POTENTIAL APPLICATIONS OF DIGITAL TWIN AND BIM TECHNOLOGY IN CONSTRUCTION INDUSTRY

Ngoc-Hieu Tran, Ngoc-Tri Ngo*

The University of Danang - University of Science and Technology, Viet Nam

*Corresponding author: trinn@dut.udn.vn

(Received: April 29, 2025; Revised: June 15, 2025; Accepted: June 18, 2025)

DOI: 10.31130/ud-jst.2025.23(9D).573E

Abstract - The advent of Industry 4.0 has significantly transformed the construction sectors through the integration of intelligent digital technologies. Among these, the Digital Twin (DT) has emerged as a transformative tool capable of bridging the physical and virtual worlds. This paper investigates the conceptual framework, practical applications, and implementation challenges of DT technology within the Architecture, Engineering, and Construction industry, with a particular focus on its integration with Building Information Modeling. The study outlines how DT enables real-time monitoring, predictive maintenance, and lifecycle optimization of built assets. Furthermore, it identifies key technical, organizational, and standardization issues that limit the scalability of DT in current construction practice. This research contributes to the understanding of DT's role in enhancing performance, sustainability, and digital governance in the built environment. The findings highlight the necessity of developing interoperable systems, standardized frameworks, and cross-disciplinary collaborations to unlock the full potential of DT in smart construction.

Key words - Digital Twin; Building Information Modeling (BIM); Asset Lifecycle Management; Internet of Things (IoT); Virtual Representation; Data Integration.

1. Introduction

The Fourth Industrial Revolution (Industry 4.0) has catalyzed a digital transformation that is reshaping how assets and systems are designed, constructed, and maintained. Among the transformative technologies, the Digital Twin (DT) stands out as a key enabler. A Digital Twin is a dynamic, real-time digital replica of a physical object, system, or process, driven by continuous data streams from embedded sensors and enhanced by AI and simulation tools [1, 2]. Initially developed for aerospace applications, DT is now being adopted across sectors such as manufacturing, healthcare, and notably, the Architecture, Engineering, and Construction (AEC) industry [3]. In this context, Building Information Modeling (BIM) serves as a foundational technology, providing geometric and semantic representation of assets and facilitating integration with Digital Twin models.

The adoption of DT in construction and real estate signals a paradigm shift toward intelligent asset management and performance optimization. Unlike static models such as traditional CAD or even early-generation BIM, a Digital Twin evolves continuously through the project lifecycle - from design and construction to operations and maintenance - by integrating real-time data streams and analytical models [4]. This integration enhances Asset Lifecycle Management by enabling features such as predictive maintenance, scenario simulation, risk assessment, energy optimization, and improved occupant experience. These capabilities are particularly crucial in smart construction projects and smart buildings where real-time responsiveness and data-driven decisions are essential [5].

One of the most promising synergies is the integration between DT and BIM. While BIM provides the geometric and semantic foundation for asset representation, DT extends this by incorporating temporal (4D), cost (5D), and performance-based dimensions (6D and beyond), effectively turning static building models into intelligent, self-updating systems [6]. This integration enables seamless monitoring of facility status, early detection of anomalies, and more sustainable building operation strategies [7]. Moreover, the Internet of Things (IoT) serves as the backbone of DT by providing continuous data streams from embedded devices within buildings - such as temperature, humidity, motion, and energy sensors, allowing the digital model to mirror and even anticipate changes in the physical environment [8]. Additionally, cloud computing and AI/ML (Machine Learning) algorithms process this data to enhance decision support, optimize resource allocation, and enable autonomous system control [9].

However, the practical implementation of Digital Twin in the construction sector still faces several challenges. These include issues of data interoperability across platforms, the lack of unified standards for digital models, high costs associated with sensor infrastructure, and the complexity of integrating real-time feedback loops [10]. Furthermore, the accuracy of a Digital Twin depends on the fidelity of the initial BIM model and the quality and granularity of live data inputs. As such, research continues to focus on developing robust frameworks, standardized protocols, and advanced computational models to support scalable DT adoption in the built environment [10].

Over the past years, researchers have proposed frameworks that enhance the connection between BIM and DT through semantic enrichment, cloud-based platforms, and real-time data pipelines. Others have focused on enhancing data fusion from heterogeneous sources and ensuring cybersecurity in DT ecosystems. As the industry moves toward smart asset ecosystems and carbon-neutral buildings, Digital Twin is expected to become a central component of sustainable development and digital governance strategies.

2. Literature review

2.1. Overview of Previous Models: Strengths and Limitations

Digital Twin (DT) technology has evolved through various conceptual and implementation models across different industries. Early applications in manufacturing introduced DT as a real-time feedback loop system connecting virtual simulations to physical assets [1]. When adapted to construction, several DT frameworks emerged from extensions of BIM, with integrated Internet of Things (IoT) data streams and simulation modules. These models enabled better visualization, progress tracking, and condition monitoring of buildings and infrastructure [8].

The main strength of earlier DT models in construction is their ability to integrate static BIM data with dynamic sensor inputs, thereby enhancing operational awareness and responsiveness. However, many models remain fragmented and are often developed for specific use cases such as structural health monitoring, rather than supporting full lifecycle applications. Common limitations include low interoperability, lack of standardized data formats, delayed synchronization, and difficulty scaling across large projects.

2.2. Research Gaps and Model Improvement Needs

Despite progress in DT development, current research shows that most models lack a unified architecture that seamlessly connects BIM, IoT, and AI across all construction phases. Real-time feedback and bidirectional data flows are limited, and current DT systems are often rigid, making it difficult to adapt to changing project conditions. Moreover, most existing models do not incorporate user interaction, human behavior simulation, or energy feedback loops, which are essential for comprehensive building operation scenarios [6].

These gaps underscore the need for improved DT models that are scalable, modular, and able to support predictive analytics, lifecycle integration, and stakeholder collaboration. Particularly in large-scale infrastructure and smart city projects, the demand for flexible, interoperable DT frameworks is increasing. Addressing these issues can significantly advance automation, sustainability, and decision-making quality in the construction industry. The hypothesis of this research suggests that the potential integration of DT with BIM and IoT data streams will enhance asset management, predictive maintenance, operational efficiency, and sustainability within the construction industry. This study aims to explore the potential applications of DT and BIM in the construction industry. Accordingly, this research addresses the following question: *How can an integrated Digital Twin framework enhance decision-making and operational efficiency across the construction lifecycle?*

2.3. Theoretical Basis for Model Development

The development of DT models in construction has been strongly influenced by systems theory, cyber-physical systems (CPS), and lifecycle management theory. BIM provides the foundational data environment, offering spatial geometry, semantic relationships, and metadata. When combined with CPS concepts, DT models simulate the behavior of physical assets under real-time operating conditions. In parallel, theories from facilities management support the integration of operational data, maintenance routines, and performance analytics throughout the building lifecycle.

To develop these DT models, a combination of modeling methodologies has been employed, including discrete-event simulation, agent-based modeling, and system dynamics. These approaches are used to structure data flows, decision-making logic, and predictive capabilities in DT frameworks. Discrete-event simulation, for instance, models the occurrence of events and their impact on system behavior over time, while agent-based modeling simulates individual entities and their interactions within a system. System dynamics focuses on feedback loops and time delays, helping to understand how different variables influence the overall performance of construction systems. These methodologies enable adaptive control and optimization in construction environments, improving decision-making and resource allocation.

3. Research Methodology

3.1. Orientation and Identification of Asset Owner's Objectives

In accordance with ISO 19650 Part 1, the definition of information requirements must follow a hierarchical structure, beginning with Organizational Information Requirements (OIR), followed by Asset Information Requirements (AIR) and Project Information Requirements (PIR) is described in Figure 1.

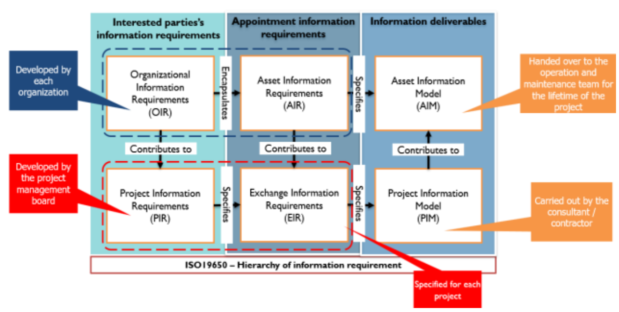

***Figure 1**. Hierarchy of information requirements*

As an asset owner, the first critical step is to identify what constitutes the asset, the scope of its lifecycle, and the nature of information needed to support strategic, operational, and technical decision-making.

This involves translating high-level organizational goals (OIR) into specific, measurable asset-level information needs (AIR), which then inform project-specific requirements (PIR) across procurement, design, construction, and operation phases.

Clearly defining these information needs at the digital level enables the seamless interaction between the physical asset and its digital representation (i.e., Digital Twin), fostering real-time data exchange, predictive maintenance, and lifecycle optimization (Figure 2). This structured approach ensures that BIM and Digital Twin initiatives are purpose-driven, cost-effective, and aligned with long-term asset strategies.

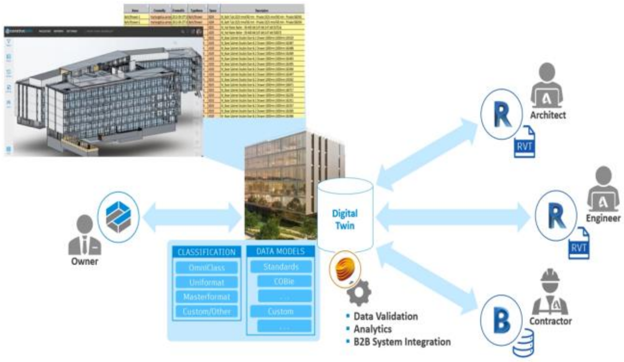

Figure 2. *Stakeholder interactions within the Digital Twin environment [11]*

3.2. Data Collection and Processing

3.2.1. Expectation of Data Collection

To implementing the DT system, the hypothesis proposes that the data for developing the Digital Twin model is simulated from two core sources: (1) a Building Information Modeling (BIM) system, which is assumed to be implemented throughout the entire project lifecycle, and (2) real-time data simulated from virtual sensors embedded in the physical built environment.

Specifically, the BIM model serves as a foundational digital repository that captures geometric data, structural elements, material specifications, and technical systems. Rather than being limited to the design phase, the BIM model is dynamically updated during construction and as-built documentation, thereby offering a comprehensive view of both the physical configuration and spatial logic of the facility.

In parallel, IoT sensors are deployed at critical locations within the facility to monitor and transmit operational parameters, such as temperature, humidity, energy consumption, mechanical load, vibration, and air quality. These sensors continuously stream data to centralized, cloud-based platforms, thereby transforming the Digital Twin from a static replica into a dynamic, living system that mirrors the real-time state of the physical asset.

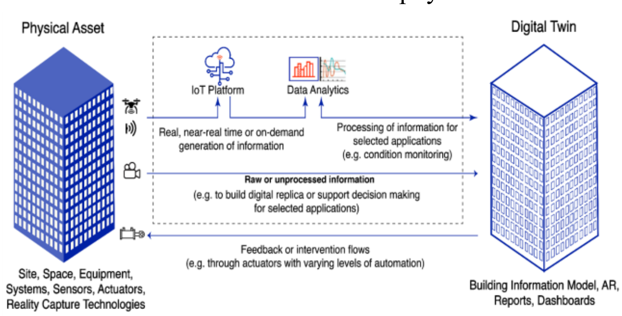

Figure 3. *Physical Asset to DT Transformation [6]*

The tight integration between the BIM model (capturing the geometric–logical state of the facility) and sensor data (reflecting its operational dynamics) is a prerequisite for constructing a comprehensive Digital Twin. This approach enables the reproduction not only of the "physical appearance" but also of the "behavioral patterns" of the building, thus laying the foundation for advanced analytics such as performance forecasting, operational optimization, and predictive maintenance (Figure 3).

3.2.2. 3D Digital Model Construction

The 3D digital model serves as the structural backbone of the Digital Twin system, providing the spatial digital foundation for integrating geometric, technical, and operational data. The construction process requires the fusion of traditional design sources (e.g., CAD drawings, MEP schematics) with standardized BIM models (e.g., IFC or Revit), ensuring geometric accuracy and data interoperability throughout the building lifecycle. To achieve a model that accurately reflects the as-built and as-operated condition of the facility, the construction of the 3D digital model typically involves the following sequential steps:

a. Design BIM Standardization:

The original design models are reviewed and adapted to comply with standardized data structures, typically aligning with Levels of Development (LOD) ranging from 300 to 500. This ensures sufficient geometric detail and semantic richness to support integration with sensor networks and operational models.

b. Reality Capture using LiDAR/Scan-to-BIM:

When updating the model to reflect post-construction conditions, laser scanning (LiDAR) or 3D photogrammetry is employed to generate accurate point cloud datasets. These datasets serve as the basis for validating and refining the original design model, thus achieving an as-built representation that mirrors the physical reality.

c. Metadata Linking and Technical Attribute Integration:

Each digital element (e.g., walls, doors, equipment, HVAC systems) is enriched with metadata such as material specifications, manufacturer details, capacity, and maintenance schedules. This creates a digital logbook or “semantic passport” for every object within the model.

d. Sensor Binding to the 3D Model:

IoT sensors deployed throughout the facility are spatially and logically linked to their corresponding digital elements in the 3D model. For instance, a temperature sensor in Room 305 is precisely mapped to its location in the digital environment, enabling spatiotemporal monitoring and live performance visualization.

To achieve an accurate as-built and as-operated representation, the 3D modeling process typically includes: (1) BIM model standardization to ensure LOD compliance; (2) reality capture using LiDAR or photogrammetry to update the physical status; (3) metadata enrichment for all components; and (4) real-time sensor binding to link physical data with digital geometry.

Overall, the 3D model is not merely a geometric representation, but a smart digital surrogate capable of integrating technical metadata and dynamic inputs to support simulations, what-if analyses, and facility performance optimization.

3.2.3. Simulations and Analysis

Within the Digital Twin framework, the simulation and analysis layer serves as a pivotal component, enabling comprehensive insights into the dynamic behavior of buildings and systems. By fusing real-time data from IoT sensors with detailed 3D digital models, this layer facilitates advanced simulations that go beyond mere performance forecasting. It supports the optimization of operational processes, enhances overall efficiency, and proactively identifies potential risks. As a result, it becomes a powerful tool for informed decision-making and the development of resilient, sustainable operational strategies under diverse real-world scenarios.

a. Building Automation System (BAS) Simulation

In BAS, simulations focus on optimizing the building's heating, ventilation, air conditioning (HVAC), lighting, and other environmental control systems. Using real-time data from sensors, these simulations provide insights into energy usage patterns, identify inefficiencies, and recommend adjustments to improve operational efficiency. For example, energy consumption can be modeled under varying occupancy levels or changing weather conditions, leading to better optimization of energy resources (Figure 4).

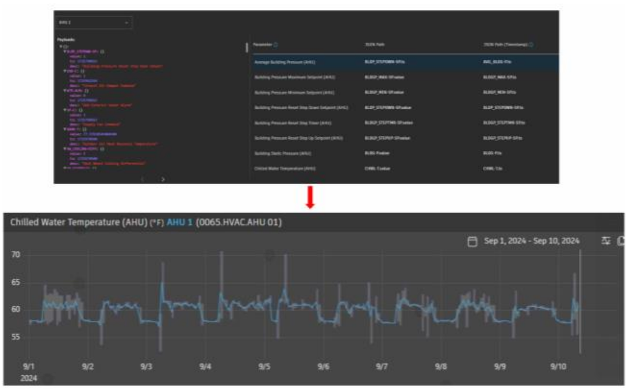

***Figure 4**. The payloads received from the building automation system & The output stream inside Tandem [12]*

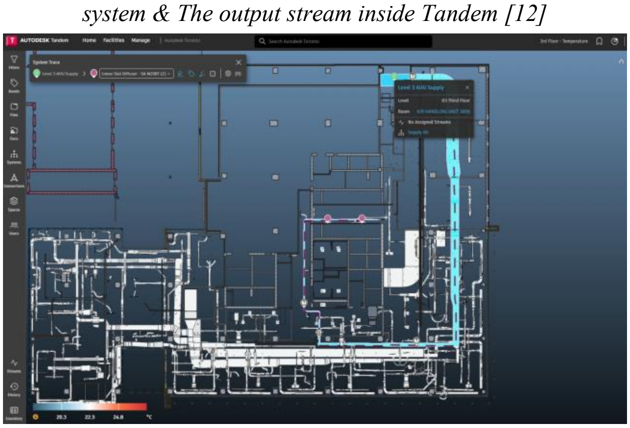

***Figure 5**. Airflow streams [13] (Adapted from Autodesk, n.d.)*

This simulation also helps ensure that HVAC systems are operating efficiently, thereby reducing energy costs while maintaining comfort levels. Airflow direction and volume passing through HVAC components - such as diffusers, ducts, and return vents - are simulated using Computational Fluid Dynamics (CFD) models integrated into the Digital Twin environment. These simulations assist in identifying zones with uneven ventilation, stagnant air, or thermal discomfort. Real-time insights are visualized using dynamic charts and airflow streams, allowing facility managers to monitor, analyze, and adjust system settings promptly for optimal performance (Figure 5).

Simulation outcomes, visualized through platforms like Autodesk Tandem using Chart modules, help pinpoint high-consumption zones, detect inefficiencies, and optimize equipment performance. In addition, the platform allows real-time temperature simulations for individual rooms and functional spaces, facilitating the identification of thermal imbalances, underperforming HVAC zones, or areas requiring environmental adjustments. This not only leads to lower utility costs but also supports long-term sustainability goals (Figure 6).

***Figure 6**. Real-time temperature simulations Asset Management System (AMS) Simulation [13]*

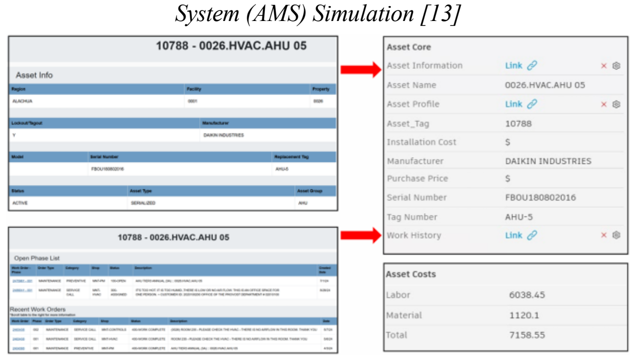

***Figure 7**. Element-level data extracted from Autodesk Tandem [12]*

AMS simulations are focused on maintaining and optimizing the lifecycle of assets within a building, such as elevators, HVAC units (), lighting, and other critical infrastructure. By integrating data from IoT sensors and historical maintenance records, these simulations predict the failure or performance degradation of assets, allowing for predictive maintenance strategies to be implemented.

These predictive models are essential for reducing unplanned downtime, maximizing asset lifespan, and optimizing maintenance schedules. Real-time dashboards and alert systems ensure that facility managers can act promptly on critical maintenance needs.

b. Space Management System (SMS) Simulation

Simulating space utilization is a critical application of the SMS, as it helps building managers optimize room usage, occupancy levels, and layout designs. By integrating sensor data from people counters and occupancy sensors, the system can simulate various scenarios to analyze how space is used over time.

The simulation outputs can be used to predict space congestion, optimize energy use based on real-time occupancy, and plan for future facility needs. Heatmaps generated from the data also provide a visual representation of high-usage areas, allowing for more efficient space planning (Figure 8).

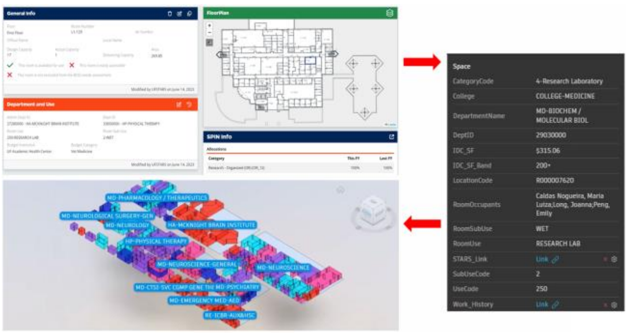

Figure 8 *- Space management simulations [12]*

c. Document Management System (DMS) Simulation

In a Document Management System (DMS) embedded within a Digital Twin framework, simulations play a critical role in analyzing the flow, accessibility, and lifecycle of digital documents. Information is continuously tracked from the digital model, making it essential that all document-related metadata be accurately defined, standardized, and properly tagged. Each document - such as technical drawings, equipment manuals, compliance certificates, and maintenance records - is linked to its corresponding physical or virtual asset in the model through structured metadata.

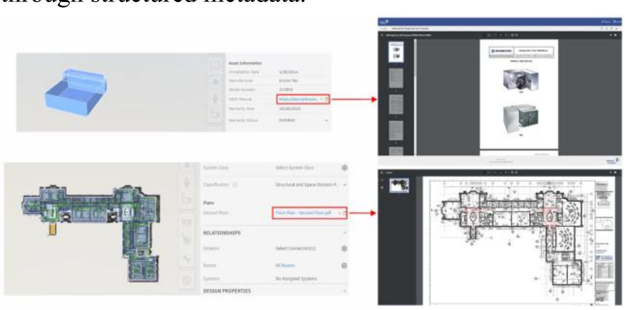

Figure 9 *- Component information is continuously tracked from digital model [12]*

Machine learning algorithms are utilized to simulate and optimize document categorization, access workflows, and user interaction patterns. These simulations facilitate the detection of bottlenecks in retrieval processes, enhance search efficiency, and support regulatory compliance. Real-time data analysis further allows the system to propose improvements in document lifecycle management, ensuring that critical documents are available, searchable, and up-to-date when needed. Poorly tagged or inconsistent metadata can lead to inefficiencies, increased operational risk, and reduced system interoperability throughout the facility's lifecycle (Figure 9).

3.2.4. Implementation workflow

Throughout the project lifecycle, from design development to operation handover, this study employed a suite of tools from the Autodesk ecosystem, notably Autodesk Revit and Autodesk Tandem.

Autodesk Revit was utilized during the design and coordination phase to develop the Building Information Model (BIM) with high geometric fidelity and parametric accuracy (LOD 300–400). Its support for Industry Foundation Classes (IFC) ensured interoperability across platforms and disciplines. Revit's ability to embed metadata into model elements enabled early-stage integration of asset-related information such as material properties, manufacturer data, and maintenance schedules.

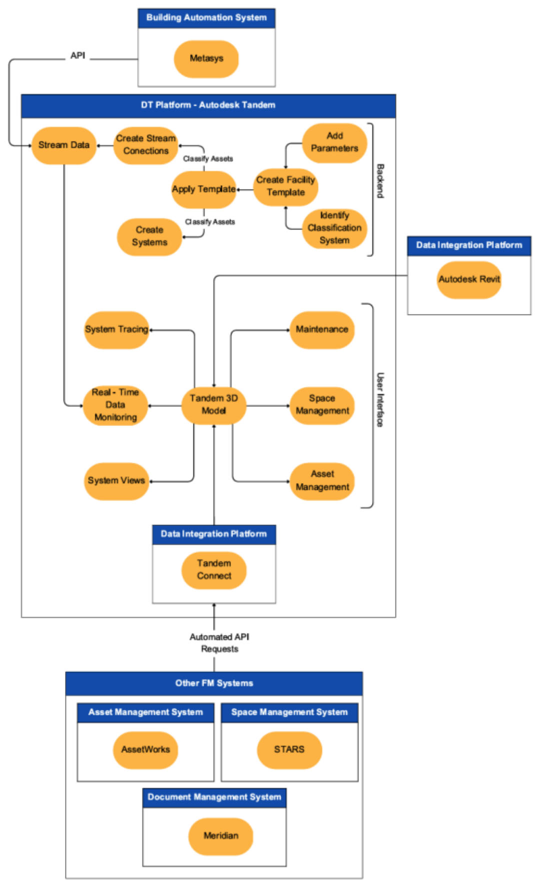

Figure 10 *- Implementation Workflow [12]*

In the post-construction phase, Autodesk Tandem, a cloud-based digital twin platform, was employed to host the as-built model enriched with sensor data and operation metadata. The seamless connection between Revit and Tandem allowed for model transfer and data synchronization, thus enabling the creation of a live digital twin that supports real-time monitoring, system diagnostics, and predictive maintenance.

4. Result analysis

The analysis indicates that Digital Twin technology offers significant potential when integrated with existing facility management systems, including Building Automation Systems (BAS), Asset Management Systems (AMS), Space Management Systems (SMS), and Document Management Systems (DMS). This integration supports a more holistic, data-driven approach to building operations. The findings are grouped into three key thematic areas:

4.1. Real-time Monitoring and Fault Detection

By incorporating data streams from BAS into the Digital Twin environment, facility managers gain real-time visibility over critical building parameters such as temperature, humidity, lighting, and HVAC performance. These operational metrics are spatially linked to corresponding components in the 3D model through SMS integration, enabling location-specific anomaly detection. This connection improves responsiveness and allows for early intervention, reducing the reliance on manual inspection routines and enhancing situational awareness across different building zones.

4.2. Predictive Maintenance through Semantic Data Enrichment

The integration of AMS with semantically enriched BIM data provides a robust framework for predictive maintenance. Equipment specifications, operational thresholds, service records, and maintenance schedules are embedded within the Digital Twin, allowing maintenance teams to anticipate issues before they escalate. This proactive approach helps prioritize interventions, optimize resource allocation, and extend asset lifecycles. By aligning real-time operational data with long-term asset information, the systems support informed decision-making and more sustainable maintenance strategies.

4.3. Interoperability and Lifecycle Synchronization

Document Management Systems (DMS) play a critical role in supporting the traceability and accessibility of technical documentation throughout the building lifecycle. Within the Digital Twin environment, documents such as design drawings, technical manuals, commissioning records, and maintenance logs are directly linked to their respective model elements. This connection not only streamlines document retrieval but also ensures consistency between digital records and on-site conditions. Furthermore, seamless interoperability between design platforms like Autodesk Revit and operational platforms like Autodesk Tandem ensures that updates made during the design or construction phase are accurately reflected in the operational model, maintaining data fidelity and facilitating smoother asset handovers.

5. Discussion

The Digital Twin (DT) technology has the potential to revolutionize the Architecture, Engineering, and Construction (AEC) industry by providing real-time, data-driven insights into building performance. By creating a dynamic digital representation of a physical asset, DT allows for predictive maintenance, energy optimization, and performance forecasting throughout the asset's lifecycle. The integration with Building Information Modeling (BIM) extends this capability by adding dimensions like time (4D), cost (5D), and performance (6D), which enables ongoing monitoring and decision-making based on real-time data [5].

Despite its advantages, the widespread adoption of DT faces several challenges. One major issue is data interoperability, as sensor data from IoT devices often faces compatibility problems across platforms. This lack of standardization can hinder the scaling of DT across larger projects. Additionally, the high costs of implementing IoT sensors and the complexity of integrating real-time data into existing workflows can limit adoption, especially for smaller organizations [10]. Furthermore, the accuracy of DT is highly dependent on the quality of the initial BIM model and sensor data, and any discrepancies can lead to suboptimal decisions [10].

Organizational barriers also play a significant role in limiting DT adoption. Many construction firms still work in silos, making it difficult to foster collaboration across disciplines. Overcoming these barriers will be essential to realize the full potential of DT. Moreover, cybersecurity concerns related to the integration of real-time data streams further complicate its implementation.

Looking ahead, the future of DT in the AEC industry seems promising, especially with the continued evolution of emerging technologies. As 5G and edge computing become more widely adopted, the ability to process and transfer large volumes of data in real-time will significantly improve, enabling more dynamic and responsive Digital Twin models. Additionally, advances in artificial intelligence (AI) and machine learning (ML) are expected to enhance the predictive capabilities of DT, allowing for smarter maintenance, better forecasting, and more efficient resource management. With the integration of blockchain, DT systems could see improved security and transparency, addressing many of the current concerns related to data integrity and cybersecurity.

The construction industry’s shift toward sustainability highlights DT's importance in achieving carbon-neutral goals. By optimizing energy management and improving the environmental performance of buildings, DT can help reduce carbon footprints and resource waste [7]. However, the fragmented nature of current DT models and the lack of a unified architecture across all phases of construction present barriers to its widespread use. The development of modular, customizable frameworks will be key to addressing these challenges and enabling greater DT adoption in the industry.

6. Conclusions

The integration of simulation and analysis within the Digital Twin ecosystem represents not merely a technological advancement, but a paradigm shift in how modern buildings and infrastructure are managed. Through the fusion of 3D digital models, real-time sensor data, and advanced simulation algorithms, the Digital Twin delivers a comprehensive platform for monitoring current states, forecasting future behavior, and optimizing operational performance across the entire asset lifecycle.

This paper has provided a theoretical overview of existing DT models, identified current limitations and research gaps, and proposed the potential integration of DT and Building Information Modeling (BIM) technologies across various phases of the construction lifecycle. The key contribution lies in presenting the potential applications of Digital Twin and BIM frameworks - ranging from energy performance analysis and predictive maintenance to occupant behavior modeling and lifecycle optimization.

By combining BIM's structured digital representation of built assets with DT's real-time data and simulation capabilities, these integrated systems enable more intelligent, adaptive, and sustainable approaches to construction management. Such integration enhances operational decision-making and long-term asset resilience.

Therefore, as digital transformation accelerates, investing in simulation-driven Digital Twin frameworks supported by BIM not only yields immediate operational benefits but also lays the foundation for future-ready, data-driven construction systems. This study contributes a consolidated foundation for future empirical research and practical implementations in smart construction and infrastructure management.

Future research may focus on developing and validating specific Digital Twin frameworks tailored to distinct phases of the construction lifecycle. Empirical studies and real-world case applications are particularly needed to further test and refine the theoretical insights presented in this paper.

REFERENCES

[1] M. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems", *in Transdisciplinary Perspectives on Complex Systems*: Kahlen, J., Flumerfelt, S., Alves, A. (eds), 2016, Springer, Cham, pp. 85-113. https://doi.org/10.1007/978-3-319-38756-7_4.

[2] S. Boschert and R. Rosen "Digital Twin - The Simulation Aspect", In *Mechatronic Futures*, Hehenberger, P., Bradley, D. (eds) 2016 Springer, Cham, pp. 59-74, 2016. https://doi.org/10.1007/978-3-319-32156-1_5.

[3] F. Tao, Q. Qi, L. Wang, and A.Y.C. Nee, "Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison", *Engineering*, vol. 5, no. 4, pp. 653–661, 2018.

[4] R. Sacks, C. Eastman, G. Lee, and P. Teicholz, "*BIM Handbook: A Guide to Building Information Modeling for Owners, Designers, Engineers, Contractors, and Facility Manager"*, New Jersey, USA, Wiley, 2018.

[5] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the Digital Twin: A systematic literature review", *CIRP Journal of Manufacturing Science and Technology,* vol. 29, part A, pp. 36-52, 2020.

[6] S. H. Khajavi, N. H. Motlagh, A. Jaribion, L. C. Werner, and J. Holmstrom, "Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings". *IEEE Access*, vol. 7, pp. 147406–147419, 2019.

[7] Q. Lu, X. Xie, and C. J. Webster, "Digital Twin enable anomaly detection for built asset monitoring in operation and maintains", *Automation in Construction*, vol. 118, pp. 103277, 2020.

[8] Q. Qi, *et al*, "Enabling Technologies and Tools for Digital Twin. Journal of Manufacturing Systems", *Journal of Manufacturing Systems,* vol. 48, pp. 3–21, 2018.

[9] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research", *IEEE Access*, vol. 8, pp. 108952–108971, 2020.

[10] P. Wang, P. Wu, J. Wang, H. L. Chi, and X. Wang, "A Critical Review of the Use of Digital Twin in Construction". *Automation in Construction*, vol. 93, pp. 123–135, 2018.

[11] R. Bray and T. Kelly, "*Delivering the Value of BIM to Owners with a Digital Twin*", Autodesk University, San Francisco, California, United States, Class handout BLD473618, 2020.

[12] R. Issa and F. Phillips, "*Boosting Campus Operational Efficiency Through the Power of Autodesk Tandem Digital Twins*", Autodesk University, San Francisco, California, United States, Class handout BLD4024, 2024.

[13] Autodesk, Inc., "Twinning Autodesk", *intandem.autodesk.com*. Available: https://intandem.autodesk.com/resource/twinning-autodesk, [Accessed April 12, 2025].