure system	It enables architects and designers to simulate and optimize security system installation. This ensures that it is integrated effectively, reducing vulnerabilities and flaws.	Internal	(Boje et al. 2020; Samanta, Sarkar, and Bulo 2022)
D8	Effective coordination between stakeholders	By providing a virtual replica of the building that facilitates real-time collaboration, DT allows early detection of design clashes and allows stakeholders to explore design options before implementation.	Internal	(Bohner et al. 2019; Broo and Schooling 2020; Camposano, Smolander, and Ruippo 2021; Jiang et al. 2023; Naderi and Shojaei 2022)
D9	Ability to enhance building data management	DT allows real-time monitoring and analysis of data across different systems. This helps to centralize and streamline building data management processes, improving overall efficiency and data-driven decision-making.	Internal	(Alaloul et al. 2022; Almatared et al. 2022; Ariyachandra, Samarakkody, and Perera 2019; Belaroussi et al. 2023; Bello et al. 2021)
D10	Evaluating and identifying the design flaws	Real-time simulation and monitoring in DT enable continuous testing and analysis to quickly identify and evaluate design flaws.	Internal	(Boje et al. 2020; Opoku et al. 2022; Deng, Menassa, and Kamat 2021; Hosamo, Imran, et al. 2022)

	Drivers	Description	Internal/ External	References
D11	Aid discussion with customers during the development process	DT offers interactive building design representation, enabling customers to explore and understand the project comprehensively. This promotes informed and collaborative customer feedback, leading to improved decisions and greater satisfaction.	Internal	(Alanne and Sierla 2022; Opoku et al. 2022)
(b) Construction Phase				
D1	Improvement in the selection of materials	DT can be used to simulate different materials performance under various conditions. This aids in the evaluation of factors such as sustainability, cost, and performance.	Internal	(Ali and Badinelli 2016; Baduge et al. 2022; Bohner et al. 2019; Cogswell et al. 2022; Niu et al. 2016)
D2	Enhance logistics monitoring	DT integrates data from sensors, drones, and schedules for real-time logistics monitoring, improving coordination, resource allocation, and risk mitigation on construction sites.	Internal	(Greif, Stein, and Flath 2020; Opoku et al. 2021)
D3	Mitigating risks of climate change	The development of accurate DT is essential for understanding how climate change and associated risks affect buildings and advising on ways to mitigate these risks.	External	(Petri et al. 2023)
D4	Better management	DT helps manage construction projects by providing real-time progress updates, resource allocation, and issue identification.	Internal	(Liu, Han, and Zhu 2023; Oliveira 2020; Ozturk 2021; Lu, Parlikad, et al. 2020)
D5	Remote monitoring and control	Due to technological advancements, construction operations and assets can be monitored and controlled remotely, leading to the development of DT for constructed facilities.	External	(Khallaf et al. 2022a)
D6	Resource management	DT optimizes resource management by providing real-time data on equipment, materials, and manpower utilization.	Internal	(Bohner et al. 2019; Cogswell et al. 2022; Kineber et al. 2023)
D7	Automated progress monitoring	Progress monitoring is automated by integrating data from sensors and BIM models, providing a real-time visual representation of construction activities.	Internal	(Greif, Stein, and Flath 2020; Opoku et al. 2022)
D8	Reducing the number of injuries	Proactive risk mitigation strategies are identified by simulating and identifying potential construction risks, thus improving safety.	Internal	(Park et al. 2023; Akanmu, Anumba, and Ogunseiju 2021; Ghansah and Lu 2023; Teizer, Johansen, and Schultz 2022)
D9	Enhanced Construction Site Management.	In the AECO industry, DT appeals to a broad range of stakeholders due to their ability to manage and monitor construction sites by extending levels of detail for BIM models	External	(Opoku et al. 2022)
D10	Accurate information on	By combining data from various sources, DT offers real-time, data-driven insights into a project's status, ensuring accurate and up-to-date monitoring.	Internal	(Khallaf et al. 2022b; Ammar et al. 2022a; Opoku et al. 2021)

	Drivers	Description	Internal/ External	References
	the status of the Project			
D11	Reducing construction costs	DT can reduce construction costs by optimizing resource allocation, detecting issues early on to minimize rework, and enhancing project efficiency, resulting in cost savings throughout the construction process.	Internal	(Khallaf et al. 2022b; Ariyachandra, Samarakkody, and Perera 2019)
D12	Enhanced Collaboration between stakeholders	DT allows stakeholders to collaborate in real-time on project data and make informed decisions together.	Internal	(Bohner et al. 2019; Broo and Schooling 2020)
(c)	**Operation and Maintenance Phase**			
D1	Real-time safety assessment	DT integrates sensors and data analytics to monitor building conditions for real-time safety assessments.	Internal	(Arsiwala, Elghaish, and Zoher 2023; Petri et al. 2023; Opoku et al. 2021; Henzel et al. 2022)
D2	Effective decision-making	DT allows facility managers to make informed decisions about maintenance, energy efficiency, and resource allocation through real-time data and simulations.	Internal	(Evangelou, Gkeli, and Potsiou 2022; Greif, Stein, and Flath 2020; Henzel et al. 2022; Kor, Yitmen, and Alizadehsalehi 2023; Naderi and Shojaei 2022; Parusheva and Aleksandrova 2021; Rojas-Mercedes, Erazo, and Di Sarno 2022; Torrecilla-García, Pardo-Ferreira, and Rubio-Romero 2021)
D3	Continuous asset surveillance	DT integrates sensors and IoT devices to monitor building components in real-time, enabling continuous asset surveillance of their condition and performance.	Internal	(Alshammari, Beach, and Rezgui 2021; Boje et al. 2020; Angjeliu, Coronelli, and Cardani 2020; Akanmu, Anumba, and Ogunseiju 2021; Rojas-Mercedes, Erazo, and Di Sarno 2022)
D4	Reduction in operational cost	Real-time data is provided to enable efficient resource allocation, predictive maintenance, and energy management, resulting in lower energy consumption and maintenance expenses.	Internal	(Harode, Thabet, and Dongre 2023; Opoku et al. 2022; Seo and Yun 2022; Spudys et al. 2023)
D5	Increasing Business Competition and Demand	Increasing business competition has led companies to look for solutions to reduce costs and improve quality and productivity. This has resulted in increased demand for DT.	External	(Ammar et al. 2022b; Shahzad et al. 2022)
D6	Increased productivity	DT improves productivity by automating tasks, monitoring systems for anomalies, and optimizing space and resource allocation.	Internal	(Alaloul et al. 2022; Azimi and O'Brien 2022; Opoku et al. 2021; Sajjad and Pan 2019; Drobnyi et al. 2023)
D7	Resilience and sustainability	DT continuously monitors building systems, predicting and preventing failures and optimizing energy usage.	Internal	(Bortolini et al. 2022; Kaewunruen and Xu 2018; Sajjad and Pan 2019; Tagliabue et al. 2021)

	Drivers	Description	Internal/ External	References
		This reduces environmental impact and ensures long-term functionality in a changing environment.		
D8	Increased Transparency of Information	DT enhances transparency by allowing stakeholders to access real-time data on building operations and performance. This promotes accountability, informed decision-making, and improved collaboration.	Internal	(Opoku et al. 2022; Ammar et al. 2022b; Napp 2022)
D9	Enhanced safety and risk management	DT offers real-time data and simulations that enable predictive maintenance and risk assessment, ultimately enhancing safety by proactively identifying potential risks and optimizing maintenance strategies.	Internal	(Afzal, Shafiq, and Al Jassmi 2021; Baduge et al. 2022; Haupt, Akinlolu, and Raliile 2019; Levine and Spencer 2022; Newaz et al. 2022; Park et al. 2023; Xu, Duo, and Tang 2022; Aribisala et al. 2022; Torrecilla-García, Pardo-Ferreira, and Rubio-Romero 2021)
D10	Preservance of historic buildings	DT can aid in the preservation of historic buildings by monitoring and analyzing their structural integrity for early signs of deterioration or damage.	Internal	(Ni et al. 2022; Shishehgarkhaneh et al. 2022; Ćosović and Maksimović 2022; Opoku et al. 2022)
D11	Improved retrofitting for buildings	DT offers detailed insights into a building's infrastructure, enabling accurate retrofit planning and design.	Internal	(Arsiwala, Elghaish, and Zoher 2023; Zhao et al. 2021; Almatared et al. 2022; Opoku et al. 2022; Duch-zebrowska and Zielonko-jung 2021)
D12	Optimization of space utilization and energy performance	DT allows for real-time monitoring of space usage and energy consumption data, enabling data-driven decisions to optimize layouts and HVAC systems for improved space utilization and energy efficiency.	Internal	(Opoku et al. 2022; Azimi and O'Brien 2022; Spudys et al. 2023)
D13	Integration of Historical Data	A DT can be used to integrate historical data from past usage in order to compare deviations from a baseline and inform future decisions.	External	(Almatared et al. 2022)
D14	Anomaly Detection	DT compares real-time sensor data to expected performance, flagging anomalies like temperature fluctuations or equipment malfunctions.	Internal	(Hosamo, Nielsen, et al. 2022; Peng et al. 2020; Rojas-Mercedes, Erazo, and Di Sarno 2022; Lu, Xie, Parlikad, and Schooling 2020)
D15	Improved Planning	DT offers a detailed 3D model of a building, improving data-driven planning and decision-making by providing insights into asset conditions and performance trends.	Internal	(Torrecilla-García, Pardo-Ferreira, and Rubio-Romero 2021; Xia et al. 2022; Zhao et al. 2022; Broo and Schooling 2020; Bujari et al. 2021)
D16	Asset Management	DT provides real-time data on asset conditions, usage patterns, and maintenance history, streamlining asset management.	Internal	(Evangelou, Gkeli, and Potsiou 2022; Guo et al. 2022; Lu, Xie, Parlikad, Schooling, et al. 2020; Lu, Xie, Parlikad, and Schooling 2020; Xie, Moretti, et al. 2022; Azimi and O'Brien 2022)

	Drivers	Description	Internal/ External	References
D17	Enhanced renovation projects	DT aids in precise visualization and analysis of building components for renovation planning and execution.	Internal	(Banfi et al. 2022; Daniotti et al. 2022; Kaewunruen and Xu 2018)
D18	Predictive maintenance	DT utilizes real-time data and analytics to predict equipment failures and maintenance needs, enabling timely interventions before critical issues arise.	Internal	(Arsiwala, Elghaish, and Zoher 2023; Hosamo, Imran, et al. 2022; Khajavi et al. 2019; Ozturk 2021; Opoku et al. 2021; Hosamo et al. 2023)
(d) Demolition Phase				
D1	Data Utilization	DT uses accumulated data throughout the building's development process to develop comprehensive demolition plans, incorporating insights from the building's history.	Internal	(Ammar et al. 2022b) (Ammar et al. 2022b; Jin et al. 2021)
D2	Sustainable resource management and waste reduction	DT utilize the sustainable materials to effectively manage demolition waste, thereby reducing environmental impact and promoting circular economy principles.	Internal	(Yang, Lv, and Wang 2022)
D3	Circular economy	It helps to promote circular economy strategies in the construction industry by facilitating the reuse and recycling of building demolition waste,	External	(Su, Yu, et al. 2023; Meng, Das, and Meng 2023) (Su, Yu, et al. 2023; Meng, Das, and Meng 2023)
D4	Efficient resource management	By digitally representing the demolition process, it helps to optimize the allocation of resources, such as labor and materials, leading to cost savings and reduced waste	Internal	(Su, Yu, et al. 2023; Jin et al. 2021; Kang et al. 2022)
D5	Real-time monitoring	It facilitates the provision of real-time data during demolition activities, ensuring improved oversight and management of the operations.	Internal	(Meng, Das, and Meng 2023)
D6	Virtual site accuracy	DT enhances demolition site mapping accuracy, allowing for precise planning and execution, and minimizing risks, thereby improving safety.	Internal	(Su, Yu, et al. 2023)
D7	Technology Integration for building demolition waste Management	It utilizes IoT, big data, and robotics to accurately track and manage building demolition waste, enhancing efficiency and sustainability.	Internal	(Su, Yu, et al. 2023)

Based on the literature review, the internal and external drivers of DT adoption in building construction can be divided into four categories: design, construction, operation and maintenance, and demolition. They are explored in more detail in Table 3.

4.1.1 Design Phase

During the design phase, DT offers architects and engineers a virtual environment to test and optimize building systems, design, and performance(Xia et al. 2022; Osadcha, Jurelionis, and Fokaides 2023). This allows designers to create accurate simulations and evaluate different design options. This can help them make better-informed decisions throughout the whole building development process(Rafsanjani and Nabizadeh 2023). Furthermore, DT in the design phase can improve communication and collaboration among various stakeholders, reducing the possibility of errors and delays by providing accurate and up-to-date information (Broo and Schooling 2020). DT enhances project efficiency by allowing managers to simulate design options and assess performance prior to construction, eliminating errors and delays.

4.1.2 Construction Phase

During construction, DT can monitor project progress, provide real-time information about material usage, and manage resources efficiently to prevent delays and cost overruns (Ariyachandra, Samarakkody, and Perera 2019). By providing comprehensive visibility into the construction process from start to finish, DT can lead to efficient construction (Oliveira 2020). Before using DT on a construction site, firms need to ensure compliance with local laws and regulations. However, DT should allow contractors to accelerate the processes of approval and permitting, as well as facilitate the rapid development of executable plans (Al-Sehrawy and Kumar 2021).

4.1.3 Operation and Maintenance Phase

The operation and maintenance phase of a building is critical for DT implementation. In this phase, the building development process is characterized by a heterogeneous, complex structure and multiple layers of data representing the utilization and operation of buildings. A defect during this phase could result in system malfunctions and safety issues (Opoku et al. 2021), which is why regular maintenance in this phase is of the utmost importance to the building. It collects real-time data and information relevant to a wide range of applications, from stakeholder communication to energy usage monitoring in the building.

Through continuous monitoring of various building systems and data analytics, DT can preemptively detect potential problems, consequently reducing maintenance costs and minimizing operational downtime (Khajavi et al. 2019; Hosamo, Imran, et al. 2022). Furthermore, building engineers are equipped with essential data and knowledge to promptly address issues. This results in improved system reliability and enhanced occupant experience.

DT in maintenance makes it easy to track the history of building systems, giving engineers access to data that can help identify patterns and optimization opportunities. A DT of a commercial office building can continuously monitor the HVAC system and detect any abnormal fluctuations in temperature or pressure (Ammar et al. 2022b). This information can help the building engineer identify a potential malfunctioning compressor and schedule a repair before it completely fails (Zhao et al. 2022).

4.1.4 Demolition Phase

In the demolition phase of a building, the adoption of Digital Twins (DT) is driven by factors that enhance process efficiency, safety, and sustainability(Su, Zhong, et al. 2023). Utilizing data from a building's entire development process, DT creates effective demolition plans, offering a predictive and adaptive planning approach that minimizes unforeseen risks(Jin et al. 2021). DT also promotes sustainable resource management and waste reduction by advocating the use of environmentally friendly materials, which contributes to resource conservation and diminishes environmental impact(Yang, Lv, and Wang 2022). This strategy involves prioritizing materials for repurposing or recycling, thereby extending their lifecycle.

Furthermore, DT supports Circular Economy strategies, encouraging the recycling and reuse of demolition materials, and integrates advanced technologies such as IoT, big data, and robotics to manage demolition waste more effectively(Su, Yu, et al. 2023). This technological integration not only ensures precise tracking but also efficient handling of waste, thereby enhancing the demolition process's overall effectiveness. In doing so, DT transitions waste management towards a circular approach, aligning with global environmental goals.

4.2 Barriers to the Adoption of DT in the Building Development Process

There has been significant progress in DT technology in the building industry. However, numerous internal and external barriers must be thoroughly examined to understand this paradigm shift. Internally, organizations struggle with data integration, cultural resistance, and a shortage of skilled employees. Externally, issues like regulatory constraints, interoperability, and cybersecurity pose significant challenges on the path to widespread DT adoption. Based on a comprehensive review of existing literature, the barriers to DT adoption in the building Industry can be classified into four distinct phases: design, construction, operation and maintenance, and demolition. Table 4 represents the internal and external barriers to the adoption of DT.

Table 4: Internal and external Barriers to the adoption of DT in buildings across four development phases.

	Barriers	Description	Internal/ External	References
(a) Design Phase				
B1	Lack of standardization	It impedes DT adoption by creating data compatibility issues and integration challenges between different design tools and disciplines.	Internal	(Shahzad et al. 2022; Xie, Qiu, et al. 2022)
B2	Lack of confidence in data security	Sharing sensitive design information in the DT environment can be discouraging, leading to incomplete and inaccurate adoption.	Internal	(Shahzad et al. 2022; Opoku et al. 2023)
B3	Silos between departments	The fragmentation of data and lack of effective collaboration can hinder the adoption of DT.	Internal	(Rafsanjani and Nabizadeh 2023; Xia et al. 2022)
B4	Difficulties in setting realistic expectations	It hinders DT adoption by leading to overambitious goals or underestimating implementation complexity.	Internal	(Greif, Stein, and Flath 2020; Opoku et al. 2023)
B5	Permitting and licensing obstacles	Legal and regulatory complexities can hinder DT adoption. Unclear or outdated regulations regarding DT data use and sharing may impede the free flow of information.	External	(Opoku et al. 2023)
B6	Lack of research and development	Limiting the availability of innovative tools and methodologies tailored for DT implementation hinders its adoption.	External	(Opoku et al. 2021; Napp 2022)
B7	Absence of necessary Infrastructure	Limitations in collecting, storing, and processing large amounts of data restrict DT adoption.	Internal	(Napp 2022; Opoku et al. 2023)
B8	Challenges in validating and verifying	The difficulties in validating and verifying data and models limit the use of DT by undermining confidence in its accuracy and reliability.	Internal	(Ammar et al. 2022b)
B9	Shortage of Skilled Professionals	It limits the ability to effectively create and manage complex digital models, reducing design quality and efficiency and potentially resulting in costly errors.	Internal	('Lack of Vision, Organizational Silos Challenge Strategy for Industry 4.0' 2020)
(b) Construction Phase				
B1	Technology and sensor availability	The lack of real-time data acquisition and monitoring infrastructure makes it more difficult to update and maintain an accurate DT representation.	Internal	(Opoku et al. 2023)
B2	Lack of data interoperability	Incompatible data formats and systems create data silos, hindering comprehensive representation of building progress and performance.	Internal	(Boje et al. 2020; Shahzad et al. 2022; Sacks, Girolami, and Brilakis 2020; Osadcha, Jurelionis, and Fokaides 2023)

	Barriers	Description	Internal/ External	References
B3	Lack of constant internet connectivity	The connectivity gap between the physical and digital realms can reduce DT technology effectiveness in construction projects.	Internal	(Opoku et al. 2021; Opoku et al. 2022; Greif, Stein, and Flath 2020; Rafsanjani and Nabizadeh 2023; Broo and Schooling 2023; Barkokebas, Al-Hussein, and Hamzeh 2023)
B4	High Construction Cost	Smaller organizations with tight budgets may see DT technology as a financial burden rather than a cost-effective investment in project management.	External	(Broo and Schooling 2023)
B5	Scalability issues	Creating and maintaining accurate virtual representations of complex, large-scale building projects is challenging, hindering DT adoption and often resulting in incomplete or outdated DT.	Internal	(Rafsanjani and Nabizadeh 2023; Greif, Stein, and Flath 2020; Opoku et al. 2023; Kineber et al. 2023)
B6	Uncertainties with data quality and reliability	Fluctuations in data quality can compromise the effectiveness of DT in managing construction projects by producing flawed insights.	Internal	(Opoku et al. 2023; Jacobellis and Ilbeigi 2022; Alaloul et al. 2021; Belaroussi et al. 2023)
B7	Transparency in data sharing.	It prevents collaboration between project stakeholders and restricts access to crucial data needed for maintaining an accurate DT.	Internal	(Ammar et al. 2022a; Broo and Schooling 2023)
B8	Resistance to change and traditional construction practices.	Integrating DT into established workflows is hindered by the slow adoption of cutting-edge technologies and methods.	Internal	(Napp 2022; Opoku et al. 2023; Zhang et al. 2022)
B9	Limited availability of case studies	Industry professionals are deprived of practical examples and success stories that showcase the benefits and potential applications of DT.	Internal	(Ammar et al. 2022b; Khallaf et al. 2022b; Salem and Dragomir 2022)
B10	Integration of software and tools	The integration of multiple construction software and tools into a DT platform is complex and requires substantial resources and expertise, which may result in compatibility issues and implementation delays.	Internal	(Opoku et al. 2021; Osadcha, Jurelionis, and Fokaides 2023)
(c) Operation and Maintenance Phase				
B1	Static nature of building data	DT functionality depends on current data, and static data can result in inaccuracies and reduced relevance in ongoing operational decision-making.	Internal	(Boje et al. 2020; Opoku et al. 2021; Khajavi et al. 2019; Broo and Schooling 2020; Turner et al. 2021)
B2	Project complexities	The complexity of creating and maintaining an accurate virtual replica of the building is crucial for effective monitoring and management of complex systems and processes within the facility.	Internal	(Lu, Chen, et al. 2020; Greif, Stein, and Flath 2020; Rafsanjani and Nabizadeh 2023)
B3	Effective governance and management	DT projects may become disorganized or stagnant, limiting their ability to deliver value for ongoing facility operation and maintenance.	Internal	(Broo and Schooling 2023; Salem and Dragomir 2022)
B4	Difficulties in systems integration	Limitations in connecting building systems and IoT devices hinder DT adoption, limiting its ability to provide real-time insights and control.	Internal	(Rafsanjani and Nabizadeh 2023; Mavrokapnidis et al. 2021)

	Barriers	Description	Internal/ External	References
B5	Legal and regulatory challenges	Introducing complexities related to data privacy, security, and compliance hinders DT adoption, which makes it challenging to navigate the legal landscape and ensure DT responsible use.	External	(Hoeft and Trask 2022; Ammar et al. 2022a)
B6	Integration with existing legacy systems and databases	It hinders DT adoption by creating compatibility issues and data silos that limit the ability to leverage historical data. It also limits the ability to establish complete connectivity between the DT and a well-established operational infrastructure.	Internal	(Fuller et al. 2020; Kineber et al. 2023)
B7	Issues of maintainability	The challenge of maintaining data accuracy and updating it continually can lead to reduced effectiveness of the DT over time and increased resource demands for upkeep.	Internal	(Meža et al. 2021; Opoku et al. 2023)
B8	Insufficient knowledge of the use of complex databases.	It limits the ability of DT to effectively manage and extract valuable information from intricate data structures, impeding the efficiency of DT to optimize building operations and maintenance.	Internal	(Ammar et al. 2022a; Napp 2022; Guo et al. 2022)
B9	Multicultural project challenges	Diverse cultural norms, communication styles, and expectations can hinder effective DT management.	Internal	(Rafsanjani and Nabizadeh 2023; Opoku et al. 2023)
B10	Limited availability of DT technology service providers	Implementing and managing DT systems can be challenging for organizations due to insufficient expertise and support.	Internal	(Opoku et al. 2023)
B11	Lack of Standard Protocols	Currently, there are no standard protocols for data exchange and communication between different types of software and systems used in building operation and maintenance.	External	(Opoku et al. 2023; Kineber et al. 2023)
B12	System instability and sudden failure	Disruptions to data streams can make the DT unreliable, posing risks to building management.	Internal	(Li et al. 2021; Opoku et al. 2023)
B13	Scope management	Defining the boundaries and objectives of DT projects in building management can be complex. Overambitious or vague scopes can hinder DT implementation and maintenance.	Internal	(Opoku et al. 2023; Salem and Dragomir 2022)
B14	Methodological Gaps	This makes it difficult for organizations to create effective maintenance plans, leading to potential errors and inefficiencies in managing DT systems.	External	(Lünnemann, Lindow, and Goßlau 2023)
B15	Limited interoperability solution between different software and systems	Impeded by the lack of seamless integration, diverse data sources and tools hamper the DT's ability to provide comprehensive insights and optimization capabilities for building operation and maintenance.	Internal	(Fuller et al. 2020; Opoku et al. 2023; Kineber et al. 2023)

	Barriers	Description	Internal/ External	References
	(d) Demolition Phase			
B1	Low digitalization in demolition	Challenge in adopting advanced digital technologies like DT, in the traditionally low-tech demolition phase, where manual processes are predominant	Internal	(Su, Yu, et al. 2023; Su, Zhong, et al. 2023)
B2	Systematic technology convergence challenges	The complexities in harmonizing various advanced technologies like IoT and big data within demolition processes of buildings to effectively manage demolition waste.	Internal	(Su, Yu, et al. 2023)
B3	Lack of building demolition waste market mechanism	There is absence of a well-developed market framework for trading and recycling building demolition waste, which is crucial for the effective implementation of DT in demolition phase.	External	(Su, Yu, et al. 2023; Al-Raqeb et al. 2023)
B4	Regulatory Challenges	Inadequate regulatory frameworks in construction impede the integration of DT, as they provide little motivation for stakeholders to adopt these advanced technological systems.	External	(Al-Raqeb et al. 2023; Opoku et al. 2023)
B5	Logistical Challenges	It involves the integration and management of complex data systems and coordinating physical processes like waste transport and site access, which are critical for effective DT implementation.	Internal	(Al-Raqeb et al. 2023)
B6	Human capital and organizational barriers	Limited training and reluctance to share data among stakeholders affect the collaborative efforts required for effective demolition planning.	External	(Jin et al. 2021; Su, Jiang, et al. 2023)

4.2.1 Design Phase

The adoption of DT during the design phase of the building development process faces several barriers (Shahzad et al. 2022). One of the primary barriers is the lack of research and development within the industry (Napp 2022). A traditional design approach has been deeply ingrained in the industry for many years, and transitioning to a DT approach requires a significant change in mindset and working methods. Another challenge is the absence of standardized industry-wide protocols and standards for implementing DT technology, making it difficult to ensure compatibility and interoperability between different software tools and platforms (Attaran and Celik 2023). Furthermore, the complexity and scale of building projects can pose challenges in accurately capturing and modeling the entire structure within the DT. This requires comprehensive data collection and integration from various stakeholders involved in building construction (Shahzad et al. 2022).

4.2.2 Construction Phase

Various obstacles impede DT implementation in the construction phase of a the building (Opoku et al. 2023). Firstly, resistance to changing traditional construction practices has hindered DT adoption (Napp 2022). Many individuals in the AECO industry fail to grasp the potential benefits and applications of DT, leading to hesitancy in its implementation. The complexity and interoperability challenges of integrating building information systems with DT can create technical barriers (Boje et al. 2020; Kineber et al. 2023). Construction processes involve various stakeholders and numerous data sources, making it difficult to streamline and synchronize information effectively. Furthermore, the limited availability of case studies in the industry has made DT adoption difficult (Khallaf et al. 2022b).

4.2.3 Operation and Maintenance Phase

The adoption of DT technology in the building development process can be hindered by several internal and external barriers during the operation and maintenance phase. The primary obstacle to DT implementation is a lack of awareness and understanding among building operators and management (Ammar et al. 2022a; Napp 2022). Due to this limited understanding of the intricate nature of this technology, companies may be hesitant to invest in DT platforms or allocate resources for personnel training. As well as apprehensions regarding the integration of emerging technology into existing systems or concerns regarding potential disruptions during the transition phase have contributed to the barriers to DT adoption (Mavrokapnidis et al. 2021).

DT in building operation and maintenance requires close coordination and cooperation among operational teams, facility managers, and other relevant personnel (Broo and Schooling 2023). In the absence of a unified approach, fragmented data management systems, duplicated efforts, and inconsistent decision-making could undermine the implementation of digital transformations.

During this phase, various software and systems are utilized to monitor energy consumption, analyze structural integrity, manage assets, ensure compliance with regulations, and schedule maintenance activities. However, these software and systems may come from different vendors or be developed independently, resulting in limited interoperability (Fuller et al. 2020). Another barrier encountered in this process is scope management, where the complexity of DT projects may require diligent monitoring and control to ensure effective implementation (Salem and Dragomir 2022). Further, the integration of DT technology with existing tools can be challenging, as the compatibility and integration of these systems may pose technical difficulties (Botín-Sanabria et al. 2022).

4.2.4 Demolition Phase

The integration of DT in the demolition phase is hindered by several interconnected barriers. A primary challenge is the prevalence of low digitalization in demolition, where manual processes are still the norm, making the adoption of advanced technologies difficult. This issue is compounded by systematic technology convergence challenges, where harmonizing technologies like IoT and big data with demolition processes poses significant difficulties (Su, Yu, et al. 2023). Another external barrier is the absence of a robust market mechanism for building demolition waste, essential for DT effectiveness. Regulatory challenges further complicate this integration, as inadequate frameworks provide little motivation for stakeholder adoption.

Additionally, logistical challenges, such as managing complex data systems and coordinating physical processes, are critical for digital twin implementation (Al-Raqeb et al. 2023). Lastly, human capital and organizational barriers, including limited training and data-sharing reluctance among stakeholders, impede the collaborative efforts necessary for effective demolition planning (Su, Jiang, et al. 2023). These barriers represent a complex mix of technological, regulatory, logistical, and human factors that need addressing for successful DT adoption in the building demolition phase.

5. DISCUSSION

In this article, we have investigated both the drivers and the barriers related to the adoption of DT in the building development process through a systematic literature review. Furthermore, we raised a flag for the integration of diverse, specialized simulation models, which we elaborate on in the following. To structure this section comprehensively, we cite and answer the research questions presented in the introduction.

5.1 Understanding the Impact and Implications of Key Drivers

The findings section on DT drivers summarizes how the increasing complexity and size of construction projects drive the need for DT to enhance efficiencies and reduce errors. Secondly, technological advancements such as IoT and AI enable the development and implementation of DT solutions. Furthermore, the demand for real-time monitoring and data-driven decision-making drives DT adoption. Finally, the potential benefits of cost reduction, improved sustainability, and improved project management motivate organizations to invest in building DT. Figure 9 represents the selected drivers in the adoption of DT in different phases.

There are various successful case studies in the building industry where DT has been effectively implemented, and its associated challenges have been successfully addressed. One of the possible applications is to reduce energy consumption. According to (Peng et al. 2020), their research indicates that DT can achieve an annual energy

CC BY

consumption savings of 1% and reduce requests for repairs and facility faults by 10%. (Zhao et al. 2021) demonstrated in their study that DT can significantly reduce building energy consumption by 7.52% through retrofitting existing buildings into nearly zero-energy buildings (nZEBS), resulting in an 85.9% reduction in carbon emissions. Similarly, (Kaewunruen, Rungskunroch, and Welsh 2019) highlighted in their study that a Net zero energy building (NZEB) solution for an existing building can provide a 23-year return period. (Arsiwala, Elghaish, and Zoher 2023) also highlighted DT's capability to predict buildings' CO2 emissions by utilizing AI, which processes time series data from installed devices. In a study, (Khajavi et al. 2019) established that DT can aid architects in designing buildings that optimize airflow and lighting by leveraging natural resources.

DT can also be used to improve the efficiency of management processes. (Zhao et al. 2022) reported a 10% increase in management staff satisfaction when using DT in the facility management system of a hospital building. Their study concluded that DT improves efficiency by 50% during university building maintenance and operation. Security can also be enhanced by using DT. (Gopinath et al. 2018) reported in their research that DT for smart buildings can enhance security by automatically notifying owners and locking doors if an intruder attempts unauthorized access.

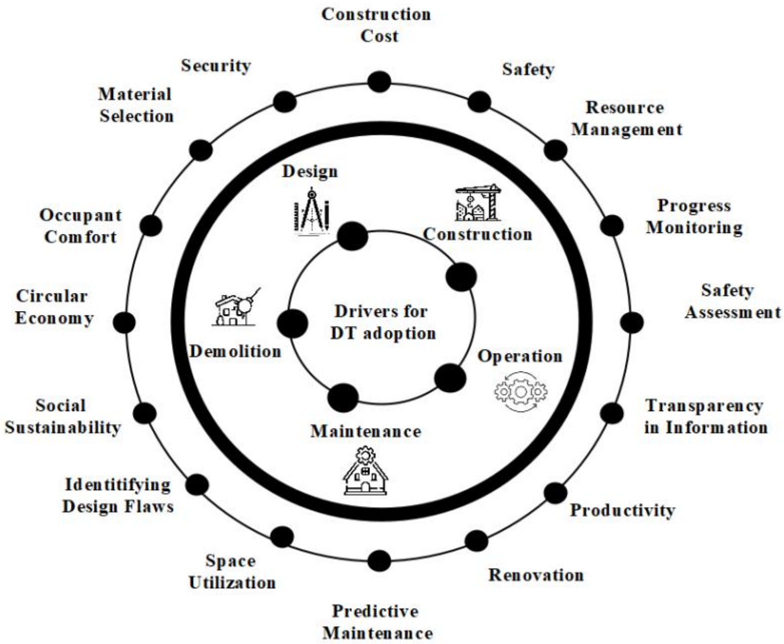

Figure 9: Drivers in the adoption of DT.

(Ghansah and Lu 2023) outlined DT's potential to create virtual environments of physical sites, providing on-site operators with guidance during work execution. Similarly, (Xu, Duo, and Tang 2022) introduced a framework for implementing DT in a radioactive waste repository (RWR), offering comprehensive 7D management capabilities.

5.2 Analyzing Challenges and Overcoming Barriers to Implementation

Although DT technology has a large number of applications in the building industry, many barriers hinder its widespread adoption. These barriers include high implementation costs, a lack of standardized data integration methods, a scarcity of skilled professionals, concerns about data security and privacy, and organizational resistance to change. Figure 10 represents the selected barriers to the adoption of DT in different phases.

Based on the research findings, several studies have identified various approaches to mitigate challenges hindering DT adoption in the building industry. (Tagliabue et al. 2021) suggested implementing data collection systems to address the challenge of evolving information needs throughout the lengthy process of creating a DT project. Their primary objective was to facilitate data mining for predictive maintenance, with a specific emphasis on energy efficiency. In their study, (Broo and Schooling 2023) introduced a technique aimed at overcoming technology adoption barriers by raising awareness among individuals both within and outside the organization about DT

CC BY

advantages. Additionally, it emphasizes the importance of identifying and aligning achievements through DT implementation, thereby facilitating a clearer understanding and acceptance of the technology.

(Paolo Pileggi 2021) in their position paper, discussed strategies to mitigate the nine barriers related to DT for manufacturing SMEs. These barriers are consistent with the external and internal barriers discussed in the findings section of our paper. To address these barriers, the paper proposes a mitigation process that begins with identifying the problems faced by stakeholders. Next, a joint system creates and innovates scenarios to solve these identified problems. The marketplace offers a range of solutions to support the transformation towards a DT, and careful selection is necessary. Additionally, it should be considered if new technology is required to overcome these barriers. Lastly, ensuring that the introduced framework is sustainable and facilitates a seamless transition is crucial.

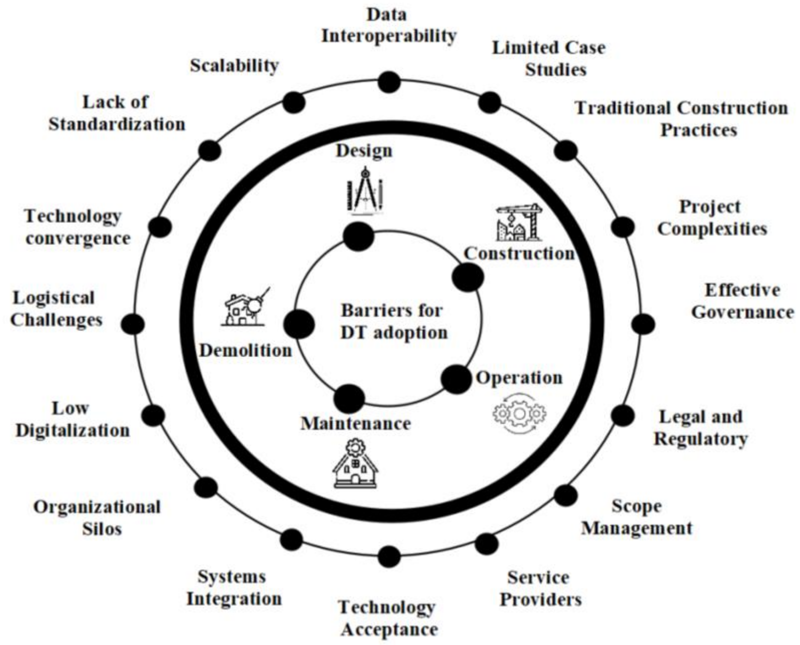

Figure 10: Barriers to the adoption of DT.

Similarly, for enhancing DT understanding and integration into the AECO industry, (Opoku et al. 2023) proposed organizing various workshops, science fairs, innovative forums, conferences, and seminars to educate stakeholders, top-level management, and clients on DT benefits. Furthermore, it was suggested by (Naderi and Shojaei 2022) that conducting interdisciplinary research across various knowledge domains is crucial for DT implementation. Additionally, they proposed that prominent journals should establish special issues focused on sustainability, encompassing the social, organizational, and economic dimensions of implementing DT.

5.3 BSIC: A new Approach Enabling Simulation Integration

During the process of introducing a DT for predictive simulation in the different phases of building development process, a frequent challenge is the lack of shared terminology, from the extraction of data to the simulation model integration phase. Consequently, this increases the likelihood of errors in the simulation model integration phase due to inaccurate or insufficient knowledge. To overcome the challenges of standardized storage and sharing simulation model information, we introduce the concept of a Building Simulation Identity Card (BSIC).

The core idea of BSIC is to develop a standard formal framework for characterizing specialized building simulators. This encompasses the creation of standardized building simulator ontologies and meta-models, along with standardized interfaces, frameworks, and algorithms for their integration in collaborative simulations. This would then enable users (i.e., design teams) to make informed choices about the combination of building simulators that they will integrate to answer specific questions about a building when conducting collaborative simulations.

CC BY

BSIC can be a potential solution for addressing the challenges of collaboration, coordination, cooperation, and communication among the various stakeholders involved in the creation of a DT simulation model. An effective strategy involves the design of a BSIC that can be shared among stakeholders. This BSIC would assign a distinct identifier to each DT simulation model (Angjeliu, Coronelli, and Cardani 2020). It would also encompass pertinent information pertaining to DT objectives, ownership, and data access authorizations. Through creating a BSIC, various stakeholders can readily recognize and establish lines of communication with one another. They can also seamlessly exchange data and foster efficient collaboration. This solution holds significant promise in resolving the challenges encountered in managing DT simulation models, ultimately leading to enhanced stakeholder engagement and more streamlined cooperation within the system. Figure 11 illustrates the importance of BSIC for collaborative simulations.

Let us discuss the concept of BSIC in light of the above-provided example of emergency evacuation of a building during an earthquake. In addressing occupant safety challenges in buildings, an engineer will be tasked with developing a comprehensive digital model for the target building. This model will then be meticulously validated. If any discrepancies or inaccuracies are discovered, they will be calibrated and reorganized accordingly. The engineer will use specific scenarios, such as densities and flows of dynamic occupant crowds during egress, and test them on various DT simulators. These simulators will undergo a thorough evaluation process to ensure they adequately address safety concerns. However, the lack of a common vocabulary for determining which simulator to use and for integrating different simulators poses a high risk of simulation model integration failure. To address this problem, the concept of BSIC will be employed. This decision is based on the simulator's underlying physics model, its interface, and its context.

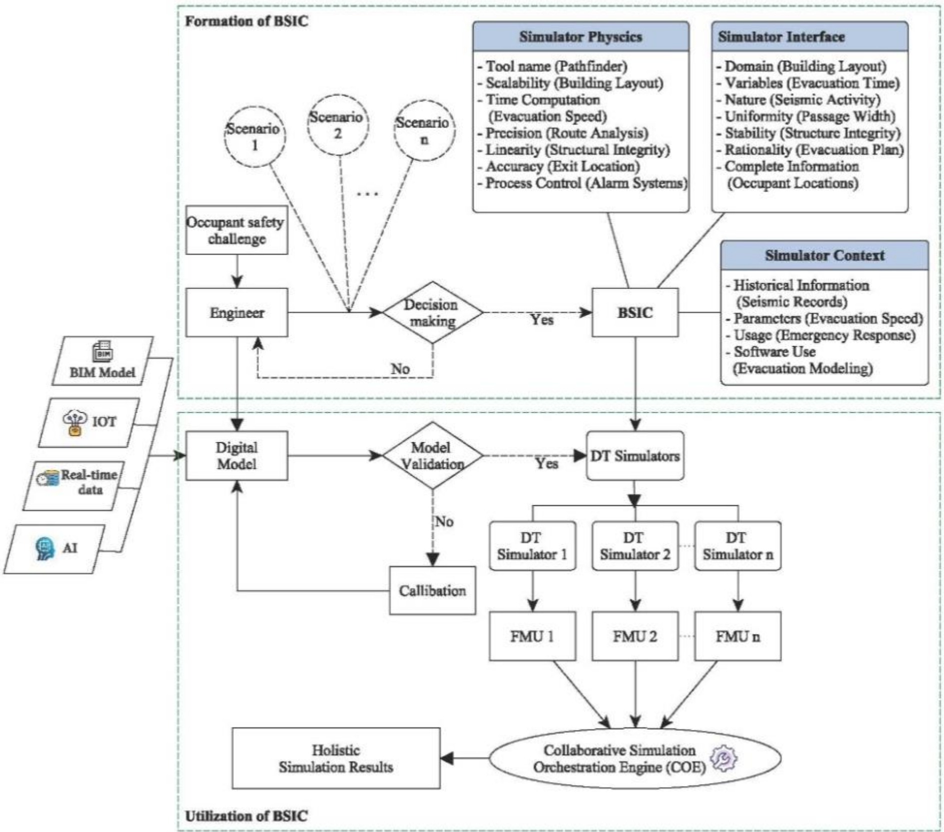

Figure 11: Process diagram for occupant safety concerns with the help of BSIC.

The characteristics of a simulation model's physics can be divided into several subcategories. These elements encompass features related to the model's description, such as its inception date and associated documentation. In this classification, a subset of attributes deals with the methodology used, which includes the chosen techniques, computational time considerations, and levels of precision. The usage segment involves exploring the tools used for developing the simulation model. This includes specific details about the tool's version and the model's

CC BY

scalability. Lastly, the validation and verification process evaluate critical factors like accuracy and process control, among others.

The simulator interface is crucial in facilitating communication between various components of the integrated model, whether that communication occurs within the model itself or between these components and the external environment (Halbach et al. 2010). The interface specification defines the simulation model's scope, including variables and pertinent attributes. Additionally, the simulation model's context includes historical data, distinct parameters, and usage, among other relevant considerations. This integrated approach ensures a cohesive and structured understanding of the simulation model.

BSIC is critical to determining the importance of each simulator in the context of a specific safety problem. The identified simulators through BSIC will then be converted into FMUs, which will be integrated and linked together in a so-called meta-model. A Co-sim Orchestration Engine (COE) finally executes a collaborative simulation using this meta-model. The outcome is a series of holistic simulation runs for analysing occupant safety challenges in building design.

6. CONCLUSIONS

This study presents a thorough analysis of DT integration in the building industry, identifying various internal organizational and external market-related drivers and barriers. A framework categorizes these factors across different building development phases—design, construction, operation, maintenance, and demolition. This approach provides a holistic view of DT adoption challenges and opportunities, facilitating more effective implementation of DT technologies throughout the building development process. In the following, we highlight the contribution based on the three key questions presented in the introduction:

In response to our first research question (RQ1), we have identified and thoroughly analyzed drivers to DT adoption in the building industry. These drivers include the increasing complexity of construction projects, advancements in technology, the demand for real-time monitoring, and the potential advantages in terms of cost reduction and sustainability. These drivers underscore the substantial benefits DT can offer in enhancing efficiency, sustainability, and security across the entire building development process.

In response to our second research question (RQ2), we have identified that adopting DT is associated with significant challenges. High implementation costs, issues related to data integration, a shortage of skilled professionals, concerns about data security, and resistance to organizational change all constitute significant barriers to DT adoption.

To address these challenges and answer our third research question (RQ3), we introduced the first concept for a Building Simulation Identity Card (BSIC) as a potential solution. This standardized framework facilitates collaboration, coordination, cooperation, and communication among stakeholders engaged in DT simulation models. BSIC aims to establish a shared platform for selecting and integrating various simulation models to enhance the effectiveness of DT simulations.

6.1 Limitations and Plan for Future Work

Because this study is based solely on the Scopus and Web of Science databases, some publications on factors affecting DT implementation in buildings may not have been included. Therefore, this research may not comprehensively represent all available literature on this topic. In addition, although significant publications were carefully selected, some specific keywords may have been overlooked in the literature search. This review considers the adoption of DT in the building industry from a global perspective. However, factors affecting DT adoption can vary significantly by region due to differences in regulations, industry standards, and technological infrastructure. The robustness of the findings depends on the quality and availability of the literature reviewed. The limitations of the individual studies included in this review may affect the scope and validity of the conclusions drawn.

The existing literature has inconsistencies and challenges when attempting to achieve optimal model accuracy and performance. This is because no clear criteria exist for selecting and integrating simulations into DT systems. Future research will focus on advancing BSIC as a transformative tool for the building industry. The goal will be to create a well-structured BSIC framework incorporating standardized ontologies, meta-models, and interfaces for characterizing simulators and their associated data. The BSIC framework will be thoroughly tested and refined through collaboration with building industry experts, software developers, and stakeholders to ensure its practicality and effectiveness. To implement BSIC, software ecosystems and technical challenges, i.e., interfaces and data integration protocols, need to be addressed to facilitate seamless communication and data exchange between specialized simulation models.

Future research can also consist of case studies and pilot projects in various scenarios to demonstrate the practicality of BSIC and identify areas for improvement. Similarly, there is a need to investigate the interrelated factors that impact DT adoption and formulate strategies to enhance its adoption. Additionally, there is a need to explore advanced simulation and modeling techniques that integrate physics-based and data-driven approaches to assess how these methods can improve the accuracy and efficiency of DT. This effort aims to create a more efficient and connected future for building simulations and DT.

REFERENCES

Afzal, M., M. T. Shafiq, and H. Al Jassmi. 2021. 'IMPROVING CONSTRUCTION SAFETY WITH VIRTUAL-DESIGN CONSTRUCTION TECHNOLOGIES - A REVIEW', Journal of Information Technology in Construction, 26: 319-40.

Akanmu, Abiola Abosede, Chimay J. Anumba, and Omobolanle O. Ogunseiju. 2021. 'Towards next generation cyber-physical systems and digital twins for construction', J. Inf. Technol. Constr., 26: 505-25.

Al-Raqeb, Hanan, Seyed Hamidreza Ghaffar, Mazen J. Al-Kheetan, and Mehdi Chougan. 2023. 'Understanding the challenges of construction demolition waste management towards circular construction: Kuwait Stakeholder's perspective', Cleaner Waste Systems, 4: 100075.

Al-Sehrawy, Ramy, and Bimal Kumar. 2021. "Digital twins in architecture, engineering, construction and operations. A brief review and analysis." In Proceedings of the 18th International Conference on Computing in Civil and Building Engineering: ICCCBE 2020, 924-39. Springer.

Alaloul, W. S., K. M. Alzubi, A. B. Malkawi, M. Al Salaheen, and M. A. Musarat. 2022. 'Productivity monitoring in building construction projects: a systematic review', Engineering, Construction and Architectural Management, 29: 2760-85.

Alaloul, W. S., A. H. Qureshi, M. A. Musarat, and S. Saad. 2021. 'Evolution of close-range detection and data acquisition technologies towards automation in construction progress monitoring', Journal of Building Engineering, 43.

Alanne, K., and S. Sierla. 2022. 'An overview of machine learning applications for smart buildings', Sustainable Cities and Society, 76.

Aleksandrova, E., V. Vinogradova, and G. Tokunova. 2019. 'Integration of digital technologies in the field of construction in the Russian Federation', Engineering Management in Production and Services, 11: 38-47.

Ali, A. K., and R. Badinelli. 2016. "Novel Integration of Sustainable and Construction Decisions into the Design Bid Build Project Delivery Method Using BPMN." In Procedia Engineering, 164-71.

Almatared, M., H. Liu, S. Tang, M. Sulaiman, Z. Lei, and H. X. Li. 2022. "Digital Twin in the Architecture, Engineering, and Construction Industry: A Bibliometric Review." In Construction Research Congress 2022: Computer Applications, Automation, and Data Analytics - Selected Papers from Construction Research Congress 2022, 670-78.

Almusaed, A., and I. Yitmen. 2023. 'Architectural Reply for Smart Building Design Concepts Based on Artificial Intelligence Simulation Models and Digital Twins', Sustainability (Switzerland), 15.

Alshammari, Kaznah, Thomas Beach, and Yacine Rezgui. 2021. 'Cybersecurity for digital twins in the built environment: current research and future directions', Journal of Information Technology in Construction, 26: 159-73.

Ammar, A., H. Nassereddine, N. AbdulBaky, A. AbouKansour, J. Tannoury, H. Urban, and C. Schranz. 2022a. 'Digital Twins in the Construction Industry: A Perspective of Practitioners and Building Authority', Frontiers in Built Environment, 8.

Ammar, Ashtarout, Hala Nassereddine, Nadine AbdulBaky, Anwar AbouKansour, Juliano Tannoury, Harald Urban, and Christian Schranz. 2022b. "Digital Twins in the Construction Industry: A Perspective of Practitioners and Building Authority." In Frontiers in Built Environment.

Angjeliu, Grigor, Dario Coronelli, and Giuliana Cardani. 2020. 'Development of the simulation model for Digital Twin applications in historical masonry buildings: The integration between numerical and experimental reality', Computers & Structures, 238: 106282.

Antonino, M., M. Nicola, D. M. Claudio, B. Luciano, and R. C. Fulvio. 2019. 'Office building occupancy monitoring through image recognition sensors', International Journal of Safety and Security Engineering, 9: 371-80.

Aribisala, O. D., S. G. Yum, M. D. Adhikari, and M. S. Song. 2022. 'Flood Damage Assessment: A Review of Microscale Methodologies for Residential Buildings', Sustainability (Switzerland), 14.

Ariyachandra, M. R. M. F., A. Samarakkody, and B. A. K. S. Perera. 2019. "Real-virtual synchronisation: A review on the state-of-the-art geometric digital twinning of infrastructure." In World Construction Symposium, 502-12.

Arsiwala, A., F. Elghaish, and M. Zoher. 2023. 'Digital twin with Machine learning for predictive monitoring of CO2 equivalent from existing buildings', Energy and Buildings, 284.

Attaran, Mohsen. 2017. 'The internet of things: Limitless opportunities for business and society', Journal of Strategic Innovation and Sustainability Vol, 12: 11.

Attaran, Mohsen, and Bilge Gokhan Celik. 2023. 'Digital Twin: Benefits, use cases, challenges, and opportunities', Decision Analytics Journal: 100165.

Azimi, S., and W. O'Brien. 2022. 'Fit-for-purpose: Measuring occupancy to support commercial building operations: A review', Building and Environment, 212.

Baduge, S. K., S. Thilakarathna, J. S. Perera, M. Arashpour, P. Sharafi, B. Teodosio, A. Shringi, and P. Mendis. 2022. 'Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications', Automation in Construction, 141.

Bambara, Joseph J, and Paul R Allen. 2018. 'Blockchain', A practical guide to developing business, law and technology solutions. New York City: McGraw-Hill Professional.

Banfi, F., R. Brumana, G. Salvalai, and M. Previtali. 2022. 'Digital Twin and Cloud BIM-XR Platform Development: From Scan-to-BIM-to-DT Process to a 4D Multi-User Live App to Improve Building Comfort, Efficiency and Costs', Energies, 15.

Barkokebas, B., M. Al-Hussein, and F. Hamzeh. 2023. 'Assessment of Digital Twins to Reassign Multiskilled Workers in Offsite Construction Based on Lean Thinking', Journal of Construction Engineering and Management, 149.

Belaroussi, R., H. Y. Dai, E. D. Gonzalez, and J. M. Gutierrez. 2023. 'Designing a Large-Scale Immersive Visit in Architecture, Engineering, and Construction', Applied Sciences-Basel, 13.

Bello, S. A., L. O. Oyedele, O. O. Akinade, M. Bilal, J. M. D. Delgado, L. A. Akanbi, A. O. Ajayi, and H. A. Owolabi. 2021. 'Cloud computing in construction industry: Use cases, benefits and challenges', Automation in Construction, 122.

Blattnig, Steve, Lawrence Green, James Luckring, Joseph Morrison, Ram Tripathi, and Thomas Zang. 2008. "Towards a credibility assessment of models and simulations." In 49th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, 16th AIAA/ASME/AHS Adaptive Structures Conference, 10th AIAA Non-Deterministic Approaches Conference, 9th AIAA Gossamer Spacecraft Forum, 4th AIAA Multidisciplinary Design Optimization Specialists Conference, 2156.

Bohner, E., T. Vehmas, A. Laikari, M. Okkonen, M. Kiviniemi, P. Lahdenpera, and M. Ferreira. 2019. "Digitalisation of the quality control of concrete manufacturing and construction." In fib Symposium, 1435-42.

Boje, C., A. Guerriero, S. Kubicki, and Y. Rezgui. 2020. 'Towards a semantic Construction Digital Twin: Directions for future research', Automation in Construction, 114.

Bolton, Alexandra, Lorraine Butler, Ian Dabson, Mark Enzer, Matthew Evans, Tim Fenemore, Fergus Harradence, Emily Keaney, Anne Kemp, and Alexandra Luck. 2018. 'Gemini principles'.

Bortolini, R., R. Rodrigues, H. Alavi, L. F. D. Vecchia, and N. Forcada. 2022. 'Digital Twins' Applications for Building Energy Efficiency: A Review', Energies, 15.

Botín-Sanabria, Diego M., Adriana-Simona Mihaita, Rodrigo E. Peimbert-García, Mauricio A. Ramírez-Moreno, Ricardo A. Ramírez-Mendoza, and Jorge de J. Lozoya-Santos. 2022. 'Digital Twin Technology Challenges and Applications: A Comprehensive Review', Remote Sensing, 14: 1335.

Boyes, Hugh, and Tim Watson. 2022. 'Digital twins: An analysis framework and open issues', Computers in Industry, 143: 103763.

Broo, D. G., and J. Schooling. 2020. "Towards data-centric decision making for smart infrastructure: Data and its challenges." In IFAC-PapersOnLine, 90-94.

Broo, D. G., and J. Schooling. 2023. 'Digital twins in infrastructure: definitions, current practices, challenges and strategies', International Journal of Construction Management, 23: 1254-63.

BuildingSMART. 'buildingSMART International'. https://www.buildingsmart.org/.

Bujari, A., A. Calvio, L. Foschini, A. Sabbioni, and A. Corradi. 2021. "IPPODAMO: A digital twin support for smart cities facility management." In GoodIT 2021 - Proceedings of the 2021 Conference on Information Technology for Social Good, 49-54.

Camposano, J. C., K. Smolander, and T. Ruippo. 2021. 'Seven Metaphors to Understand Digital Twins of Built Assets', IEEE Access, 9: 27167-81.

Catapult, High Value Manufacturing. 2018. "Feasibility of an immersive digital twin: The definition of a digital twin and discussions around the benefit of immersion." In UK: HVM Catapult Visualisation and VR Forum.

Clausen, A., K. Arendt, A. Johansen, F. C. Sangogboye, M. B. Kjærgaard, C. T. Veje, and B. N. Jørgensen. 2021. 'A digital twin framework for improving energy efficiency and occupant comfort in public and commercial buildings', Energy Informatics, 4.

Cogswell, D., C. Paramatmuni, L. Scotti, and J. Moffat. 2022. 'Guidance for Materials 4.0 to interact with a digital twin', Data-Centric Engineering, 3.

Ćosović, M., and M. Maksimović. 2022. "Application of the digital twin concept in cultural heritage." In CEUR Workshop Proceedings.

Daniotti, B., G. Masera, C. M. Bolognesi, S. L. Spagnolo, A. Pavan, G. Iannaccone, M. Signorini, S. Ciuffreda, C. Mirarchi, M. Lucky, and M. Cucuzza. 2022. 'The Development of a BIM-Based Interoperable Toolkit for Efficient Renovation in Buildings: From BIM to Digital Twin', Buildings, 12.

Datta, Shoumen Palit Austin. 2016. 'Emergence of digital twins', arXiv preprint arXiv:1610.06467.

Deng, M., C. C. Menassa, and V. R. Kamat. 2021. 'From Bim to Digital Twins: A Systematic Review of the Evolution of Intelligent Building Representations in the Aec-Fm Industry', Journal of Information Technology in Construction, 26: 58-83.

Digital, GE. 2017. 'Digital twins: The bridge between industrial assets and the digital world'.

Drobnyi, V., Z. Hu, Y. Fathy, and I. Brilakis. 2023. 'Construction and Maintenance of Building Geometric Digital Twins: State of the Art Review', Sensors, 23.

Duch-zebrowska, P., and K. Zielonko-jung. 2021. 'Integrating digital twin technology into large panel system estates retrofit projects', Urban Planning, 6: 164-71.

Eastman, Charles M, Chuck Eastman, Paul Teicholz, Rafael Sacks, and Kathleen Liston. 2011. BIM handbook: A guide to building information modeling for owners, managers, designers, engineers and contractors (John Wiley & Sons).

Ebert, Christof, and Carlos Henrique C Duarte. 2018. 'Digital transformation', IEEE Softw., 35: 16-21.

Erikstad, Stein Ove. 2017. 'Merging physics, big data analytics and simulation for the next-generation digital twins', High-Performance Marine Vehicles: 141-51.

Evangelou, T., M. Gkeli, and C. Potsiou. 2022. "Building Digital Twins for Smart Cities: A Case Study in Greece." In ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 61-68.

Fotland, Gaute, Cecilia Haskins, and Terje Rølvåg. 2020. 'Trade study to select best alternative for cable and pulley simulation for cranes on offshore vessels', Systems Engineering, 23: 177-88.

Fowler, Martin. 2010. Domain-specific languages (Pearson Education).

Fuller, Aidan, Zhong Fan, Charles Day, and Chris Barlow. 2020. 'Digital twin: Enabling technologies, challenges and open research', IEEE Access, 8: 108952-71.

Ghansah, F. A., and W. Lu. 2023. 'Major opportunities of digital twins for smart buildings: a scientometric and content analysis', Smart and Sustainable Built Environment.

Ghobakhloo, M. 2020. 'Industry 4.0, digitization, and opportunities for sustainability', Journal of cleaner production, 252: 119869.

Glaessgen, Edward, and David Stargel. 2012. "The digital twin paradigm for future NASA and US Air Force vehicles." In 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, 1818.

Gomes, Cláudio, Torsten Blochwitz, Christian Bertsch, Karl Wernersson, Klaus Schuch, R Pierre, Oliver Kotte, Irina Zacharias, Matthias Blesken, and Torsten Sommer. 2021. "The fmi 3.0 standard interface for clocked and scheduled simulations." In Modelica Conferences, 27-36.

Gopinath, V., A. Srija, C. N. Sravanthi, and Iop. 2018. "Re-design of smart homes with digital twins." In International Conference on Computer Vision and Machine Learning (ICCVML). Sir C R Reddy Coll Engn, Eluru, INDIA.

Greif, Toni, Nikolai Stein, and Christoph M. Flath. 2020. 'Peeking into the void: Digital twins for construction site logistics', Computers in Industry, 121: 103264.

Grieves, Michael, and John Vickers. 2017. 'Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems', Transdisciplinary perspectives on complex systems: New findings and approaches: 85-113.

Guo, C., X. Xu, J. Hu, J. Zhang, and Z. Zhou. 2022. "Intelligent Design and Construction Coordination of Nuclear Power Based on Digital Twin." In Advances in Transdisciplinary Engineering, 144-53.

Gusenbauer, M., and N. R. Haddaway. 2020. 'Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources', Research synthesis methods, 11: 181-217.

Halbach, Shane, Phillip Sharer, Sylvain Pagerit, Aymeric P Rousseau, and Charles Folkerts. 2010. "Model architecture, methods, and interfaces for efficient math-based design and simulation of automotive control systems." In.: SAE Technical paper.

Hansen, Simon Thrane, Casper Thule, Cláudio Gomes, Kenneth Guldbrandt Lausdahl, Frederik Palludan Madsen, Giuseppe Abbiati, and Peter Gorm Larsen. 2024. 'Co-simulation at different levels of expertise with Maestro2', Journal of Systems and Software, 209: 111905.

Harode, A., W. Thabet, and P. Dongre. 2023. 'A TOOL-BASED SYSTEM ARCHITECTURE FOR A DIGITAL TWIN: A CASE STUDY IN A HEALTHCARE FACILITY', Journal of Information Technology in Construction, 28: 107-37.

Hasan, H. R., K. Salah, R. Jayaraman, M. Omar, I. Yaqoob, S. Pesic, T. Taylor, and D. Boscovic. 2020. 'A Blockchain-Based Approach for the Creation of Digital Twins', IEEE Access, 8: 34113-26.

Haupt, T. C., M. Akinlolu, and M. T. Raliile. 2019. "Applications of digital technologies for health and safety management in construction." In World Construction Symposium, 88-97.

Henzel, J., Ł Wróbel, M. Fice, and M. Sikora. 2022. 'Energy Consumption Forecasting for the Digital-Twin Model of the Building', Energies, 15.

Hermann, Mario, Tobias Pentek, and Boris Otto. 2016. "Design principles for industrie 4.0 scenarios." In 2016 49th Hawaii international conference on system sciences (HICSS), 3928-37. IEEE.

Hoeft, Madeleine, and Catherine Trask. 2022. 'Safety Built Right in: Exploring the Occupational Health and Safety Potential of BIM-Based Platforms throughout the Building Lifecycle', Sustainability, 14: 6104.

Hosamo, H. H., A. Imran, J. Cardenas-Cartagena, P. R. Svennevig, K. Svidt, and H. K. Nielsen. 2022. 'A Review of the Digital Twin Technology in the AEC-FM Industry', Advances in Civil Engineering, 2022.

Hosamo, H. H., H. K. Nielsen, A. N. Alnmr, P. R. Svennevig, and K. Svidt. 2022. 'A review of the Digital Twin technology for fault detection in buildings', Frontiers in Built Environment, 8.

Hosamo, H. H., H. K. Nielsen, D. Kraniotis, P. R. Svennevig, and K. Svidt. 2023. 'Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method', Energy and Buildings, 288.

ISO_29481-1. 2016. "Building Information Models–Information Delivery Manual–Part 1: Methodology and Format." In.: International Organization for Standardization.

Jacobellis, M., and M. Ilbeigi. 2022. "Digital Twin Cities: Data Availability and Systematic Data Collection." In Construction Research Congress 2022: Infrastructure Sustainability and Resilience - Selected Papers from Construction Research Congress 2022, 437-44.

Jiang, F., L. Ma, T. Broyd, and K. Chen. 2021. 'Digital twin and its implementations in the civil engineering sector', Automation in Construction, 130: 103838.

Jiang, Y., M. Li, W. Wu, X. Wu, X. Zhang, X. Huang, R. Y. Zhong, and G. G. Q. Huang. 2023. 'Multi-domain ubiquitous digital twin model for information management of complex infrastructure systems', Advanced Engineering Informatics, 56.

Jin, R., K. Panuwatwanich, Z. Adamu, U. Madanayake, and O. J. Ebohon. 2021. "Developing a methodological framework for adopting digitalization for deconstruction planning." In AIP Conference Proceedings, edited by T. Q. Nguyen, E. C. W. Lou, P. H. Chen, Q. Phung and K. S. Park. American Institute of Physics Inc.

Jung, Nusrat, Tarja Häkkinen, and Mirkka Rekola. 2018. 'Extending capabilities of BIM to support performance based design', J. Inf. Technol. Constr., 23: 16-52.

Kaewunruen, S., P. Rungskunroch, and J. Welsh. 2019. 'A digital-twin evaluation of Net Zero Energy Building for existing buildings', Sustainability (Switzerland), 11.

Kaewunruen, S., and N. Xu. 2018. 'Digital twin for sustainability evaluation of railway station buildings', Frontiers in Built Environment, 4.

Kang, K., S. Besklubova, Y. Dai, and R. Y. Zhong. 2022. 'Building demolition waste management through smart BIM: A case study in Hong Kong', Waste Management, 143: 69-83.

Kaware, Sudhir Sudam, and Sunil Kumar Sain. 2015. 'ICT application in education: an overview', International Journal of Multidisciplinary Approach & Studies, 2: 25-32.

Khajavi, S. H., N. H. Motlagh, A. Jaribion, L. C. Werner, and J. Holmstrom. 2019. 'Digital Twin: Vision, benefits, boundaries, and creation for buildings', IEEE Access, 7: 147406-19.

Khallaf, R., L. Khallaf, C. J. Anumba, and O. C. Madubuike. 2022a. 'Review of Digital Twins for Constructed Facilities', Buildings, 12.

Khallaf, Rana, Lama Khallaf, Chimay J. Anumba, and Obinna C. Madubuike. 2022b. 'Review of Digital Twins for Constructed Facilities', Buildings, 12: 2029.

Kim, Z., and R. Nevatia. 2004. 'Automatic description of complex buildings from multiple images', Computer Vision and Image Understanding, 96: 60-95.

Kineber, A. F., A. K. Singh, A. Fazeli, S. R. Mohandes, C. Cheung, M. Arashpour, O. Ejohwomu, and T. Zayed. 2023. 'Modelling the relationship between digital twins implementation barriers and sustainability pillars: Insights from building and construction sector', Sustainable Cities and Society, 99.

Knapp, G. L., T. Mukherjee, J. S. Zuback, H. L. Wei, T. A. Palmer, A. De, and T. DebRoy. 2017. 'Building blocks for a digital twin of additive manufacturing', Acta Materialia, 135: 390-99.

Kor, M., I. Yitmen, and S. Alizadehsalehi. 2023. 'An investigation for integration of deep learning and digital twins towards Construction 4.0', Smart and Sustainable Built Environment, 12: 461-87.

Kritzinger, W., M. Karner, G. Traar, J. Henjes, and W. Sihn. 2018. 'Digital Twin in manufacturing: A categorical literature review and classification', Ifac Papersonline, 51: 1016-22.

Kugley, Shannon, Anne Wade, James Thomas, Quenby Mahood, Anne-Marie Klint Jørgensen, Karianne Hammerstrøm, and Nila Sathe. 2016. 'Searching for studies: A guide to information retrieval for Campbell', Campbell Systematic Reviews.

'Lack of Vision, Organizational Silos Challenge Strategy for Industry 4.0'. 2020. deloitte. https://deloitte.wsj.com/articles/lack-of-vision-organizational-silos-challenge-strategy-for-industry-4-0-01548640934.

Ladj, A., Z. Q. Wang, O. Meski, F. Belkadi, M. Ritou, and C. Da Cunha. 2021. 'A knowledge-based Digital Shadow for machining industry in a Digital Twin perspective', Journal of Manufacturing Systems, 58: 168-79.

Larsen, Peter Gorm, Casper Thule, Kenneth Lausdahl, Victor Bandur, Carl Gamble, Etienne Brosse, Andrey Sadovykh, Alessandra Bagnato, and L Couto. 2016. "Integrated tool chain for model-based design of cyber-physical systems." In The 14th Overture Workshop: Towards Analytical Tool Chains, 63-79. Aarhus University, Department of Engineering.

Levine, N. M., and B. F. Spencer. 2022. 'Post-Earthquake Building Evaluation Using UAVs: A BIM-Based Digital Twin Framework', Sensors, 22.

Li, Mingchao, Qiaorong Lu, Shuo Bai, Mengxi Zhang, Huijing Tian, and Liang Qin. 2021. 'Digital twin-driven virtual sensor approach for safe construction operations of trailing suction hopper dredger', Automation in Construction, 132: 103961.

Li, S. C., L. D. Xu, and S. S. Zhao. 2015. 'The internet of things: a survey', Information systems frontiers, 17: 243-59.

Liu, H. X., S. Han, and Z. H. Zhu. 2023. 'Blockchain Technology toward Smart Construction: Review and Future Directions', Journal of Construction Engineering and Management, 149.

Liu, J. F., H. G. Zhou, X. J. Liu, G. Z. Tian, M. F. Wu, L. P. Cao, and W. Wang. 2019. 'Dynamic Evaluation Method of Machining Process Planning Based on Digital Twin', IEEE Access, 7: 19312-23.

Liu, M. N., S. L. Fang, H. Y. Dong, and C. Z. Xu. 2021. 'Review of digital twin about concepts, technologies, and industrial applications', Journal of Manufacturing Systems, 58: 346-61.

Lu, Q. C., X. Xie, J. Heaton, A. K. Parlikad, and J. Schooling. 2020. 'From BIM Towards Digital Twin: Strategy and Future Development for Smart Asset Management', Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future, 853: 392-404.

Lu, Q. C., X. Xie, A. K. Parlikad, and J. M. Schooling. 2020. 'Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance', Automation in Construction, 118.

Lu, Q., L. Chen, S. Li, and M. Pitt. 2020. 'Semi-automatic geometric digital twinning for existing buildings based on images and CAD drawings', Automation in Construction, 115.

Lu, Q., X. Xie, A. K. Parlikad, J. M. Schooling, and E. Konstantinou. 2020. 'Moving from building information models to digital twins for operation and maintenance', Proceedings of the Institution of Civil Engineers: Smart Infrastructure and Construction, 174: 46-56.

Lu, Qiuchen, Ajith Kumar Parlikad, Philip Woodall, Gishan Don Ranasinghe, Xiang Xie, Zhenglin Liang, Eirini Konstantinou, James Heaton, and Jennifer Schooling. 2020. 'Developing a digital twin at building and city levels: Case study of West Cambridge campus', Journal of Management in Engineering, 36: 05020004.

Lu, Qiuchen, Xiang Xie, Ajith Kumar Parlikad, Jennifer Schooling, and Michael Pitt. 2022. Digital twins in the built environment: Fundamentals, principles and applications (ICE Publishing).

Lünnemann, Pascal, Kai Lindow, and Leo Goßlau. 2023. 'Implementing digital twins in existing infrastructures', Forschung im Ingenieurwesen, 87: 421-29.

cc BY

Madakam, Somayya, Vihar Lake, Vihar Lake, and Vihar Lake. 2015. 'Internet of Things (IoT): A literature review', Journal of Computer and Communications, 3: 164.

Madni, AM, C Madni, and SD Lucero. 2019. 'Leveraging digital twin technology in model-based systems engineering. Systems 7 (1): 7', Article-Number, 7.

Mavrokapnidis, D., K. Katsigarakis, P. Pauwels, E. Petrova, I. Korolija, D. Rovas, and Acm. 2021. "A linked-data paradigm for the integration of static and dynamic building data in Digital Twins." In ACM International Conference on Systems for Energy-Efficient Built Environments (BuildSys), 369-72. Coimbra, PORTUGAL.

Meng, Xianhai, Simran Das, and Junyu Meng. 2023. 'Integration of Digital Twin and Circular Economy in the Construction Industry', Sustainability, 15: 13186.

Meža, Sebastjan, Alenka Mauko Pranjić, Rok Vezočnik, Igor Osmokrović, and Stanislav Lenart. 2021. 'Digital Twins and Road Construction Using Secondary Raw Materials', Journal of Advanced Transportation, 2021: 8833058.

Moher, D., A. Liberati, J. Tetzlaff, D. G. Altman, and Prisma Group. 2010. 'Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement', Int J Surg, 8: 336-41.

Naderi, H., and A. Shojaei. 2022. 'Civil Infrastructure Digital Twins: Multi-Level Knowledge Map, Research Gaps, and Future Directions', IEEE Access, 10: 122022-37.

Naderi, H., and A. Shojaei. 2023. 'Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects', Automation in Construction, 149: 104785.

Napp, N. 2022. "Digital Twins in the Real World." In Proceedings - 2022 IEEE 2nd International Conference on Intelligent Reality, ICIR 2022, 17-20.

Nees Jan van Eck, Ludo Waltman. 2019. "VOSviewer Manual." In.

Neto, Anis Assad, Fernando Deschamps, Elias Ribeiro da Silva, and Edson Pinheiro de Lima. 2020. 'Digital twins in manufacturing: an assessment of drivers, enablers and barriers to implementation', Procedia CIRP, 93: 210-15.

Newaz, M. T., M. Ershadi, L. Carothers, M. Jefferies, and P. Davis. 2022. 'A review and assessment of technologies for addressing the risk of falling from height on construction sites', Safety Science, 147.

Ni, Z., Y. Liu, M. Karlsson, and S. Gong. 2022. 'Enabling Preventive Conservation of Historic Buildings Through Cloud-Based Digital Twins: A Case Study in the City Theatre, Norrköping', IEEE Access, 10: 90924-39.

Niu, Y., W. Lu, K. Chen, G. G. Huang, and C. Anumba. 2016. 'Smart construction objects', Journal of Computing in Civil Engineering, 30.

Oliveira, P. P. 2020. 'Digital twin development for airport management', Journal of Airport Management, 14: 246-59.

Opoku, D. G. J., S. Perera, R. Osei-Kyei, and M. Rashidi. 2021. 'Digital twin application in the construction industry: A literature review', Journal of Building Engineering, 40.

Opoku, D. G. J., S. Perera, R. Osei-Kyei, M. Rashidi, K. Bamdad, and T. Famakinwa. 2023. 'Barriers to the Adoption of Digital Twin in the Construction Industry: A Literature Review', Informatics, 10.

Opoku, De-Graft Joe, Srinath Perera, Robert Osei-Kyei, Maria Rashidi, Tosin Famakinwa, and Keivan Bamdad. 2022. 'Drivers for Digital Twin Adoption in the Construction Industry: A Systematic Literature Review', Buildings, 12: 113.

Osadcha, I., A. Jurelionis, and P. Fokaides. 2023. 'Geometric parameter updating in digital twin of built assets: A systematic literature review', Journal of Building Engineering, 73.

Ozturk, G. B. 2021. 'Digital Twin Research in the AECO-FM Industry', Journal of Building Engineering, 40.

Pan, Y., and L. M. Zhang. 2023. 'Integrating BIM and AI for Smart Construction Management: Current Status and Future Directions', Archives of Computational Methods in Engineering, 30: 1081-110.

Panetta, Kasey. 2017. 'Top Trends in the Gartner Hype Cycle for Emerging Technologies,'. https://www.gartner.com/smarterwithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017.

Panetta, Kasey. 2018. '5 Trends Emerge in the Gartner Hype Cycle for Emerging Technologies, 2018'. https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018.

Paolo Pileggi, Armir Bujari, Oliver Barrowclough,Jochen Haenisch, Robert Woitsch,. 2021. 'Overcoming Digital Twin barriers for manufacturing SMEs'.

Park, J. S., D. G. Lee, J. A. Jimenez, S. J. Lee, and J. W. Kim. 2023. 'Human-Focused Digital Twin Applications for Occupational Safety and Health in Workplaces: A Brief Survey and Research Directions', Applied Sciences (Switzerland), 13.

Parusheva, S., and Y. Aleksandrova. 2021. "Technologies, tools, and resources - Driving forces in construction sector digitalization." In Proceedings - 2021 IEEE 10th International Conference on Intelligent Computing and Information Systems, ICICIS 2021, 219-23.

Peng, Y., M. Zhang, F. Yu, J. Xu, and S. Gao. 2020. 'Digital Twin Hospital Buildings: An Exemplary Case Study through Continuous Lifecycle Integration', Advances in Civil Engineering, 2020.

Petri, Ioan, Yacine Rezgui, Ali Ghoroghi, and Ateyah Alzahrani. 2023. 'Digital twins for performance management in the built environment', Journal of Industrial Information Integration, 33: 100445.

Pires, F., A. Cachada, J. Barbosa, A. P. Moreira, and P. Leitão. 2019. "Digital Twin in Industry 4.0: Technologies, Applications and Challenges." In 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), 721-26.

Pishdad-Bozorgi, P., X. H. Gao, C. Eastman, and A. P. Self. 2018. 'Planning and developing facility management-enabled building information model (FM-enabled BIM)', Automation in Construction, 87: 22-38.

Qian, C., X. Liu, C. Ripley, M. A. Qian, F. Liang, and W. Yu. 2022. 'Digital Twin-Cyber Replica of Physical Things: Architecture, Applications and Future Research Directions', Future Internet, 14: 64.

Rafsanjani, H. N., and A. H. Nabizadeh. 2023. 'Towards digital architecture, engineering, and construction (AEC) industry through virtual design and construction (VDC) and digital twin', Energy and Built Environment, 4: 169-78.

Ram, Jiwat, Numan Khan Afridi, and Khawar Ahmed Khan. 2019. 'Adoption of Big Data analytics in construction: development of a conceptual model', Built Environment Project and Asset Management, 9: 564-79.

Ravi, Srivathsan, Laura Beermann, Oliver Kotte, Paolo Pazzaglia, Mythreya Vinnakota, Dirk Ziegenbein, and Arne Hamann. 2023. "Timing-Aware Software-in-the-Loop Simulation of Automotive Applications with FMI 3.0." In 2023 ACM/IEEE 26th International Conference on Model Driven Engineering Languages and Systems (MODELS), 62-72. IEEE.

Rojas-Mercedes, N., K. Erazo, and L. Di Sarno. 2022. 'Seismic fragility curves for a concrete bridge using structural health monitoring and digital twins', Earthquake and Structures, 22: 503-15.

Sacks, Rafael, Mark Girolami, and Ioannis Brilakis. 2020. 'Building Information Modelling, Artificial Intelligence and Construction Tech', Developments in the Built Environment, 4: 100011.

Sagiroglu, Seref, and Duygu Sinanc. 2013. "Big data: A review." In 2013 international conference on collaboration technologies and systems (CTS), 42-47. IEEE.

Sajjad, M., and Z. Pan. 2019. "Analysis of key factors causing delay in green buildings: An empirical study in China." In 2nd International Conference in Sustainable Buildings & Structures (ICSBS), 256-62. Xian Jiaotong Liverpool Univ, Suzhou, PEOPLES R CHINA.

Salem, Tareq, and Mihai Dragomir. 2022. 'Options for and Challenges of Employing Digital Twins in Construction Management', Applied Sciences, 12: 2928.

Samanta, S., A. Sarkar, and Y. Bulo. 2022. "Secure Smart City Infrastructure Using Digital Twin and Blockchain." In Lecture Notes in Networks and Systems, 367-75.

Santos, R., A. A. Costa, and A. Grilo. 2017. 'Bibliometric analysis and review of Building Information Modelling literature published between 2005 and 2015', Automation in Construction, 80: 118-36.

Schroeder, Greyce N., Charles Steinmetz, Carlos E. Pereira, and Danubia B. Espindola. 2016. 'Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange', IFAC-PapersOnLine, 49: 12-17.

Schwan, Torsten, René Unger, and Jörg Pipiorke. 2017. "Aspects of FMI in Building Simulation." In Modelica, 132:007.

Seo, H., and W. S. Yun. 2022. 'Digital Twin-Based Assessment Framework for Energy Savings in University Classroom Lighting', Buildings, 12.

Sepasgozar, S. M. E. 2021. 'Differentiating Digital Twin from Digital Shadow: Elucidating a Paradigm Shift to Expedite a Smart, Sustainable Built Environment', Buildings, 11: 151.

Sepasgozar, S. M. E., F. K. P. Hui, S. Shirowzhan, M. Foroozanfar, L. Yang, and L. Aye. 2021. 'Lean practices using building information modeling (Bim) and digital twinning for sustainable construction', Sustainability (Switzerland), 13: 1-22.

Shahzad, M., M. T. Shafiq, D. Douglas, and M. Kassem. 2022. 'Digital Twins in Built Environments: An Investigation of the Characteristics, Applications, and Challenges', Buildings, 12.

Shishehgarkhaneh, M. B., A. Keivani, R. C. Moehler, N. Jelodari, and S. R. Laleh. 2022. 'Internet of Things (IoT), Building Information Modeling (BIM), and Digital Twin (DT) in Construction Industry: A Review, Bibliometric, and Network Analysis', Buildings, 12.

Sirin, G., C. J. J. Paredis, B. Yannou, E. Coatanéa, and E. Landel. 2015. 'A Model Identity Card to Support Simulation Model Development Process in a Collaborative Multidisciplinary Design Environment', IEEE Systems Journal, 9: 1151-62.

Smith, P. 2014. 'BIM implementation - global strategies', Creative Construction Conference 2014, 85: 482-92.

Spudys, P., N. Afxentiou, P. Z. Georgali, E. Klumbyte, A. Jurelionis, and P. Fokaides. 2023. 'Classifying the operational energy performance of buildings with the use of digital twins', Energy and Buildings, 290.

Su, S., Y. Jiang, C. Yu, and R. Y. Zhong. 2023. "Digital Twin-Enabled Building Demolition Waste Trading Workflow." In IEEE International Conference on Automation Science and Engineering. IEEE Computer Society.

Su, Shuaiming, Chenglin Yu, Yishuo Jiang, Kai Kang, and Ray Y. Zhong. 2023. 'Trading building demolition waste via digital twins', Automation in Construction, 156: 105105.

Su, Shuaiming, Ray Y. Zhong, Yishuo Jiang, Jidong Song, Yang Fu, and Hongrui Cao. 2023. 'Digital twin and its potential applications in construction industry: State-of-art review and a conceptual framework', Advanced Engineering Informatics, 57: 102030.

Söderberg, Rikard, Kristina Wärmefjord, Johan S. Carlson, and Lars Lindkvist. 2017. 'Toward a Digital Twin for real-time geometry assurance in individualized production', CIRP Annals, 66: 137-40.

Tagliabue, L. C., F. R. Cecconi, S. Maltese, S. Rinaldi, A. L. C. Ciribini, and A. Flammini. 2021. 'Leveraging Digital Twin for Sustainability Assessment of an Educational Building', Sustainability, 13.

Tao, F., J. F. Cheng, Q. L. Qi, M. Zhang, H. Zhang, and F. Y. Sui. 2018. 'Digital twin-driven product design, manufacturing and service with big data', International Journal of Advanced Manufacturing Technology, 94: 3563-76.

Teizer, J, KW Johansen, and C Schultz. 2022. "The concept of digital twin for construction safety." In Construction Research Congress 2022, 1156-65.

Torrecilla-García, J. A., M. C. Pardo-Ferreira, and J. C. Rubio-Romero. 2021. 'Overall introduction to the framework of BIM-based digital twinning in decision-making in safety management in building construction industry', Direccion y Organizacion: 31-38.

Tuhaise, V. V., J. H. M. Tah, and F. H. Abanda. 2023. 'Technologies for digital twin applications in construction', Automation in Construction, 152.

Turner, C. J., J. Oyekan, L. Stergioulas, and D. Griffin. 2021. 'Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities', IEEE Transactions on Industrial Informatics, 17: 746-56.

Vardi, Moshe Y. 2009. "Conferences vs. journals in computing research." In, 5-5. ACM New York, NY, USA.

Vial, G. 2019. 'Understanding digital transformation: A review and a research agenda', Journal of Strategic Information Systems, 28: 118-44.

Wang, J. J., L. K. Ye, R. X. Gao, C. Li, and L. B. Zhang. 2019. 'Digital Twin for rotating machinery fault diagnosis in smart manufacturing', International Journal of Production Research, 57: 3920-34.

Wang, P., M. Yang, Y. Peng, J. Zhu, R. Ju, and Q. Yin. 2019. 'Sensor Control in Anti-Submarine Warfare-A Digital Twin and Random Finite Sets Based Approach', Entropy (Basel), 21: 767.

Winston, Patrick Henry. 1984. Artificial intelligence (Addison-Wesley Longman Publishing Co., Inc.).

Wuni, Ibrahim Y., Geoffrey Q. P. Shen, and Robert Osei-Kyei. 2019. 'Scientometric review of global research trends on green buildings in construction journals from 1992 to 2018', Energy and Buildings, 190: 69-85.

Xia, H., Z. Liu, M. Efremochkina, X. Liu, and C. Lin. 2022. 'Study on city digital twin technologies for sustainable smart city design: A review and bibliometric analysis of geographic information system and building information modeling integration', Sustainable Cities and Society, 84.

Xie, Mingjing, Yangzi Qiu, Yishuang Liang, Yuekuan Zhou, Zhengxuan Liu, and Guoqiang Zhang. 2022. 'Policies, applications, barriers and future trends of building information modeling technology for building sustainability and informatization in China', Energy Reports, 8: 7107-26.

Xie, X., N. Moretti, J. Merino, J. Y. Chang, P. Pauwels, and A. K. Parlikad. 2022. "Enabling building digital twin: Ontology-based information management framework for multi-source data integration." In IOP Conference Series: Earth and Environmental Science.

Xu, H., Y. Duo, and T. Tang. 2022. 'A digital twin framework for construction and operation of the radio active waste repository', Nuclear Technology and Radiation Protection, 37: 181-92.

Yang, Bin, Zhihan Lv, and Faming Wang. 2022. 'Digital Twins for Intelligent Green Buildings', Buildings, 12: 856.

Yaqoob, I., K. Salah, M. Uddin, R. Jayaraman, M. Omar, and M. Imran. 2020. 'Blockchain for Digital Twins: Recent Advances and Future Research Challenges', IEEE Network, 34: 290-98.

Zhang, Anshan, Jian Yang, and Feiliang Wang. 2023. 'Application and enabling technologies of digital twin in operation and maintenance stage of the AEC industry: A literature review', Journal of Building Engineering: 107859.

Zhang, J., J. C. P. Cheng, W. Chen, and K. Chen. 2022. 'Digital Twins for Construction Sites: Concepts, LoD Definition, and Applications', Journal of Management in Engineering, 38.

Zhao, J. F., H. B. Feng, Q. Chen, and B. G. de Soto. 2022. 'Developing a conceptual framework for the application of digital twin technologies to revamp building operation and maintenance processes', Journal of Building Engineering, 49.

Zhao, L., H. Zhang, Q. Wang, and H. Wang. 2021. 'Digital-Twin-Based Evaluation of Nearly Zero-Energy Building for Existing Buildings Based on Scan-to-BIM', Advances in Civil Engineering, 2021.

Zhou, L., C. An, J. Shi, Z. Lv, and H. Liang. 2021. "Design and Construction Integration Technology Based on Digital Twin." In Proceedings - 2021 Power System and Green Energy Conference, PSGEC 2021, 7-11.