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A comprehensive digital twin framework for building environment monitoring with emphasis on real-time data connectivity and predictability

Tae Wook Kang [a], Yunjeong Mo [b,*]

[a] Korea Institute of Civil Engineering and Building Technology, Seoul, South Korea

[b] Department of Civil, Construction, and Environmental Engineering, Iowa State University, Ames, IA, USA

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ABSTRACT

The concept of digital twins, initially developed in manufacturing, has found applications in various industries. However, its adoption in the construction field is still nascent, with a limited understanding of its benefits and implications. Existing examples of digital twin implementation in construction mainly provide general frameworks or possibilities for performance. To effectively harness the potential of digital twins in construction, establishing connectivity and predictability for data exchange between the physical and virtual realms is crucial. This research defines the essential requirements for real-time connectivity and predictability in digital twin implementation and proposes a framework and architecture based on these principles. The proposed method is evaluated through the implementation of a digital twin for monitoring the environmental performance of existing buildings, revealing its effectiveness and challenges. This study serves as a valuable exemplar for the development of a digital twin platform dedicated to construction monitoring.

1. Introduction

Buildings encompass diverse intricate components, comprising building envelopes, structural elements, and mechanical, electrical, and plumbing (MEP) systems, along with occupants and indoor environments. In addition, throughout the building's life cycle, a vast volume of data is generated for design, construction, and operations. Effectively managing buildings necessitates the integration of heterogeneous data from diverse systems and the delivery of pertinent information to relevant stakeholders during the phases. Real-time building data linked to the 3D building model enhances comprehension of complex building systems, with digital twins playing a pivotal role in providing support.

Digital twin technology, originally developed for manufacturing, is now being utilized across various industries. In the field of smart factories, the use of digital twins is becoming more common. Digital twins enable a virtual world to replicate the physical world and simulate real-world data in a virtual environment, leading to more cost-effective processes with reduced rework (Boje et al., 2020). The application of digital twin technology has expanded to the architectural, engineering, and construction (AEC) field, and numerous studies have been actively conducted for the last decade. However, the existing studies are more focused on establishing the framework and possibilities of digital twins, and proposing architecture specific to certain use cases, making these approaches hard to generalize. Thus, this study proposes a more comprehensive digital twin framework in the AEC field, highlighting the importance of both connectivity for seamless data exchange between the virtual and physical realms and predictability for effective model-based simulations.

Although existing studies adopt the concepts of connectivity and predictability, they are still relatively vague and often not clearly defined in their digital twin framework (ARUP, 2019). Functions such as model simulation and sensor data processing are often presented without other layers of digital twin characteristics encompassing such individual functions and providing more holistic perspectives. Defining the digital twin functions in terms of characteristics can help explain the implementation methods more clearly, considering the level of application requirements. For example, the level of connectivity can vary depending on how data is exchanged between physical and virtual worlds (Harode et al., 2023). Additionally, the simulation function of one application field may differ from the simulation function of another, so they cannot be understood at the same level of digital twin requirement. More apparent distinctions between the levels of connectivity and predictability are needed for more efficient functional implementation of digital twins. To overcome such research gaps, this study presents a

* Corresponding author.
E-mail addresses: laputa99999@gmail.com (T.W. Kang), ymo@iastate.edu (Y. Mo).

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digital twin implementation strategy, framework, and architecture for the AEC industry to overcome current limitations, considering data connectivity and predictability.

Other characteristics can also define the concept of the digital twin, but this study focuses on connectivity and predictability as core characteristics, including functions of the real world, real-time monitoring, and data analysis. Broader characteristics of digital twins, such as intelligence and decision-making process optimization, were not discussed in the scope of this study.

Fig. 1 summarizes the research flow and the organization of this paper. In Section 2, a comprehensive literature review is conducted to understand recent digital twin studies by the phases of building lifecycle and larger scale. In Section 3, the importance of connectivity and predictability is explained, and the research gaps are identified. Based on the findings, in Section 4, the core digital twin concepts, use cases, and functions are defined, considering the level of connectivity and predictability. By applying the components and framework, a case study of digital twin-based building environment monitoring is introduced in Section 5. Then, the findings and contributions of this study are discussed in the last section.

2. Conventional approaches: literature review

The concept of digital twin in the AEC field lacks a clear consensus among researchers and practitioners, and only a few applications have been implemented (Sacks et al., 2020a). To address this gap, this study reviews existing digital twin studies in the AEC field, with a focus on building design, construction, and operations, and identifies the distinctions between this study and previous research. The syntax presented below was used to gather relevant literature.

“Digital Twin" AND "AEC" AND "BIM" AND "Building"

After limiting the search to papers published within four years, a total of 43 papers were initially selected for consideration. Out of these, 30 papers were ultimately included in the literature review and analysis for this study, after excluding less relevant ones. The existing studies on digital twin in the building sector were found to be applicable in areas such as concept development, design and construction, operations and management, smart city initiatives, and other related fields.

2.1. Concept development

Due to the novelty of the digital twin concept, several studies have compared it with other related technologies to gain a clearer understanding. For instance, Douglas et al. (2021) compared digital twins with building information modeling (BIM) and cyber-physical systems (CPS) and analyzed their similarities and differences. Their review revealed different perspectives on digital twins, with some viewing it as a continuation of BIM, while others see it as distinct or complementary. Similarly, while CPS shares similarities with digital twins in terms of interchangeable components, they are considered separate concepts, with digital twins being viewed as a broader and integrated concept of CPS.

Researchers have analyzed the existing digital twin studies in the AEC field to gain insights into the current trends, patterns, and gaps. For instance, Ozturk (2021) conducted a bibliometric search, scientometric mapping, and analysis of digital twin studies and found the need to prioritize the full integration of digital and physical features throughout the building lifecycle in future studies. Similarly, Jiang et al. (2021) defined a clearer concept of the digital twin by comparing it with BIM and CPS and proposed its roles in civil engineering as providing data for design, enabling smart construction, and enhancing operations and management.

The use of digital twins for more specific purposes in the AEC industry has also been explored. Opoku et al. (2021) analyzed the concept, technologies, and applications of digital twins in the construction industry to address various challenges, such as low productivity and technological barriers. Tagliabue et al. (2021) proposed a framework for sustainability assessment using digital twins and Internet of Things (IoT) with a dynamic approach that enables real-time evaluation of sustainability criteria and decision-making processes throughout the building life cycle. Alonso et al. (2019) developed the BIM-based digital twin

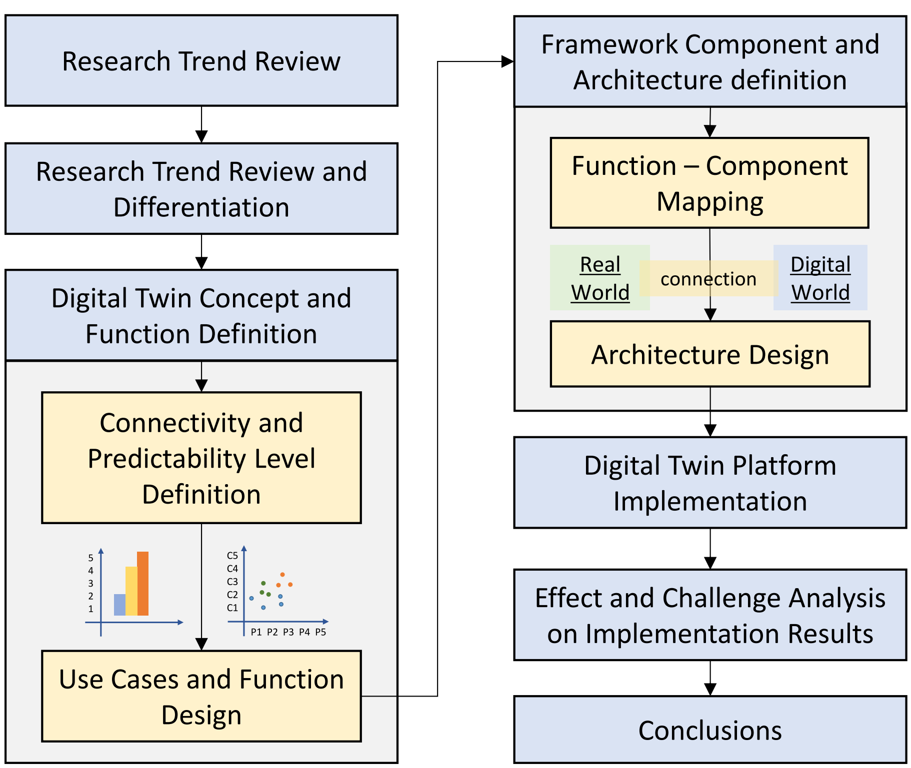

Fig. 1. Research flow.

platform, SPHERE, to enhance the energy efficiency of buildings, construction process efficiency, and indoor environment by integrating the building life cycle. However, this study mainly focuses on the concept and objectives of the BIM-based digital twin platform.

2.2. Design and construction

The benefits of digital twins in the building design and construction phases lie in their ability to provide integrated information on physical and spatial data. As a result, researchers have been actively studying the application of digital twin technologies in these areas. In the design phase, checking the design requirements and complying with the building code is critical. BIM with natural language processing has been actively utilized for code compliance checking (Lee et al., 2023). Also, BIM with an interactive visualization approach supports life cycle assessments of buildings in early design phases (Forth et al., 2023), and the digital twin has the potential to be applied to those areas. Latifah et al. (2021) conducted a study on workspace design prediction, aiming to manage various types of uncertainty and identify design changes using digital twins. They examined the architecture of digital twins at the building level, which consists of a data acquisition layer, data/model integration layer, digital modeling layer, transmission layer, and service layer.

Construction sites need diverse technologies to support the dynamic activities and interactions between massive materials, equipment, and laborers, and the growth of BIM tools has supported the technical functions of the construction process (Sacks et al., 2018). To support the complex activities and interactions at construction sites, Hasan et al. (2022) explored how digital twins, augmented reality, and construction machinery could work together to track and operate machinery. They proposed a practical application of digital twins by developing a physical model using IoT sensors and motors. Effective progress monitoring of construction sites is also crucial for successfully completing building and infrastructure projects, and Pal et al. (2023) explored construction progress monitoring using automated vision technologies. Based on the knowledge gaps found in the results, they proposed a closed-loop construction control framework with the digital twin construction approaches. Field-to-BIM tools refer to software and hardware systems that enable information exchange between the site and control systems, and they contributed to initiating digital twins for construction (Sacks et al., 2020b). Sacks et al. (2020b) indicated that projecting information on the irregular as-built construction work surfaces is one of the major challenges in the field-to-BIM technologies, and it might be overcome if the digital twin supports the system with more direct and accurate correspondence with the as-designed surfaces of finished products in the BIM model. Pan and Zhang (2021) suggested a digital twin framework for project management that integrated BIM, IoT, and Data Mining. They also created a data-driven prototype that used BIM and point cloud data from UAVs equipped with LiDAR. While these studies focused on specific areas of the construction process, Boje et al. (2020) provided a more comprehensive review of digital twins in construction. They analyzed the main components and potential uses of digital twins across engineering domains and suggested a 3-tier evolution of digital twins in construction: monitoring platforms, intelligent semantic platforms, and agent-driven socio-technical platforms.

2.3. Operation and management

Effective management strategies are critical for energy efficiency, occupant comfort, mechanical and structural maintenance, and other aspects during the building lifecycle, which is the longest stage. Therefore, digital twin technologies have been actively explored to support building operations and management. In their study, Sacks et al. (2020a) outlined a construction information system workflow based on digital twins and specified the activities and processes involved. To support decision-making, they explored the physical-virtual, product-process, and intent-status dimensions of the construction workflow. They suggested that the future direction of digital twins should be data-centric construction with an appropriate database structure for a comprehensive construction mode. In another study, Deng et al. (2021) investigated the evolutionary transition from BIM to digital twins in building representations in the AEC industry. They categorized the areas of the digital twin research as construction process monitoring, energy performance management, indoor environment monitoring, space management, hazard monitoring, and community monitoring. They also examined the use of digital twins in conjunction with BIM and IoT for real-time predictions in the construction and operation phases.

Digital twins in the building sector are also being integrated with other emerging technologies. Coupry et al. (2021) reviewed the combination of BIM-based digital twins and extended reality (XR) technologies to improve building maintenance procedures. They noted the benefits of BIM-based digital twins in terms of implementation, building lifecycle management, data management, monitoring, inspection, and planning, while XR technologies improved data visualization and interaction with models in the digital twin. Another study by Götz et al. (2020) explored the integration of digital twins with blockchain for asset lifecycle management in buildings, providing both on-field applications and strategic tools for BIM level 3, such as decentralized program hubs, modular interfaces, and mergeable and scalable blockchains.

Along with the reviews of concepts of digital twins, researchers have made efforts to implement prototypes of their suggested digital twin framework or performed experiments to verify their model and test its feasibility. For instance, Nasaruddin et al. (2018) proposed a building information management system framework using digital twins, which included a prototype with integrated environment software (IES) for real-time monitoring of building technologies and optimization of building services. Lu et al. (2020a) suggested an anomaly detection system for built asset monitoring using digital twin technologies and performed a case study on the heating, ventilation, and air-cooling (HVAC) systems. Other than the building systems, researchers incorporated occupant and building environment information into their digital twin prototypes. Seghezzi et al. (2021) proposed an occupancy-oriented digital twin for testing and calibrating an occupancy monitoring system using IoT camera-based sensors for building facility management. Their framework included a post-occupancy evaluation (POE) with BIM to optimize sensor system planning and evaluate data quality and system efficiency. Khajavi et al. (2019) performed experiments on building life cycle management using a digital twin and collected light, temperature, and humidity data from a testbed building, highlighting the benefits and shortcomings of their implementation. To help adopt and implement digital twins in the AEC field, Harode et al. (2023) suggested functionality and tool-based system architecture for the implementation of digital twins in the AEC field. They developed a prototype and a case study in a healthcare facility to prove the concept. Research in prototyping the system architecture of digital twins in the AEC is rapidly growing, and a more standardized digital twin process and system architecture is expected in the near future.

2.4. Smart city

The potential of digital twins extends beyond individual buildings to larger communities and cities. Smart cities leverage new technologies to optimize a city's buildings and infrastructure. Recently, researchers have explored applying digital twins to these larger built environments. For instance, Deng et al. (2021) introduced the concept of a digital twin city and identified surveying and mapping technology, BIM, 5G-enabled IoT, blockchain, and collaborative computing as leading technologies for digital twin cities. They also proposed scenarios for using blockchain to enable smart healthcare and transportation. In another study, Shirowzhan et al. (2020) discussed technologies for developing smart cities and intelligent environments, such as Geographic information system (GIS)-BIM integration, CyberGIS, laser scanning, machine learning, and high-performance computing. They suggested ways of using these technologies to improve connectivity and infrastructure planning in smart cities.

The utilization of digital twins in smart city applications has been investigated in several studies. Lu et al. (2020b) introduced a digital twin architecture for both building and city levels, which included layers such as data acquisition, transmission, digital modeling, data/model integration, service, and interaction with people. The authors conducted a pilot study using this architecture and analyzed pump anomalies through the concept of digital twins. Similarly, Zaballos et al. (2020) proposed a smart campus concept for universities to act as a testbed for a smart city integrating BIM and IoT. They examined industry standards and indoor environment quality parameters for IEQ monitoring and suggested a conceptual system flow chart and a prototype of a digital twin using Dynamo Revit. The authors emphasized the significance of flexible organizational and network structures.

2.5. Others

Other industries have also explored the potential of digital twins. Deria et al. (2021) developed an audio-based framework for digital twins in transportation construction. Wanasinghe et al. (2020) investigated the application of digital twins in the oil and gas industry. Lee et al. (2020) integrated digital twins with deep learning to improve smart manufacturing. Li et al. (2020) explored the possibility of a sustainable business model based on digital twins.

To summarize, the application of digital twins in the AEC industry serves the following primary purposes: (1) Design, (2) Construction, (3) Operations and Management (O&M), (4) Smart city, and (5) Others. Digital twins can be utilized to manage the diverse data collected during building or infrastructure design and construction phases, and connect it to virtual models. Digital twins are also actively used in building operations and management, including building energy and facility management, for single or multiple buildings, as well as for city-level management. Additionally, digital twins can be applied in waste management from construction and demolition and for other purposes. Table 1 presents a summary of the main applications of digital twin studies in the AEC industry. If a study covers multiple application types, it is assigned to multiple categories in table. As indicated, the majority of digital twin studies in the AEC industry focus on construction and O&M applications.

Based on the findings, the studies could be categorized as follows: (1) Concept, (2) Framework, (3) Case study, (4) Prototype, and (5) Field application. Studies in the concept category aim to define and differentiate digital twins from other related terms, outlining the technical components of digital twins and identifying their applications in the AEC industry. Some studies suggest future research directions for the application of digital twins. Framework studies, on the other hand, propose a foundational structure for digital twin developments by organizing the technical components and explaining how data flows and components interact. These studies represent the early stages of digital twin developments. Case study studies validate the applicability of a framework to real-world scenarios or analyze existing digital twin applications to identify future research directions. Finally, prototype studies refine a digital twin system that is ready for real-world use. Field application studies refer to the implementation of a fully developed digital twin system in real-world scenarios such as building design, construction, operation, and management. Table 2 provides a summary of the studies based on the defined categories. In cases where a paper encompasses multiple categories, it is categorized under the higher-numbered category. For instance, if a study proposes a framework based on a conceptual literature review and then applies it to a case, it is classified under the case study category. As the adoption of digital twins is still in its nascent stage in the AEC industry, the majority of studies are categorized as concepts, frameworks, or case studies.

Table 1
Digital twin application summary.

Application	Related literature	Description
Design	(Ozturk, 2021), (Jiang et al., 2021), (Opoku et al., 2021), (Alonso et al., 2019), (Latifah et al., 2021), (Boje et al., 2020), (Deng et al., 2021), (Khajavi et al., 2019)	Apply digital twins to design strategies and methods
Construction	(Sacks et al., 2020a), (Ozturk, 2021), (Jiang et al., 2021), (Opoku et al., 2021), (Alonso et al., 2019), (Hasan et al., 2022), (Pan and Zhang, 2021), (Boje et al., 2020), (Khajavi et al., 2019), (Deria et al., 2021), (Menassa, 2021), (Shahinmoghadam and Motamedi, 2019), (Kirwan and Rogers, 2020), (Akanmu et al., 2021), (Xie and Pan, 2020), (Alizadehsalehi and Yitmen, 2023)	Apply digital twins to construction, including project management, scheduling, estimating, modular construction, etc.
Operation & Management	(Ozturk, 2021), (Jiang et al., 2021), (Opoku et al., 2021), (Tagliabue et al., 2021), (Alonso et al., 2019), (Boje et al., 2020), (Coupry et al., 2021), (Götz et al., 2020), (Lu et al., 2020a), (Seghezzi et al., 2021), (Khajavi et al., 2019), (Lu et al., 2020b), (Zaballos et al., 2020), (Menassa, 2021), (El Jazzar et al., 2020), (Brunone et al., 2021), (Nie et al., 2019), (Lu et al., 2020c), (Lu et al., 2019)	Apply digital twins to facility management, building energy management
Smart City	(Deng et al., 2021), (Shirowzhan et al., 2020), (Lu et al., 2020b), (Lu et al., 2019)	Apply digital twins to a broader range of buildings, such as university campuses, residential communities, multiple buildings, smart cities, etc.
Others	(Douglas et al., 2021), (Wanasinghe et al., 2020), (Li et al., 2020), (Ottinger et al., 2021), (Jin et al., 2021)	Apply digital twins to other uses, such as waste management

3. Connectivity and predictability: gap analysis

Connectivity refers to the extent of real-time data exchange between the physical and digital worlds, which is defined as meeting the data exchange requirements of both end systems. Data predictability, crucial for supporting simulation, is defined as the level supporting a data prediction model aligned with the application's purpose. Since digital twin systems aim to connect the physical and virtual worlds by integrating heterogeneous data from diverse data sources, connectivity is the core functionality in implementing effective digital twin systems. Predictability is critical in digital twins for ACE systems ranging from building design, construction, operation and management, and occupants' comfort and health for more informative and advanced purposes supporting users' decision-making. Thus, existing studies were reviewed according to the level definition of connectivity and predictability, and the research gap for effective digital twin platforms was identified. The analysis steps are as follows: (1) Define the levels of data connectivity and predictability, and (2) Analyze research cases at the defined levels.

The levels of capability maturity model (CMM) (Jin et al., 2021) were referenced to define each level clearly, and the DevOps concept of software engineering (Leite et al., 2019) was applied to consider the scalable platform concept. The characteristics and functions of data connectivity and predictability for this study are defined by each level in Table 3.

To analyze the levels of connectivity and predictability of existing

Table 2
Research category summary.

Research Category	Related literature	Characteristics of studies
Concept	(Sacks et al., 2020a), (Douglas et al., 2021), (Ozturk, 2021), (Jiang et al., 2021), (Opoku et al., 2021), (Latifah et al., 2021), (Boje et al., 2020), (Deng et al., 2021), (Coupry et al., 2021), (Shirowzhan et al., 2020), (Menassa, 2021), (Ottinger et al., 2021), (El Jazzar et al., 2020), (Brunone et al., 2021), (Shahinmoghadam and Motamedi, 2019), (Kirwan and Rogers, 2020), (Akanmu et al., 2021), (Özturk, 2021)	Define technical terms and components
Framework	(Alonso et al., 2019), (Götz et al., 2020), (El Jazzar et al., 2020), (Jin et al., 2021), (Kaewunruen and Xu, 2018), (Nie et al., 2019), (Lu et al., 2020c), (Xie and Pan, 2020)	Suggest fundamental structure of a digital twin development
Case study	(Tagliabue et al., 2021), (Pan and Zhang, 2021), (Lu et al., 2020a), (Seghezzi et al., 2021), (Khajavi et al., 2019), (Lu et al., 2020b), (Zaballos et al., 2020), (Deria et al., 2021), (Li et al., 2020), (Nie et al., 2019), (Lu et al., 2019)	Introduce digital twin cases, Apply a suggested framework
Prototype	Hasan et al. (2022)	Implement a refined digital twin system
Field Application		Develop a complete digital twin system in an actual building

Table 3
Digital twin data connectivity and predictability levels.

Connectivity	Predictability
C1. Transferring data from the physical world to the digital world is done manually.	P1. There is no data prediction model, but the database necessary for data prediction is implemented.
C2. Legacy systems or humans are involved in transferring data obtained from the physical world to the digital world.	P2. A trained predictive model can be developed using the data stored in the database. However, separate work is required to train the predictive model, and human intervention is required.
C3. Data from the physical world are processed in a batch process and reflected in a digital information model. There is a time gap in using the data.	P3. Predictive models can be automatically updated according to changes in the dataset, deployed in the digital world, and operated.
C4. Changes in the physical and digital world are reflected in the digital information model in real-time. Real-time can be clearly defined according to requirements.	P4. The process of training and deploying predictive models based on various use case scenarios can be rapidly changed or extended according to user requirements.
C5. It supports seamless two-way data exchange between the physical world and the digital world. It also satisfies C4.	P5. Information models such as data prediction and decision-making models based on use cases required for simulation can be changed or expanded according to user requirements. It can be optimized to support decision-making systems effectively.

research, relevant studies with similar semantics to the proposed study were selected, and then a difference analysis was conducted. Text mining techniques, specifically semantic analysis, were employed to assess the similarity between the proposed study and others. The top five studies exhibiting high similarity were then extracted for further investigation and analysis, specifically in terms of digital twin connectivity and predictability. By examining the findings, the implications and challenges of the proposed technology were derived, providing valuable insights into its significance.

In the domain of text mining, semantic similarity is achieved through the utilization of word embeddings and word vector techniques. By comparing word vectors or word embeddings, which are multidimensional representations of word meanings, cosine similarity is employed to measure the similarity as explained in Equation (1). The word vectors (W1, W2) extracted from the abstracts of the papers capture the contextual information in which the words appear. Cosine similarity, calculated using a specific formula, serves as a measure of similarity between two non-zero vectors in an inner product space (Jatnika et al., 2019).

$$similarity = cos\ (\theta) = \frac{W_1 \bullet W_2}{\|W_1\| \|W_2\|} \tag{1a}$$

Fig. 2 illustrates the similarity heat map obtained. The connectivity level and predictive implementation of the top 6 papers ((Sacks et al., 2020a), (Ozturk, 2021), (Coupry et al., 2021), (Seghezzi et al., 2021), (Khajavi et al., 2019), (Deria et al., 2021)) with high similarity (0.939, 0.935, 0.920, 0.918, 0.916, 0.906, respectively) were compared. Table 4 provides an analysis of the differences between this study and other significant studies regarding the connectivity of digital twins. The classification of whether connectivity was implemented for each module was based on the aforementioned levels. In cases where identification was challenging, it was marked as 'X' in the table below. The result reveals variations in the maturity levels of different indicators within the AEC field. Although the selected studies' connectivity levels ranged from no connectivity to levels 3 or 4, most cases remained at a low predictability level. Connectivity is the fundamental function of digital twins, and it needs to be further advanced for more stable digital twin systems. Predictability is the function for more effective and efficient digital twin systems, which currently remains at a lower level and also needs more improvement. In the next chapter, considering the literature survey results, key digital twin use cases and functions are derived, and the platform is designed.

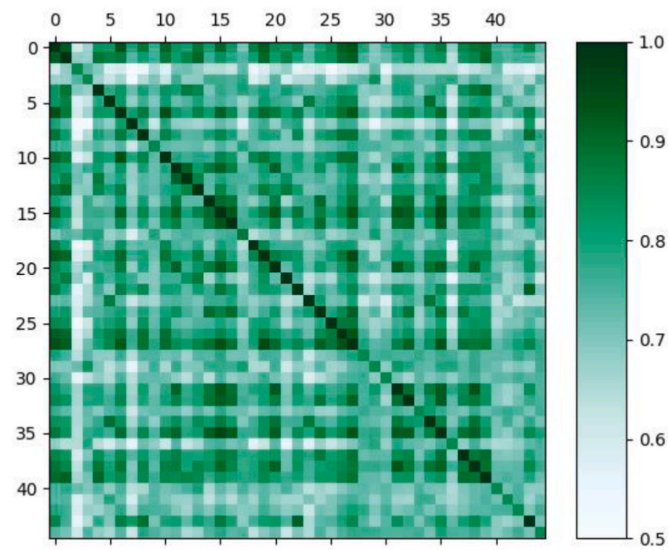

Fig. 2. Digital twin connectivity and data predictability analysis charts.

4. Digital twin platform with connectivity and predictability

To overcome the current research gap, use cases and functions were identified following the levels of connectivity and predictability for building monitoring. The derived functions were applied to the framework and architecture design by mapping those functions to the components of digital twin connectivity and predictability. Using the framework, system architecture was designed to implement a case

Table 4
Top-5 connectivity and data predictability of digital twin framework analysis.

Reference	Domain	Connectivity Level	Data Predictability Level
Sacks et al. (2020a)	Construction Management	C3: For digital twin-based construction process management, the site is periodically scanned using drones and LiDAR and then converted into a BIM model. The corresponding BIM model is updated as a digital twin model through periodic data acquisition and processing.	P1: This study uses physical construction work data, predicts the number of 4D work steps in BIM using autoregressive integrated moving average (ARIMAX), and checks bottlenecks using a fuzzy model.
(Ozturk, 2021), (Khajavi et al., 2019)	Building HVAC	C3: It obtains data from the sensor attached to the pump. It manually saves the data and transfers it to the digital twin system. No clear definition of real-time requests.	P1: It checks abnormal patterns in the acquired dataset using cumulative sum control charts (CUSUM) and Bayesian Online Change Point Detection algorithm (BOCPD) rather than predicting abnormal patterns for real-time sensor data using a learning model.
Coupry et al. (2021)	Construction Management	X: This study proposes four key elements to realize digital twin-based construction. Although there are no clear requirements or discussions about connectivity, connectivity is conceptually addressed in the proposed framework.	X: There is no clear requirement or discussion of predictability, but it is treated as a simulation concept in the proposed framework.
Seghezzi et al. (2021)	Building Management	X: This study proposes a digital twin application concept, and there is no clear requirement or discussion about connectivity.	P1: In this study, requirements such as simulation by the learned model are not specified.
Deria et al. (2021)	Construction Machine Control	C4: Requirements for real-time are specified. However, the implemented digital twin has limitations in showing an example using a machine training kit, rather than being used to control construction equipment on the site.	P1: Data is acquired from sensors, but not used to simulate or predict the future by applying it to a digital model.

study.

4.1. Function design

In the first phase, the framework was defined for designing a digital twin platform that could support data connectivity and predictability. The key use cases were developed considering monitoring the university building environment, and actors involved in building environment monitoring were identified, with use cases being derived through interviews. BIM and a sensor database were utilized for the digital model, with the application's purpose taken into account. After collecting the required data and developing the model, the data modeling engineer, field engineer, data analyst, and system user actors were defined for use, as illustrated in Fig. 3.

Table 5 shows that the identified use cases obtained their requirements and functions from the actors depicted in Fig. 3.

4.2. Framework design

In this chapter, the main components of connectivity and predictability are derived based on the use cases, and functions are mapped to the components. Then, the digital twin framework was defined to describe the relationships between components and the development process, as shown in Fig. 4.

After defining the relationships between components and their associated functions in a digital twin framework, which components collect data, where to deliver it, and where to make predictions can be clearly described. The details are explained in Table 6. For example, the connection from D3 to R3 must have an endpoint that supports the data source and exchange protocol. An object classification system should be defined in advance to connect D1, R2, R4, and R5. Additionally, the service endpoint should be defined in the digital twin framework to provide the information needed for D5, D6, and D7.

4.3. Architecture design

The architecture of the prototype was defined based on the frame design described earlier. The digital twin platform server, which is a requirement for the framework, was included in this architecture. This server had a data source connector module that enabled data exchange by connecting the physical and virtual worlds. To collect and transmit data through the Internet, IoT devices were used for data exchange in the physical world. The exchanged data was stored in the database and BIM model and provided through the Open application programming interface (API) server, which served as a platform interface and supported data interoperability between servers or services. Open APIs provided the necessary data for business logic execution. The business logic ran the required simulations based on user requirements, using machine learning models such as statistical models, big data analysis, and deep learning artificial intelligence. The key performance indicators (KPIs) that need to be monitored were rendered through the dashboard. The module architecture was designed to consider these requirements using unified modeling language (UML) (Fig. 5).

Then, the components of this framework defined in Table 5 were mapped to the modules explained in Fig. 5. The mappings and descriptions are summarized in Table 7.

The installation of IoT devices was necessary to enable the exchange of data between the physical and virtual worlds. The data schema of sensors installed in the real world must be variable depending on an application use case. For this purpose, the IoT device (M8. IoT) and data record schema (M10. Database) were defined as follows.

IoT_device = {ID, position, type, name, read_time_interval, connection_string}

IoT data record = {ID, position, type, name, value, created_date}

Each IoT device was assigned a unique *ID* value to distinguish it from others. The device's *position* was used as the information classification system to link it with BIM spatial objects. The *type* was used to categorize sensor data types. The *name* referred to the sensor's name, and the *value* indicated the reading obtained from the sensor. The *read_time_interval* parameter specified the frequency (in seconds) of the sensor data readings, and the *connection_string* parameter specified the address used for IoT database connectivity.

The object information classification system can automatically connect BIM and external data, such as IoT sensors and BIM attribute value input. In this study, the following information classification system was

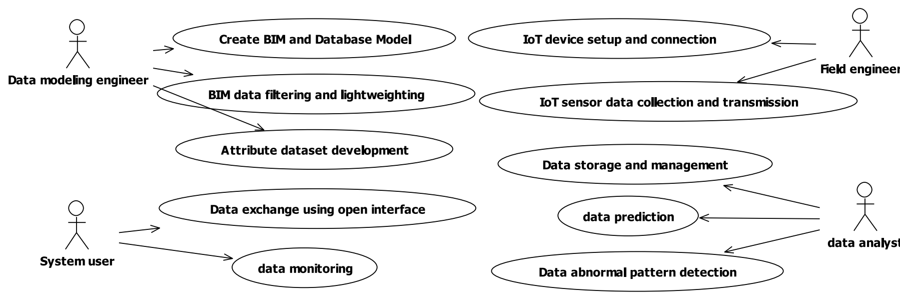

Fig. 3. Digital twin use cases.

Table 5
Use cases and functions.

Use Cases	Needs	Functions
U1. Create BIM and Database Model	Users need to monitor space-based environmental data, so BIM data processing that can define spaces is required.	F1. BIM data import F2. BIM and IoT attribute data connection F3. BIM and attribute data connection
U2. BIM data filtering and lightweight	For the system to be operated and managed lightly, noise removal, filtering, and lightweight BIM data are required.	F4. BIM data filtering F5. BIM data noise removal F6. BIM data lightweight
U3. Attribute dataset development	Developing a property data set for monitoring the building environment is necessary.	F7. Attribute data schema definition F8. Attribute data input
U4. IoT device setup and connection	For IoT devices, the device configuration and operation method must be set to suit the purpose of monitoring the building environment. In addition, network settings are required to connect to the digital twin server.	F9. IoT device basic setting and sensor parameter definition F10. Connection with BIM and communication network protocol setting for IoT data exchange
U5. IoT sensor data collection and transmission	The IoT sensor should automatically collect data considering the requirements and transmit the data through the network set up in the IoT device.	F11. IoT sensor data collection according to settings F12. Transmit the collected sensor data to the connected database server
U6. Data storage and management	Data needed to implement digital twin requirements must be stored and managed in a database.	F13. Data storage, such as sensor data and property values F14. Data discovery and management
U7. Data prediction	To obtain information necessary for decision-making, etc., it is essential to analyze and predict the collected data.	F15. Data statistical analysis F16. Data prediction
U8. Data abnormal pattern detection	For building environment management, if there is an abnormal pattern, it must be detectable.	F17. Train data and create predictive models F18. Abnormal pattern detection of data
U9. Data exchange interface support	There must be an interface for digital twin services to access the database.	F19. Running an Open application programming interface (API) server for data exchange F20. Data query through Open API
U10. Data monitoring	We need a way to monitor the collected data in real-time.	F21. Dashboard layout settings F22. Dashboard information display F23. Notification of abnormal patterns, etc.

employed.

position = <building name>.<storey name>.<room name>

Considering the connectivity between the real and digital worlds, the IoT-BIM data structure, which is the core architecture of the digital twin platform, was designed as described in Fig. 6. The main elements include *IoT_device, IoT_databased, IoT_record, IoT_database_interface, BIM_model, BIM_element, BIM_properties,* and *BIM_property*.

The roles of the main elements of IoT-BIM data structure explained in Fig. 6 are further explained in Table 8.

The data from the framework was tested using a deep learning model. The value of *IoT_record* was used as a learning dataset to predict time series data obtained from environmental sensors. The deep learning prediction model was trained in the following steps.

1) Data normalization: Using the Min-Max Normalization, the dataset values x_i were normalized from 0 to 1 with x_{min} and x_{max} (Equation 1).

$$x_j = \frac{(x_i - x_{min})}{(x_{max} - x_{min})} \quad \text{(Equation 1b)}$$

2) Data preprocessing: The dataset was divided into input and label data for learning and testing purposes. Input and label data were generated considering the prediction period.
3) Deep learning model design: A deep learning model structure was designed for time series data prediction. To learn historical data patterns, Long Short-Term Memory (LSTM) and dense layers were used.
4) Deep learning model learning: Hyperparameters were adjusted to prevent overfitting and underfitting. The learned model was saved as a file for data prediction and abnormal pattern monitoring.

5. Case study

5.1. Overview

By applying the framework, digital twin systems and components were developed in a university building using IoT sensors integrated with the virtual digital world and BIM. Throughout the process, the effectiveness and challenges of the proposed framework architecture were analyzed. Additionally, a deep learning model was developed to predict future data changes to verify the usability of the suggested framework.

A web-based system has been developed to monitor the environment of University of North Florida (UNF) campus buildings and enabled the previously defined digital twin framework. To ensure usability, the functions and modules of each component were explicitly defined and executed, as depicted in the digital twin's data flow (Fig. 7) and function mapping of the framework (Table 9).

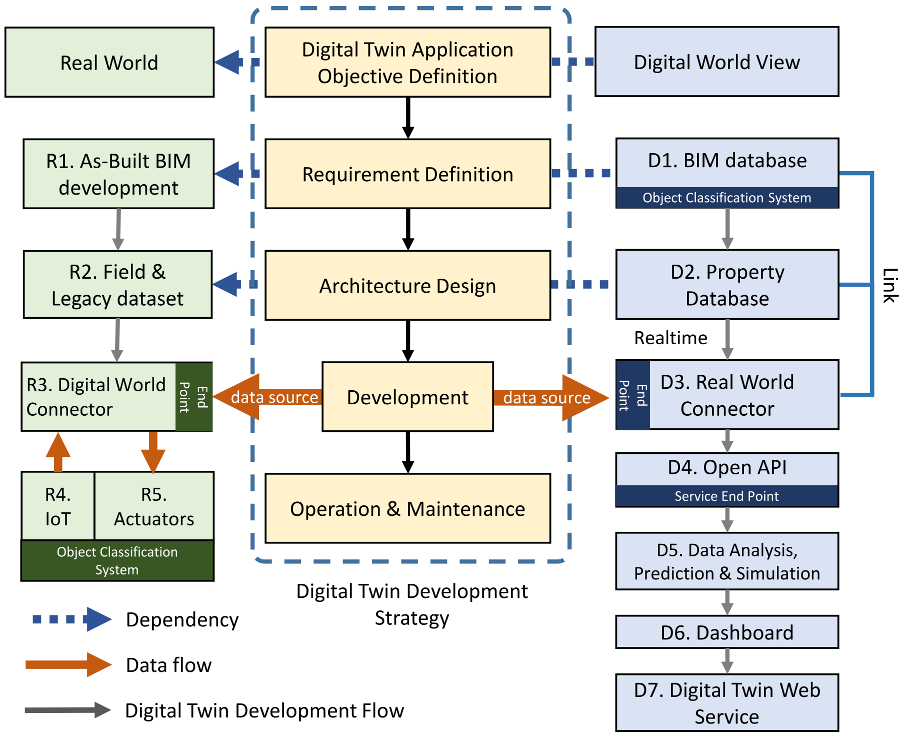

Fig. 4. Digital twin framework with connectivity and predictability.

Table 6
Digital twin framework components and related functions.

	Components	Related Functions	Description
Real World	R1	F1, F2, F3, R4, F5, F6	To support the BIM database necessary for the operation and management of buildings to satisfy the requirements.
	R2	F7, F8	To collect physical world datasets and legacy datasets required for use cases and process them.
	R3	F2, F3, F10	To exchange necessary data between the physical and digital worlds.
	R4	F9, F11	IoT system for collecting analog data of the physical world
	R5	F23	An actuator device that can change the environment by transferring information from the digital world to the physical world. E.g., Lights, switches, motors, smartphones, etc.
Digital World	D1	F13, F14	Database to manage BIM
	D2	F13, F14	Database that manages attribute information
	D3	F12, F13	A connection module for transferring data from the physical to the digital world. Controls actuators in the physical world.
	D4	F19, F20	Open API function that exchanges information with web services and heterogeneous devices
	D5	F15, F16, F17	Data analysis, prediction, and abnormal pattern analysis are required for the simulation
	D6	F21, F22	Dashboard function to monitor key performance indicators (KPIs)
	D7	F18, F23	Web-based services using the digital twin platform

5.2. Development

The digital twin platform developed in this study collected data from IoT devices installed in buildings to monitor and analyze the environment. As explained in Table 9, open-source tools were mainly used to develop the platform's functions. The BIM viewer was implemented using the cloud-based Autodesk Forge. The system was operated from March 2021 to December 2021 and collected data from IoT devices installed in the building spaces every 10 s.

The BIM model was created using Autodesk Revit, and its size was over 500 MB, which posed difficulties in rendering the model for web-based viewers. Additionally, the model contained a lot of extraneous information that made it inconvenient for users to find the necessary information. To address the issue of large file sizes and unnecessary information in the model, BIM lightweight was performed.

To make the BIM model more lightweight, all elements of the building that were not relevant to environmental monitoring were removed, including members, floors, and irrelevant data. Only spatial information was kept, as it was necessary for monitoring the building environment. All unnecessary elements were manually deleted according to the system requirements. Additionally, the classification system information needed for BIM objects and IoT connection was added. The resulting BIM model, which contained only the information necessary for the system operation, was reduced to 20 MB. The process is explained in Fig. 8.

5.3. Data collection, connectivity, and management

In order to collect environmental data, Arduino sensors were installed in multiple rooms of the UNF Engineering building. The sensors were connected to the Arduino board, which transmitted the data to the router via Bluetooth Low-Energy (BLE) communication. The IoT data collector was programmed using JavaScript-based Node-RED. The collected data was then stored in MongoDB via an internet gateway.

An information classification system has been established to facilitate the connection between BIM objects and IoT data. For instance, the

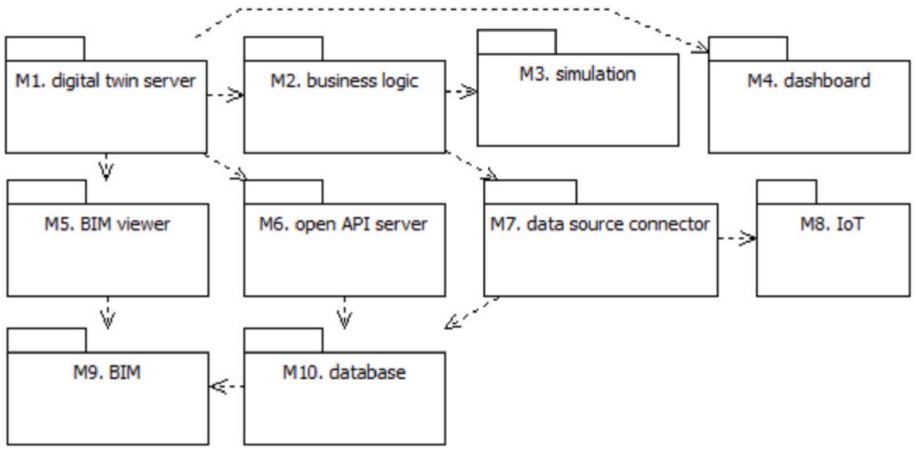

Fig. 5. Digital twin module architecture (UML).

Table 7
Digital twin framework component to module architecture mapping.

Component	Module	Description
R1	M9	BIM
R2, R3	M7	Data source connector
R4, R5	M8	IoT
D1	M9	BIM
D2	M10	Database
D3	M7	Data source connector
D4	M6	Open API server
D5	M3	Simulation
D6	M4	Dashboard
D7	M1, M2, M5	Digital twin server, Business logic, BIM viewer

designation "bldg#1.1ST FLOOR. OFFICE 1204″ indicates office room 1204, located on the first floor of building number 1. This classification system was specified in the BIM property set, and the module was responsible for gathering data from IoT devices. Fig. 9 illustrates the connection between IoT and BIM data using the information classification system.

A RESTful-based Open API server as the service endpoint was developed using node. js and MongoDB to realize connectivity between the physical and digital worlds. Users can query IoT data based on the time period, sensor type, and installation area, and obtain time series data on building environment monitoring, including date and time, sensor value, average, maximum, and data acquisition area. To estimate the necessary database storage for one year, the following calculation was performed: *48 bytes (sensor data record maximum size) x 365 days* × *24 h x 60 min* × *30 s*. For example, temperature sensor data alone for a year requires a storage capacity of 962.4 MB. However, if more types of data are included, such as temperature, humidity, and light intensity, the required storage capacity increases to 2887.2 MB.

A deep learning model using LSTM was tested to analyze patterns in sensor data. The model was trained on sensor data collected from multiple rooms over a period of three weeks. The dataset for the test included 2045 temperature and humidity data points collected between July 10, 2021 to 10/26/2021 and 1304 light intensity data points collected between 10/13/2021 to 10/26/2021. Noise data was excluded from the dataset, and the data was collected at a 10-min interval. A total of 67% of the dataset was used for validation. The trained deep learning model was utilized to predict the data, and the differences were compared, as shown in Table 10.

The Normalized Root Mean Square Error (NRMSE) 5% level was achieved for predicting sensor data using the trained model, as described

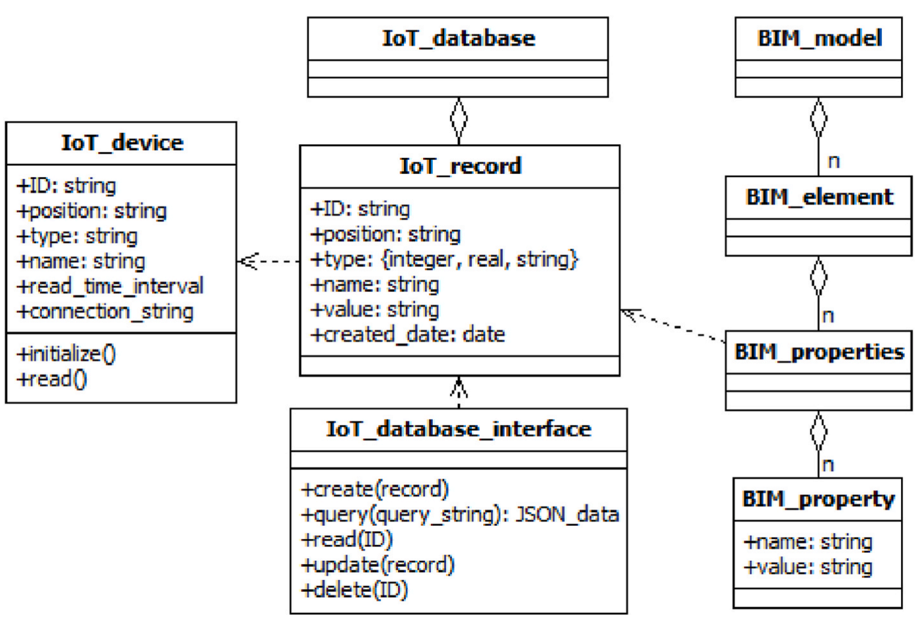

Fig. 6. IoT-BIM data structure for connection between real and digital worlds (UML).

Table 8
Role definition for elements in IoT-BIM data structure.

Elements	Roles
IoT_device	IoT device metadata to acquire sensor data and deliver it to the digital twin platform. Depending on the need, the IoT device may receive information from the digital twin platform and provide it to the user. The class members are: ID: Unique ID position: information classification system for connecting with BIM type: sensor data type. E.g., temperature, humidity name: sensor name
IoT_database	Manage IoT sensor database.
IoT_record	Define IoT sensor data records. The class members are: value: sensor value created_date: created data's date. e.g., yyyy-mm-dd, hh: mm:ss
IoT_database_interface	It provides an interface to CRUD data to the IoT database.
BIM_model	Manage BIM elements.
BIM_element	Define BIM elements. A BIM element can be a space, such as a room, or an object, such as a wall.
BIM_properties	Manage BIM properties.
BIM_property	Define BIM property, which consists of name and value.

in Fig. 10. Therefore, if the real-time sensor data exceeded the error range specified by the user utilizing the trained model, an alarm could be triggered to initiate the maintenance process automatically. The anomaly detection may be the model, such as a normal distribution-based boundary range. As a result, it was feasible to identify any abnormal patterns in the sensor data caused by improper facility or space management and address the concerns before they resulted in problems such as excessive energy consumption and space wastage.

6. Conclusion

This study presented a comprehensive strategy, framework, and architecture for effectively implementing building environment monitoring applications through the use of digital twin technology. By conducting a literature review, the key characteristics required for applying digital twins in the construction field were identified, and levels of data connectivity and predictability were defined. A framework and architecture were then designed to serve as a reference for implementing digital twins in the construction industry, and a prototype was developed and evaluated to assess its effectiveness and address challenges encountered during implementation. Throughout the process, this study evaluated the impact and obstacles of digital twins and provided suggestions for developing a general digital twin framework in the AEC field.

Existing digital twin research has primarily centered on the implementation of technologies such as intelligence and IoT. Within the framework proposed in this study, certain research efforts propose a digital twin framework or a building management system at the P1 level without taking into account the specific application's intended characteristics. Conversely, some studies have placed significant emphasis on connectivity, but the level of predictability predominantly remains at the P1 level (Table 4). Clearly defining the levels of unique characteristics, such as connectivity and predictability, before initiating development provides more precise anticipation and comprehension of digital twin implementation outcomes and functionalities tailored to specific application purposes. In this context, this study enables a more transparent evaluation and comparison of implementation levels, ultimately contributing to the cost-effective design and development of

Table 9
Function mapping of digital twin framework.

Modules	Related Functions	Tools
R1-1	F1, F2, F3, R4, F5, F6	Revit, Spreadsheet
R1-2	F7, F8	Navisworks
R3	F2, F3, F10	NVIDIA nano
R4	F9, F11	Arduino Nano Sense 33 BLE
R5	F23	Smartphone
D1	F13, F14	Autodesk Forge, MongoDB
D2	F13, F14	MongoDB
D3	F12, F13	Node-RED
D4	F19, F20	RESTful API server using node.js, express
D5	F15, F16, F17	Keras, TensorFlow
D6	F21, F22	Dashboard using Bootstrap, Node-RED
D7	F18, F23	RESTful API

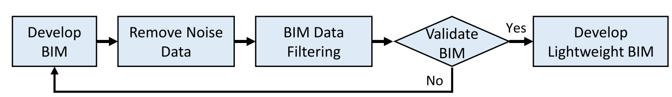

Fig. 8. Bim data development process.

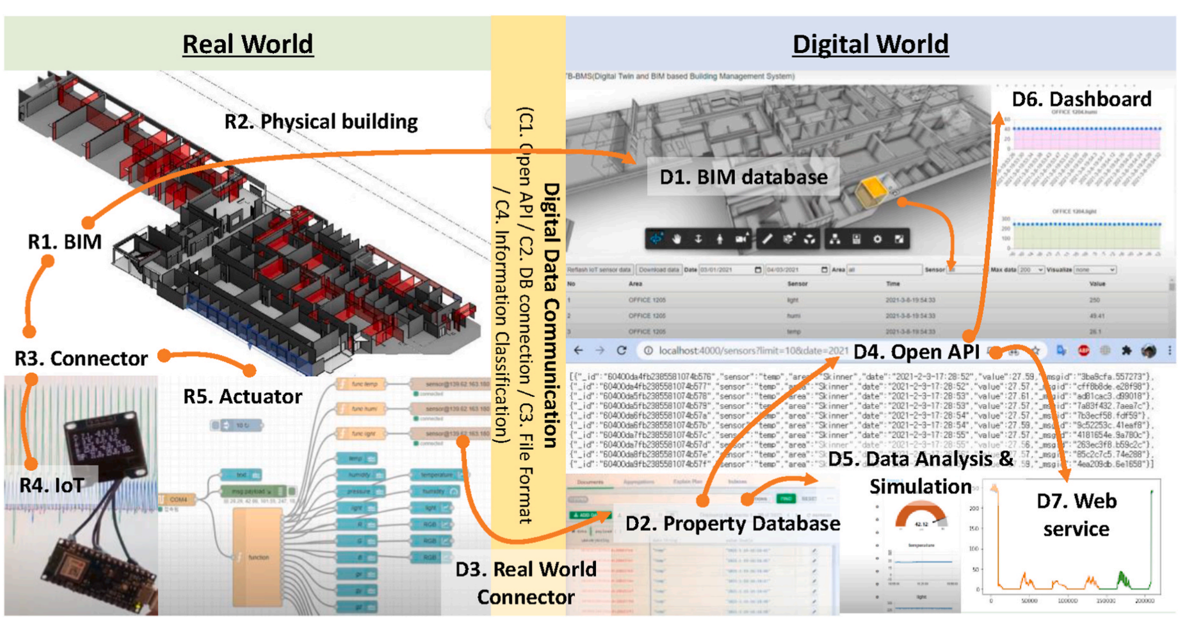

Fig. 7. Sequence flow of the case Study's digital twin system.

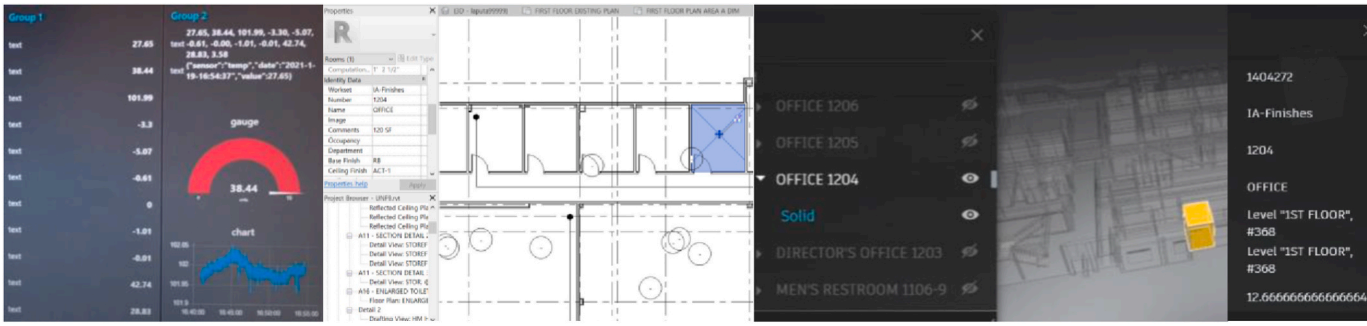

Fig. 9. Connection between IoT and BIM Data
(Left: Dataset collection, middle: Room object in revit, right: Room object in forge).

Table 10
LSTM test dataset statistics.

Sensor	Train Loss	min	max	Prediction	
				RMSE	NRMSE
Temperature	0.0006	23.51	28.11	0.13	0.03
Humidity	0.0009	44.85	54.52	0.39	0.04
Light intensity	0.0036	0.00	237.00	11.06	0.05

digital twin platforms.

Based on the analysis and comparison with the existing studies, this study proposed a digital twin framework and a case study. By improving the connectivity and predictability of the framework, the case study reached the level of C4 in connectivity and P2 in predictability. Although the major functions and relationships of components are implemented in the case study, bidirectional data exchange (the level of C5) was not supported. Automatic learning and updating datasets and models (the level of P3) were not yet employed in this case study, and they are the next targets of the implementation. Table 11 summarizes the levels of connectivity and predictability of the case study.

The extensive adoption of digital twin-based simulations for forecasting and decision-making remains limited in the AEC field. However, achieving high levels of all these characteristics can be unnecessary and resource-intensive for a complete digital twin. For instance, attaining a predictability level of P2 might suffice in certain construction site monitoring scenarios. Additionally, if real-time data exchange faces challenges due to network issues, alternative methods like data batch processing can be employed to support connectivity. On the other hand, a higher level of predictability may be required for supporting data prediction-based decision-making systems to sustain continuous platform operations and enhance simulation models. This illustrates that the characteristics of a digital twin can vary in levels depending on the specific purpose, and the implementation approach can be adapted accordingly. Thus, when project stakeholders agree on the levels of characteristics before development, it becomes easier to anticipate the outcomes of digital twin implementations. The research findings deliver insights into how future research in the AEC field can effectively develop and utilize digital twin platforms. In future studies, we intend to broaden the scope of defined digital twin characteristic indicators, conduct comparative evaluations across a wider range of implementation cases, and create problem-specific digital twin reference models.

CRediT authorship contribution statement

Tae Wook Kang: Funding acquisition, Methodology, Software, Writing - original draft. **Yunjeong Mo:** Conceptualization, Formal analysis, Project administration, Visualization, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

Table 11
Connectivity and predictability levels of the case study.

Application Domain	Connectivity Level	Data Predictability Level
Building Environment Management	C4: The proposed study implements real-time data from installed sensors to the digital twin model, enabling continuous monitoring of the operational status of the facility.	P2: It acquires data sets from sensors attached to building spaces, learns normal patterns, and then uses them for simulations such as prediction and detection of abnormal patterns. DevOps, which automatically learns and operates using sensor datasets attached to the physical space, is not implemented.

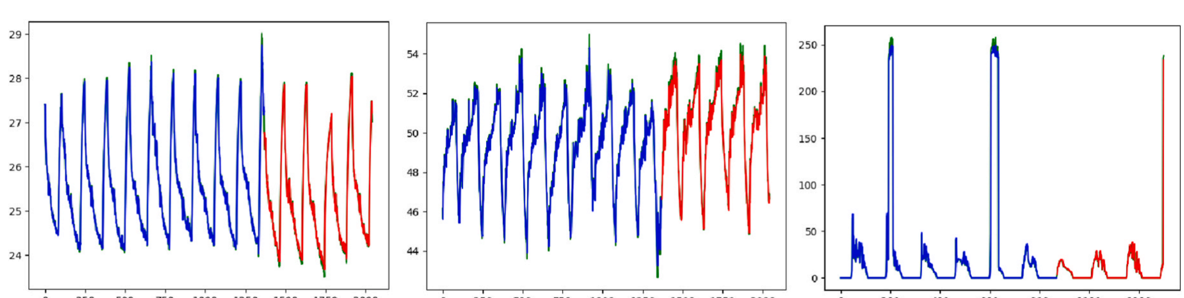

Fig. 10. Data pattern prediction using LSTM
(Left: Temperature, middle: Humidity, right: Light/blue: Train, red: Test, green: Prediction). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the work reported in this paper.

Data availability

Data will be made available on request.

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