

Review

Unlocking the Potential of Digital Twin Technology for Energy-Efficient and Sustainable Buildings: Challenges, Opportunities, and Pathways to Adoption

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Abstract

Digital Twin technology is transforming how buildings are designed, operated, and optimized, serving as a key enabler of smarter, more energy-efficient, and sustainable built environments. By creating dynamic, data-driven virtual replicas of physical assets, Digital Twins support continuous monitoring, predictive maintenance, and performance optimization across a building's lifecycle. This paper provides a structured review of current developments and future trends in Digital Twin applications within the building sector, particularly highlighting their contribution to decarbonization, operational efficiency, and performance enhancement. The analysis identifies major challenges, including data accessibility, interoperability among heterogeneous systems, scalability limitations, and cybersecurity concerns. It emphasizes the need for standardized protocols and open data frameworks to ensure seamless integration across Building Management Systems (BMSs), Building Information Models (BIMs), and sensor networks. The paper also discusses policy and regulatory aspects, noting how harmonized standards and targeted incentives can accelerate adoption, particularly in retrofit and renovation projects. Emerging directions include Artificial Intelligence integration for autonomous optimization, alignment with circular economy principles, and coupling with smart grid infrastructures. Overall, realizing the full potential of Digital Twins requires coordinated collaboration among researchers, industry, and policymakers to enhance building performance and advance global decarbonization and urban resilience goals.

Keywords: digital twin; smart buildings; energy efficiency; decarbonization; sustainability; building performance optimization; building information modelling; building management system

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1. Introduction

1.1. Background

The building sector remains one of the largest contributors to global carbon emissions, accounting for nearly 40% of energy-related greenhouse gas emissions [1]. These emissions arise not only from operational energy use but also from embodied carbon embedded in construction materials, manufacturing processes, and logistics. As global commitments to meet climate neutrality targets intensify, decarbonizing the building stock is increasingly recognized as both an environmental necessity and an economic opportunity

[2]. Traditional approaches to improving building energy performance, such as static energy audits, rule-based control systems, and periodic retrofitting, have delivered measurable gains but are limited in scope [3]. They fail to capture the dynamic complexity of modern buildings, where energy performance fluctuates in response to varying occupancy patterns, weather conditions, internal loads, and progressive equipment degradation [4]. Consequently, these methods often produce static and fragmented insights, unable to adapt to the evolving operational realities of buildings. While these challenges highlight the limitations of conventional approaches, emerging technologies offer promising solutions for adaptive, data-driven building management.

1.2. The Emergence of Digital Twins for Buildings

Digital Twin (DT) technology has emerged as a transformative paradigm for data-driven, adaptive building management. A Digital Twin is generally defined as a high-fidelity, continuously updated digital counterpart of a physical asset, system, or process, dynamically linked through real-time data streams [5,6]. In the context of sustainable buildings, Digital Twins extend beyond simple virtual models; they function as living systems that integrate data from sensors, control systems, occupant interactions, and external environmental sources. Through this integration, they enable ongoing simulation, prediction, and optimization across a building's lifecycle, from design and construction to operation, retrofitting, and decommissioning [7].

A robust DT framework typically consists of several interconnected components with varying levels of fidelity. Low-fidelity twins may simulate basic subsystems such as HVAC, lighting, or energy distribution, while high-fidelity twins capture complex interactions encompassing occupant behavior, structural dynamics, and environmental feedback [8]. Real-time data synchronization, facilitated by IoT sensors, Building Management Systems (BMSs), and cloud-based platforms, lies at the core of a DT's functionality [9]. Advanced implementations allow multiple Digital Twins to communicate and collaborate, forming networks of twin-to-twin ecosystems that optimize distributed building clusters or entire campuses [10]. When coupled with simulation engines and AI-driven analytics, DTs can conduct scenario-based simulations, predict system faults, and autonomously recommend or execute control strategies. This capability enhances both energy efficiency and indoor environmental quality while enabling predictive maintenance and operational resilience [11].

1.3. Existing Frameworks and Implementations

In recent years, several frameworks have been proposed to structure the development and deployment of DTs within the built environment. The Grieves–Parr model, originally conceived for manufacturing, has been adapted to emphasize three interconnected layers: the physical entity, its digital counterpart, and the bidirectional data exchange that links them [12]. The Center for Digital Built Britain (CDBB), through its National Digital Twin initiative, promotes a federated and layered approach that prioritizes interoperability, data governance, and secure system integration [13]. Within Europe, the FIWARE architecture and the NGSI-LD standard have gained prominence in smart building applications, providing semantic interoperability and ontology-based data modeling that facilitates integration with other urban systems [14]. While these frameworks vary in their focus, from lifecycle data management to semantic standardization, they are built on key principles: real-time data exchange, continuous feedback loops, and the generation of actionable insights to support evidence-based decision-making.

In addition, empirical studies and pilot implementations across commercial, institutional, and residential buildings have demonstrated measurable benefits, including improved energy performance, enhanced operational transparency, and reduced

maintenance costs [15]. Nonetheless, widespread adoption remains constrained by multiple challenges. Technical obstacles include sensor deployment, interoperability between legacy systems, and maintaining model fidelity over time [16]. Economic and organizational barriers, such as high initial investment, data ownership concerns, and a lack of skilled personnel, further hinder scalability. Moreover, the absence of a unified theoretical foundation or standardized reference architecture has resulted in fragmented, non-interoperable solutions across the sector.

1.4. Objectives and Methodology

This study investigates how DT technology can accelerate the decarbonization of the building sector by bridging the gap between theoretical energy models and real-world performance. It examines the role of DTs in optimizing energy use, reducing carbon emissions, and supporting integration with renewable energy and smart grid infrastructures. The paper also highlights practical applications, identifies key barriers to adoption, and outlines strategies for scaling up implementation.

To guide this investigation, the study is driven by the following research objectives:

1. Define and contextualize DT technology in the built environment, including its structural components and operational capabilities.
2. Review existing DT frameworks and applications, with an emphasis on energy performance optimization and emission reduction.
3. Identify and analyze key implementation challenges, including interoperability, data governance, scalability, and cybersecurity.
4. Assess policy and regulatory developments influencing the deployment of DTs in Europe and beyond.
5. Propose a future research agenda, highlighting opportunities for AI integration, smart grid alignment, and climate-resilient urban infrastructure.

To achieve these objectives, this study adopts a structured yet exploratory literature review methodology to balance systematic rigor with the flexibility required to capture emerging research on Digital Twins in the built environment. Key steps include:

- **Database Selection:** The literature was retrieved from Web of Science, Scopus, and IEEE Xplore, ensuring comprehensive coverage of peer-reviewed journal articles, conference proceedings, and institutional reports.
- **Keyword Search Strategy:** The search used combinations of relevant keywords, including: “Digital Twin,” “Building Digital Twin,” “Smart Buildings,” “Energy Optimization,” “Decarbonization,” “Lifecycle Carbon,” and “Sustainability in Buildings.”
- **Inclusion Criteria:** Publications from 2015 onwards were prioritized to reflect recent technological advancements. Earlier works were included when conceptually significant (e.g., foundational DT frameworks). Only documents in English and those focused on building-related applications of DTs were considered.
- **Exclusion Criteria:** Articles unrelated to building energy management, non-DT technologies, or not reporting empirical or conceptual contributions were excluded.

In this study, a qualitative thematic analysis was conducted following established guidelines to synthesize recurring patterns and identify knowledge gaps in the literature. The analysis began with familiarization, involving careful reading and re-reading of the selected studies to gain a deep understanding of their content. Relevant features of each study, including technologies employed, energy optimization strategies, emissions reduction results, interoperability solutions, and reported challenges, were then identified and coded. These codes were subsequently grouped into broader themes, such as interoperability, data governance, scalability, cybersecurity, AI integration, and policy alignment. The themes were iteratively reviewed and refined to ensure consistency and alignment

with the research objectives. Finally, the findings were synthesized and organized to support the analytical structure of the paper, guiding the identification of research gaps and informing potential future research directions.

In parallel, a comparative review of existing DT frameworks was conducted to identify conceptual gaps and lessons from ongoing initiatives. Additionally, the study examined the evolving policy landscape, with particular attention to European directives, funding programs, and standardization efforts influencing DT adoption. Together, these analyses provide a holistic understanding of the current maturity of DT technologies in the building sector, highlighting what has been achieved, what barriers remain, and what strategic actions are necessary to enable their large-scale deployment. Overall, the paper suggests that DTs represent a pivotal enabler for intelligent, adaptive, and low-carbon building systems. When effectively integrated into design and operational workflows, they can drive measurable progress toward resilient, climate-neutral cities and support the broader global transition to sustainable urban living.

1.5. Original Contributions of this Study

While a growing body of literature has explored DT applications in buildings, most existing studies focus on isolated and specific aspects such as energy monitoring, predictive maintenance, or single-building optimization. In contrast, this paper offers a system-level and integrative perspective on DT technology as a strategic enabler for large-scale building decarbonization. The originality of this study lies in four key contributions: First, it provides a holistic synthesis of DT capabilities across the entire building lifecycle, explicitly linking design, operation, retrofit, and end-of-life stages to decarbonization pathways rather than treating DTs as purely operational tools. Second, the paper systematically consolidates empirical evidence from diverse real-world case studies and translates technical outcomes into comparable energy and carbon reduction ranges, bridging the gap between conceptual frameworks and actual performance. Third, the study advances the scientific discussion by addressing adoption barriers, including interoperability, data governance, scalability, cybersecurity, and organizational readiness, which are often not sufficiently represented in technically focused DT cases. Finally, the paper presents a forward-looking research and deployment agenda, emphasizing AI integration, smart grid alignment, and policy-driven scalability, positioning DTs not only as engineering tools but as socio-technical systems incorporated within regulatory and institutional contexts. Through this integrated and critical perspective, the paper moves beyond incremental application-focused studies, offering a structured, decarbonization-oriented framework for understanding, evaluating, and scaling DT technologies in the built environment.

2. Digital Twins in the Built Environment

2.1. Definition and Core Principles

Traditional building design and assessment approaches rely on static methodologies such as Building Energy Modeling (BEM), compliance-based performance assessments, periodic energy audits, and rule-based control logic. While these methods have been instrumental in improving baseline efficiency, they typically assume fixed operating conditions and are limited in their ability to respond to real-time dynamics such as fluctuating occupancy, behavioral variability, and system degradation over time. Digital Twin technology fundamentally extends these approaches by enabling continuous synchronization between physical buildings and digital models. Unlike conventional simulations, which are often performed offline and updated infrequently, DTs evolve dynamically through real-time data integration. This enables persistent performance assessment, adaptive control, and predictive optimization rather than retrospective analysis. Crucially, DTs

support closed-loop decision-making, where simulation, monitoring, prediction, and control are integrated within a single operational framework. This is more comprehensive compared to traditional workflows, where design, operation, and retrofit decisions are typically disconnected. As a result, DTs provide superior capabilities in detecting inefficiencies, quantifying uncertainty, evaluating “what-if” scenarios, and optimizing energy performance throughout the building lifecycle. These advantages position DTs as a transformative advancement over static and fragmented assessment methods, particularly in the context of decarbonization and climate resilience.

At its foundation, a Building Digital Twin (BDT) represents a dynamic, data-driven digital counterpart of a physical building [17]. Unlike static digital models, a BDT continuously mirrors the actual state and behavior of the building, evolving in real time as new information becomes available. It is constructed through the seamless integration of diverse data sources, including BIM, Internet of Things (IoT) devices, sensor networks, and AI algorithms, each contributing to a unified and continuously updated representation of the physical asset, as noted in Figure 1.

What distinguishes a BDT from traditional digital models is its self-updating and adaptive nature. Through ongoing synchronization with real-time data streams, the twin maintains an accurate reflection of the building’s operational state, encompassing parameters such as energy use, indoor air quality, occupancy conditions, and system performance [18]. This live integration creates a comprehensive understanding of how the building functions as a complex, interconnected system. Building operators, facility managers, and energy analysts can leverage this continuously evolving digital environment to monitor operations, diagnose anomalies, and implement data-informed interventions. These capabilities support proactive maintenance, predictive optimization, and more intelligent energy management, ultimately leading to improved efficiency, enhanced occupant comfort, and reduced environmental impact.

The functionality and value of BDTs are underpinned by several interdependent principles that define their structure and operational purpose [19–21]:

- **Data Integration:** A fundamental principle of any DT is the ability to aggregate and harmonize data from heterogeneous sources. In buildings, this includes subsystems such as heating, ventilation, and air conditioning (HVAC), lighting, and electrical systems, alongside data from environmental sensors that measure parameters such as temperature, humidity, CO₂ concentration, and air quality. The fusion of these data streams provides a coherent, system-wide perspective of building operations, forming the foundation for comprehensive analysis and control.
- **Real-Time Monitoring and Feedback:** Continuous real-time monitoring distinguishes DTs from static digital models. IoT devices and sensor networks transmit live data to the DT platform, enabling dynamic tracking of key performance indicators such as energy consumption, thermal comfort, and indoor environmental quality. This real-time feedback loop allows operators to detect inefficiencies and deviations immediately, facilitating responsive decision-making and adaptive control strategies.
- **Predictive Prescriptive Intelligence:** Through the application of AI and machine learning algorithms, DT extends beyond descriptive analysis to predictive and prescriptive capabilities. By learning from historical and real-time data, the system can forecast potential faults, anticipate energy demand fluctuations, and propose optimized control actions. These predictive functions play a pivotal role in enhancing energy efficiency, minimizing operational costs, and supporting long-term sustainability objectives.

While scientific studies demonstrate these advanced capabilities, seamless integration with simulation tools, AI algorithms, and IoT systems remains a significant challenge

in real-world deployments, with issues in interoperability, calibration, and computational demands [22–24].

Together, these principles enable BDTs to function not only as digital representations but as intelligent, interactive ecosystems capable of guiding decision-making across all stages of a building's lifecycle, from design and construction to operation, renovation, and end-of-life planning. The primary services and functionalities enabled by BDT technology within the construction and building management sectors are illustrated in Figure 2, encompassing real-time monitoring, predictive maintenance, energy optimization, and advanced performance analytics.

Conceptual Architecture of a Building Digital Twin

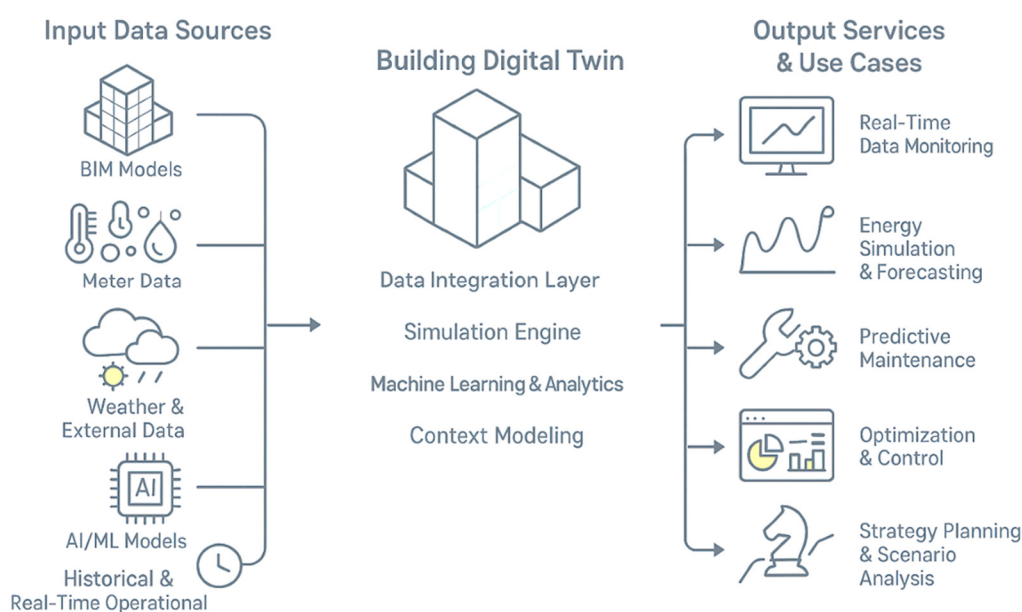


Figure 1. Integrated framework of a building Digital Twin.

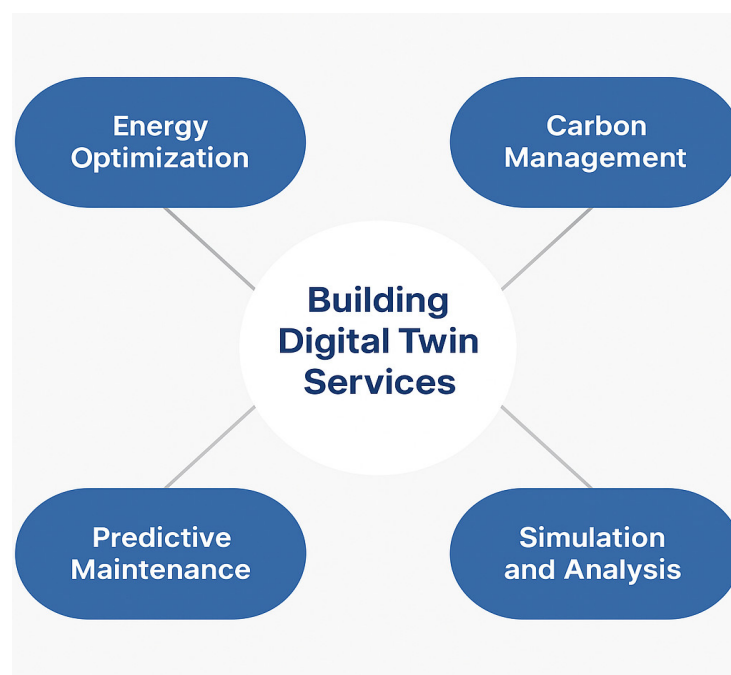


Figure 2. Key services enabled by Digital Twin technology in buildings.

2.2. Evolution of Digital Twin Technology

Over the last 2 decades, DT technology has undergone a remarkable transformation since its initial development in the aerospace and manufacturing sectors [25]. Figure 3 illustrates this evolution within the context of building applications, highlighting how the technology has progressed from simple monitoring tools to sophisticated, autonomous systems. Early implementations of DTs in buildings were primarily focused on equipment monitoring and fault detection. Systems were relatively basic, relying on simple sensor inputs and static models to identify anomalies in critical infrastructure such as HVAC units, elevators, or structural components [26]. These early models provided limited insight, primarily signaling potential issues rather than enabling proactive management or optimization. As sensor networks became more advanced and analytics capabilities expanded, the next generation of DTs emerged, emphasizing energy management and operational optimization. In this phase, DTs began integrating real-time data with predictive models to adjust lighting, heating, cooling, and ventilation according to dynamic conditions. For instance, HVAC systems could automatically respond to occupancy patterns, time-of-day schedules, or external weather fluctuations, marking the shift from reactive maintenance to proactive energy management, often facilitated through energy management systems [27].

Today, DTs represent a fully integrated, intelligent ecosystem within buildings, leveraging AI, big data, and high-fidelity simulation tools. Modern systems are capable of learning from historical and real-time data, adapting their behavior, and even executing autonomous actions. For example, a DT can anticipate an increase in energy demand due to incoming cold weather and pre-condition indoor environments efficiently, optimizing comfort and energy consumption simultaneously. Advanced AI functionalities also enable scenario-based analysis, allowing facility managers to simulate and compare different retrofit strategies, operational adjustments, or energy-saving measures before implementing them in the physical building [28–30]. This evolution demonstrates a clear trajectory: from basic monitoring to predictive optimization, and finally to autonomous, AI-driven management, positioning DTs as a cornerstone technology for energy-efficient, resilient, and intelligent buildings.

It should be noted that these examples largely reflect scientific SOTA rather than widespread real-world implementation. Full-scale operational integration is still limited due to technical, organizational, and financial constraints, such as heterogeneous data sources, model calibration, and legacy system interoperability [31,32].

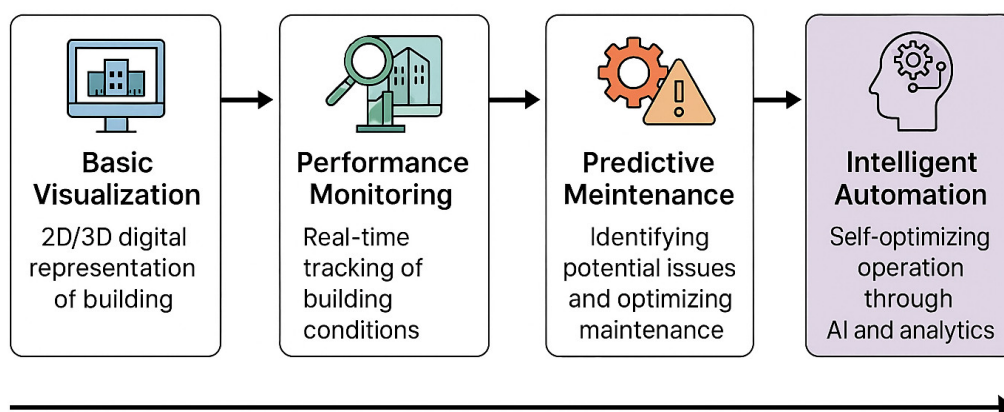


Figure 3. Evolution of Digital Twin applications in the building sector.

2.3. Integration with IoT, AI, and Simulation Models

A defining characteristic of BDTs is their ability to seamlessly integrate advanced technologies, combining the sensing capabilities of IoT devices, the analytical power of AI, and the predictive potential of simulation models to form a comprehensive ecosystem for intelligent building management [33]. At the core of this ecosystem are IoT sensors, strategically deployed throughout the building to continuously monitor critical parameters, including electricity and water consumption, indoor temperature, humidity, and air quality. This continuous stream of real-time data feeds the DT, providing a live, detailed representation of the building's operational state. Such insights enable immediate and informed interventions to maintain occupant comfort, operational safety, and energy efficiency [34]. Building upon this data foundation, AI algorithms transform raw information into actionable intelligence. Through pattern recognition, anomaly detection, and predictive modeling, AI can forecast equipment malfunctions or inefficiencies before they occur. For instance, an AI-enhanced DT can detect non-typical behavior in an HVAC system and predict its potential failure, allowing operators to schedule maintenance proactively and avoid unplanned downtime [35]. Beyond predictive maintenance, AI-driven automation dynamically optimizes building performance by adjusting heating, cooling, lighting, and ventilation systems in response to occupancy patterns, time of day, and external environmental conditions.

Furthermore, the implementation of Digital Twins in buildings relies on an ecosystem of interoperable software tools spanning design, simulation, data management, and real-time control. Building Information Modeling (BIM) platforms, such as Autodesk Revit or Archicad, often serve as the basis for digital representation of the physical asset and are widely regarded as an initial step toward DT development. BIM provides structured geometric and semantic information that supports spatial reasoning, asset identification, and system documentation. However, BIMs are inherently static and design-oriented. DTs extend BIM by integrating real-time operational data, analytics engines, and control logic, transforming static models into continuously evolving systems. This transition is typically enabled through middleware platforms, IoT frameworks, and standardized data models.

Additional software components commonly used in DT implementations include energy simulation engines (e.g., EnergyPlus (<https://energyplus.net/>), Modelica-based tools (<https://openmodelica.org/>)), data analytics and machine learning platforms, cloud-based databases, and application programming interfaces (APIs) that facilitate bidirectional data exchange with Building Management Systems. Together, these tools form a modular DT architecture in which BIM functions as a structural backbone rather than a complete solution. Recognizing BIM as a precursor rather than a substitute for DTs is essential for understanding the technological evolution toward intelligent, adaptive building systems. Operators can evaluate the potential impact of retrofit strategies or operational changes before physical implementation. These models provide quantitative predictions of energy savings, cost reductions, and improvements in occupant comfort, supporting evidence-based decision-making. Advanced simulation also facilitates strategic planning and system design. Building managers can explore alternative building layouts, operational schedules, or control strategies to optimize energy consumption and indoor environmental quality. For example, simulations can quantify the effects of different heating and cooling setpoints on overall energy use, helping stakeholders implement operational strategies that balance efficiency, cost, and comfort. Overall, the integration of IoT, AI, and performance simulations within a DT establishes a powerful, data-driven framework for managing modern buildings. Such a setup not only enhances real-time responsiveness but also enables predictive, proactive, and optimized building operation across the entire lifecycle.

2.4. Critical Comparison of Digital Twin Frameworks and Limitations

Despite the rapid proliferation of Digital Twin frameworks in the built environment, existing approaches differ significantly in scope, maturity, and practical applicability. Table 1 synthesizes key frameworks and highlights their dimensions, strengths, and reported limitations, revealing important gaps that impede large-scale deployment.

Table 1. Key DT frameworks and their respective focus, strengths, and limitations.

Dimension	Observations and Limitations
Lifecycle Coverage	Many frameworks focus heavily on operation, with limited support for construction-phase embodied carbon and end-of-life planning.
Interoperability	FIWARE/NGSI-LD promotes semantic interoperability, yet empirical studies report high integration effort with legacy BMS and proprietary protocols.
Model Fidelity vs. Scalability	High-fidelity twins offer better prediction accuracy but are difficult to scale due to data, calibration, and computational demands.
AI Integration	While AI-enhanced DTs show strong optimization potential, studies report limited robustness with data challenges.
Validation & Transferability	Contradictory findings exist regarding performance gains due to case-specific assumptions and a lack of cross-building validation.

Overall, a recurring contradiction in the literature concerns the reported energy savings achieved through DT deployment. While several studies report reductions exceeding 20–30% through predictive control and optimization, other empirical investigations highlight marginal gains once commissioning quality and occupant behavior are considered. This divergence highlights the sensitivity of DT performance to data quality, model calibration, and contextual factors such as climate, building typology, and operational practices. Furthermore, most existing frameworks lack a unified reference architecture capable of balancing semantic interoperability, cybersecurity, and real-time control. As a result, many DT implementations remain specific solutions, limiting reproducibility and applicability.

The above discussion represents the scientific SOTA, summarizing findings reported in peer-reviewed studies rather than claiming ubiquitous deployment in practice. Many challenges remain for achieving the full potential of BDTs in operational buildings, including stakeholder engagement, technical feasibility, cultural acceptance, and initial investment.

3. The Role of Digital Twins in Decarbonization

DTs have emerged as a critical enabler of decarbonization in the built environment [5,6,36]. By combining real-time monitoring, predictive analytics, and dynamic simulation capabilities, these digital platforms provide actionable insights that optimize energy consumption, reduce greenhouse gas emissions, and support the transition toward more sustainable, low-carbon buildings. This section examines the multiple pathways through which DTs contribute to decarbonization, encompassing building-level energy efficiency, integration of renewable energy sources, system-wide operational optimization, and broader environmental impacts within urban ecosystems. The discussion highlights how DTs not only enhance operational performance but also serve as a decision-support tool for designing climate-resilient and energy-conscious infrastructure.

Figure 4 presents a clear overview of how key DT capabilities, Simulation, Monitoring, Prediction, Optimization, and Control, align with the main stages of the building lifecycle: Design, Manufacturing, Operation, and Maintenance. The following connections can be established:

- Simulation plays a major role in the early phases, especially during Design and initial Manufacturing, where it is used to model and test product behavior before anything is physically built.
- Monitoring becomes essential from Manufacturing onward, helping to track real-time data and maintain system awareness throughout Operation and Maintenance.
- Prediction supports forward-looking decision-making during Operation and Maintenance by anticipating potential issues or performance drops.
- Optimization is a continuous thread across all stages, aiming to improve efficiency, performance, and resource use at every step.
- Control is crucial during Manufacturing and remains important through Operation and Maintenance to ensure systems run smoothly and respond effectively to changes. While DTs can also inform control strategies in the design phase, here the focus is on actual energy system control during building operation.

This visual summary helps clarify how DT technologies and services are integrated throughout the lifecycle, offering a practical guide for implementation and a foundation for future research.

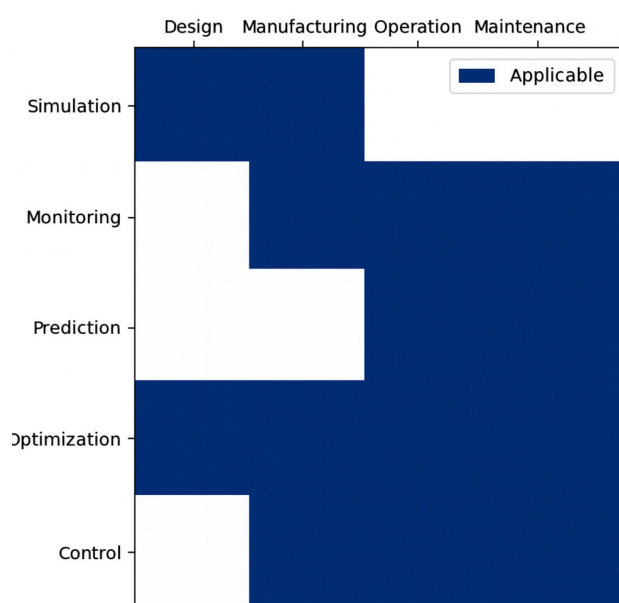


Figure 4. Mapping of DT capabilities to life cycle stages.

In the sections below, the methods illustrate the capabilities of Digital Twins (DTs) in energy modeling and optimization. It is important to note that in real-world practice, a fully developed DT is rarely available for existing building stock. Often, DTs are established post-renovation or progressively built using available building data, IoT sensors, and BMS information. Therefore, the presented energy modeling and optimization approaches represent an ideal or optimal scenario, serving as guidance for how DTs could enhance operational efficiency and energy performance once sufficient building data is accessible.

3.1. Energy Modeling and Optimization

At the heart of DTs' contribution to building decarbonization lies energy modeling and optimization. By integrating data from diverse sources, including IoT sensors, BMS, and external environmental inputs, DTs provide a holistic framework for managing energy use, improving system performance, and minimizing environmental impact [37].

Key functionalities that enable this include:

- **Automated Fault Detection & Diagnosis (FDD):** One of the most impactful capabilities of DTs is their ability to identify inefficiencies and equipment faults in real time [38]. For example, in HVAC systems, a DT continuously monitors parameters such as airflow, temperature, humidity, and energy consumption to detect abnormal patterns indicative of potential malfunctions. Early detection allows facility managers to intervene proactively, preventing system failures, reducing downtime, and maintaining optimal energy efficiency.
- **Demand-Side Management (DSM):** Demand-side management encompasses strategies designed to optimize a building's energy consumption, enhance grid stability, and reduce operational costs [39]. DTs enable real-time adaptation of energy use by analyzing data from both building systems and the electrical grid. This dynamic adjustment allows for load shifting, peak shaving, and efficient utilization of renewable energy sources, contributing directly to decarbonization efforts.
- **Predictive Analytics:** Powered by AI and machine learning, predictive analytics transforms DTs from passive monitoring tools into proactive decision-support systems [40]. By analyzing historical trends and real-time operational data, DTs can forecast energy demand, anticipate performance degradation, and optimize system operations before inefficiencies manifest. These predictive capabilities facilitate strategic planning for both daily operations and long-term sustainability initiatives.

In contrast to traditional rule-based control systems, which offer limited adaptability, AI-driven DTs deliver greater flexibility, continuous learning, and autonomous optimization [4,41]. Table 2 provides a comparative overview of these approaches, highlighting the advantages of machine learning and intelligent automation in enhancing building energy performance, reducing costs, and supporting long-term decarbonization objectives.

Table 2. Benefits of AI-enabled Digital Twins vs. rule-based systems.

Feature	AI-Enabled Digital Twins	Traditional Rule-Based Systems
Energy Forecasting	Accurate, dynamic, and learns from past trends	Static assumptions, limited accuracy
Fault Detection	Predictive, self-learning	Manual inspection or rule-triggered alerts
Control Optimization	Real-time adjustments via reinforcement learning	Predefined, non-adaptive control schedules
Adaptability to Environment	High, adjusts to weather, occupancy, etc.	Low, requires manual reconfiguration

3.2. Building Lifecycle Carbon Assessment

Reducing the carbon footprint of buildings requires addressing emissions at every stage of their lifecycle, from construction to decommissioning [42]. DTs play a key role in providing insights into these stages, making them indispensable in the journey towards decarbonization.

- **Embodied Carbon Tracking:** Embodied carbon refers to the emissions produced during the production, transportation, and installation of building materials [43]. While often overlooked, this type of carbon makes up a large portion of a building's total carbon footprint. DTs are capable of tracking and modeling the embodied carbon of materials used throughout the construction and renovation phases.

- **Operational Carbon Reduction:** A building's operational phase, primarily its energy use for heating, cooling, lighting, and ventilation, is responsible for a significant portion of its carbon emissions. DTs help reduce operational carbon by continuously monitoring and optimizing these systems [44].
- **End-of-Life Planning:** As buildings age, their carbon footprint shifts toward deconstruction, waste, and disposal. DTs can assist in planning the building's end-of-life phase by simulating demolition, material recovery, and recycling [45].

To better illustrate how DTs contribute to carbon assessment and optimization throughout the building lifecycle, Table 3 provides an organized overview of their core functions, from design through decommissioning. This table highlights the many ways DTs support the decarbonization process at every stage.

Overall, the full DT-based lifecycle carbon assessment in early-stage design remains uncommon in current practice. Embodied carbon tracking is often conducted using enriched BIMs or partial digital representations, which can later be incorporated into a DT as operational and retrofit data becomes available. Therefore, the use of DTs for lifecycle assessment represents the scientific state-of-the-art and the potential future scenario, rather than reflecting a widely established practice in current building projects.

Table 3. Functional capabilities of Digital Twins across building lifecycle stages.

Lifecycle Stage	Digital Twin Functionality	Impact on Decarbonization
Design & Construction	Virtual prototyping, material carbon analysis, and design optimization	Minimizes embodied carbon and optimizes resources
Operation & Maintenance	Real-time monitoring, predictive maintenance, energy optimization	Reduces operational carbon and enhances efficiency
Renovation & Retrofit	Scenario analysis, ROI modeling, carbon impact estimation	Informs low-carbon retrofit strategies
End-of-Life	Material inventory tracking, deconstruction planning	Enables circular economy practices

3.3. Retrofit and Renovation Strategies

Retrofitting and renovating existing buildings to enhance energy efficiency is a key component of decarbonization [46]. DTs are invaluable in this process, enabling virtual simulations and helping decision-makers make informed choices.

- **Scenario-Based Decision Support:** One of the main challenges in retrofitting buildings is figuring out the best strategy without spending significant resources on physical testing [5]. DTs can simulate various retrofitting options, like improving insulation, upgrading HVAC systems, or installing high-efficiency windows. By running these simulations, building owners can evaluate the potential energy savings and carbon reduction for each option in a virtual environment. This lets them identify the most effective retrofitting strategies before taking any physical action, ensuring the selected solution delivers optimal value in terms of energy efficiency, cost-effectiveness, and sustainability.
- **Cost-Benefit Analysis:** Retrofitting often involves considerable upfront costs. DTs can help justify these expenses by creating detailed financial models that estimate the long-term savings from reduced energy use and lower carbon emissions [47]. These models consider factors such as material costs, installation, and maintenance against the anticipated reductions in energy bills and carbon taxes. This analysis makes it easier for building owners and operators to prioritize retrofitting investments that offer the best return on investment (ROI) over time.

- **Adaptive Control Strategies:** DTs go beyond passive monitoring by integrating AI-driven control systems that dynamically adjust building operations in response to environmental or occupancy changes [33]. For example, if outdoor temperatures drop suddenly, the DT can adjust the heating settings to maintain comfort without wasting energy. These adaptive controls allow buildings to respond flexibly to changing conditions, ensuring that energy use is always optimized.
- **Renewable Energy Integration:** Incorporating renewable energy sources into buildings is crucial for decarbonization. DTs play a key role in helping buildings maximize their use of renewable energy and optimize their interaction with the grid [48,49].

In practical terms, the deployment of a DT for retrofit analysis is most feasible in buildings where some operational data exists or after initial renovation measures are undertaken. While the theoretical framework presented here assumes the presence of a DT, actual applications may begin with a BIM-based model enriched with sensor data and gradually evolve into a full DT capable of supporting scenario-based retrofit simulations and predictive control.

Quantifying the impact of DT applications is crucial for understanding their role in climate mitigation. Table 4 consolidates emissions reduction potentials across various use cases, translating technical capabilities into measurable environmental outcomes. The reported emissions reduction potentials in Table 4 reflect optimal or model-based scenarios. Actual savings depend on the availability of building data, the extent of DT deployment, and the implementation context.

Table 4. Emissions reduction potential of Digital Twin applications.

Use Case	Estimated Emissions Reduction (%)	Source or Basis
Predictive HVAC Control	10–30% [50]	Empirical studies and case-based simulations
Fault Detection and Diagnostics	5–15% [50]	Reduction in energy waste from inefficient systems
Demand-Side Management	10–20% [51]	Load shifting to off-peak or renewable hours
Retrofit Scenario Optimization	20–40% [5]	Identifying the best retrofit strategies
Renewable Energy Integration	15–25% [52]	On-site generation and dynamic load balancing

4. Digital Twin Implementations

4.1. Empirical Case Studies and Performance Evidence

To substantiate the practical benefits of Digital Twin technology, this section presents documented real-world implementations that offer measurable outcomes in building performance, decarbonization, and operational efficiency. The selected projects span different climatic regions, building typologies, and lifecycle phases, ranging from retrofitted commercial offices to large-scale infrastructure and iconic cultural buildings. In operational buildings such as Keppel Bay Tower, George’s Quay, and the University of Liverpool, Digital Twins were primarily employed to optimize HVAC operation and energy management using real-time monitoring, calibration, and predictive analytics. These buildings typically range from medium to large office or institutional facilities equipped with centralized HVAC systems and advanced BMS platforms, enabling high-frequency data exchange and closed-loop control.

In contrast, projects such as Ezhou Huahu International Airport and the Dubai Museum of the Future illustrate DT applications beyond operational optimization. In these cases, DTs supported design coordination, construction sequencing, and sustainability-driven decision-making across multiple engineering disciplines. The emphasis was placed on integrating BIM, simulation, and real-time collaboration rather than continuous operational control. Collectively, these examples demonstrate that DTs can be successfully

deployed at different stages of the building lifecycle and across vastly different scales, with benefits extending from energy efficiency and emissions reduction to cost savings, schedule acceleration, and improved interdisciplinary coordination.

- Keppel Bay Tower, Singapore

Keppel Bay Tower, a 22-year-old commercial building, became Singapore's first zero-energy commercial building following a retrofit that included the deployment of a DT developed by IES (Integrated Environmental Solutions). The DT was calibrated using live operational data, supporting optimized cooling operations and enabling energy-efficient strategies. The result was a 30% reduction in overall energy consumption and annual electricity savings of approximately \$400,000 [53].

- George's Quay, Dublin, Ireland

At this LEED Platinum-certified office building, IES implemented a data analytics platform (iSCAN) for DT integration. Post-retrofit monitoring revealed annual energy cost savings of €108,000 and a verified reduction of 302 tonnes of CO₂ emissions. Enhancements included glazing, lighting upgrades, and intelligent HVAC systems [54].

- University of Liverpool, United Kingdom

The University of Liverpool used the IES Live platform to evaluate the impact of HVAC refurbishment through a performance-calibrated DT. This integration enabled real-time energy tracking and optimization, resulting in a 23% energy reduction and over £25,000 in cost savings in just nine months [55].

- Cairo Office Building, Egypt

A LEED Gold-certified office building in Cairo utilized the PARA OS Digital Twin platform for operational optimization. The DT enabled real-time, occupancy-based environmental control, leading to a 28% reduction in total energy consumption and a LEED O+M comfort score of 16/20 [56].

- Ezhou Huahu International Airport, China

A compelling example of DT potential is the Ezhou Huahu International Airport project in Hubei Province, China, one of the country's major infrastructure developments. In this initiative, Bentley's BIM and iTwin technologies were harnessed to create a comprehensive DT of the airport, enabling real-time integration of vast engineering datasets and operational information. The impact was substantial, where the use of the DT not only streamlined coordination and decision-making but also accelerated the construction timeline by an impressive 200 days and delivered cost savings of approximately CNY 300 million [57].

- Dubai Museum of the Future, UAE

The Museum of the Future in Dubai represents a bold convergence of visionary architecture and advanced digital technology. Beyond its complex design and construction, the project leveraged a sophisticated 3D energy model that facilitated real-time collaboration among 12 engineering disciplines. This collaborative approach led to more than 50 sustainability-driven design decisions, resulting in a 25% reduction in total energy consumption and a 45% decrease in water usage, milestones that played a crucial role in achieving LEED Platinum certification [58].

These empirical cases confirm that DTs are not only conceptual tools. When implemented alongside real-time data analytics and AI-based decision-making, they contribute to substantial energy and carbon reductions, enhanced operational performance, and financially viable retrofitting strategies.

4.2. Actual Implementation of DT in a Danish Teaching Building

As part of the Twin4Build project [59], a robust digital twin platform was developed and comprehensively validated within a university teaching building in Denmark. A detailed description of the digital twin framework is provided in [6]. The digital twin model was calibrated using high-resolution operational data collected from the building's Building Management System (BMS), including airflow rates, supply and return temperatures, CO₂ concentrations, and fan electricity consumption. Calibration focused primarily on the ventilation and fan energy sub-models, as these subsystems were directly affected by the evaluated control strategies. A stepwise calibration approach was employed, where model parameters such as fan efficiency curves, pressure losses, and room-level airflow dynamics were iteratively adjusted to minimize deviations between simulated outputs and measured data during representative baseline operation periods. Calibration was performed under varying occupancy and seasonal conditions to ensure robustness across typical operational regimes. Model validation was conducted using an independent dataset that was not employed during calibration. Key performance indicators (KPIs) included room-level CO₂ concentration profiles, total airflow demand, and aggregated fan power consumption. The validation results demonstrated strong agreement between simulated and measured values, confirming that the digital twin reliably captured both transient and steady-state system behavior.

This large-scale implementation was designed to evaluate the platform's scalability, its integration with existing building systems, and its operational performance in a real-world environment. The primary focus was on the real-time monitoring and control of the HVAC system, with particular emphasis on operational status, energy consumption, and indoor environmental quality. This approach enabled continuous performance assessment and generated actionable insights for enhancing both energy efficiency and occupant comfort. To optimize HVAC system performance, advanced control strategies were implemented that leveraged real-time environmental data, occupancy patterns, and predictive analytics. These strategies enabled dynamic adjustments, effectively reducing energy consumption while maintaining optimal indoor air quality. The pilot demonstrated DT's ability to seamlessly integrate with complex building systems, combining real-time monitoring with simulation-driven insights to support more informed operational decisions. The successful implementation of this pilot established a foundation for broader adoption of digital twins in other case studies in Denmark [60], advancing long-term objectives of energy efficiency and sustainable building management.

The university teaching building's ventilation infrastructure comprises four nearly identical subsystems, each supported by an air handling unit (AHU) supplying air to classrooms, offices, and study areas via demand-controlled ventilation (DCV). Figure 5 illustrates one of the ventilation systems analyzed. For simulation and optimization purposes, the Twin4Build Python package (<https://openmodelica.org/>) [6] was employed to construct a data-driven, ontology-based digital model of the system. This model accurately replicates the building's ventilation network, encompassing both central AHUs and room-level variable air volume (VAV) boxes, which regulate the supply of fresh air to individual spaces. The digital model not only supports detailed system analysis but also enables predictive optimization, facilitating improvements in energy performance and indoor climate control.

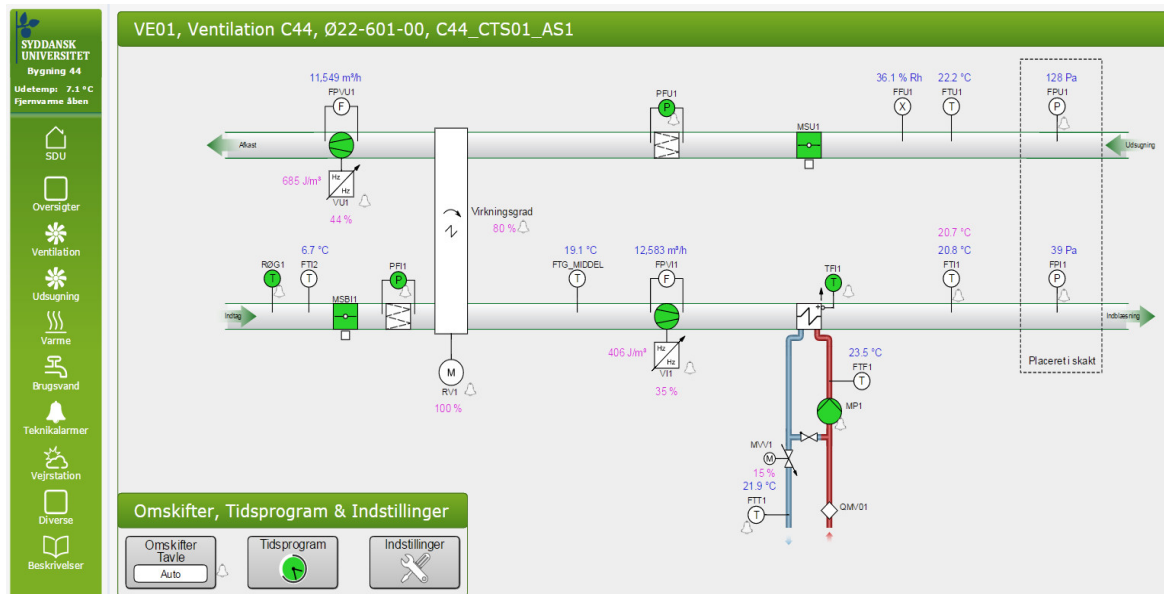


Figure 5. Ventilation system supply layout in the pilot case study.

Each room in the building was equipped with a dedicated control layer that dynamically adjusted airflow based on real-time environmental and occupancy data. These individual room simulations were aggregated to determine the overall ventilation demand, which then informed a fan energy model to estimate system-wide energy consumption. Implemented within the Twin4Build framework, the model leveraged the SAREF ontology [61] to ensure semantic consistency and was fully containerized using FastAPI v. 0.128.0 [62], providing scalability and seamless deployment in cloud environments. To evaluate the impact of different ventilation control strategies on energy efficiency and indoor comfort, three distinct room-level controllers were developed and tested within the digital twin environment:

- **Data-Driven Controller:** This approach replicates the building's existing operational logic using historical data. It serves as a baseline benchmark, allowing researchers to assess current practices under varying indoor and outdoor conditions.
- **Rule-Based Controller (RBC):** Based on simple threshold logic, the RBC triggers ventilation according to fixed CO₂ or temperature limits. Its straightforward design makes it an easy-to-implement, low-complexity solution for practical deployment.
- **PID Controller:** Employing dynamic feedback, the PID controller continuously fine-tunes airflow in real time, adjusting ventilation based on deviations from ideal conditions. This approach provides a balance of responsiveness and stability, optimizing both comfort and energy use.

The three controllers serve as a testbed for comparing the effects of each strategy on energy consumption, indoor air quality (IAQ), and occupant comfort. The entire setup was embedded within a realistic, data-driven virtual environment, integrating live building data, control algorithms, and predictive analytics. This allowed continuous testing and validation of new control strategies in a safe, simulated space without disrupting actual building operations. Each simulation scenario was assigned a unique identifier and meticulously logged, enabling researchers and facility managers to revisit, compare, and draw actionable insights. This structured approach facilitated the exploration of a wide range of “what-if” scenarios, including fluctuating occupancy patterns, seasonal variations, and alternative control logics, while immediately revealing their effects on energy demand and indoor conditions.

One particularly instructive experiment replaced all existing room controllers with a simplified RBC configured with more relaxed CO₂ thresholds. This modification yielded a substantial reduction in energy consumption. Analysis revealed that the savings originated from two key factors: reduced ventilation during low-occupancy periods and the reactivation of demand-controlled ventilation (DCV) in zones where it had previously been inactive. The DT also enabled precise tracking of actual ventilation requirements per space. For instance, it identified that some offices required only around 46% of their maximum airflow even during peak occupancy. This insight informed a more efficient and targeted ventilation schedule, minimizing energy waste while preserving air quality. As illustrated in Figure 6, these improvements resulted in a significant reduction in fan power consumption. During the evaluated operational period, the DT-enabled control strategies reduced total HVAC-related energy consumption by approximately 29%, corresponding to a reduction of roughly 3.65 MWh in combined electricity and heating demand in the month of December. Using standard Danish electricity and district heating emission factors, this translates to an estimated avoidance of around 199 kg of CO₂-equivalent emissions in this month. The majority of the savings originated from reduced fan electricity consumption and lower heating demand due to more precise ventilation control during low-occupancy periods. Importantly, these reductions were achieved without violating indoor air quality constraints, as CO₂ concentrations remained within acceptable comfort thresholds throughout the monitored zones.

The Danish teaching building case was explicitly designed as a comparative testbed. The data-driven baseline controller represented the existing operational practice, while the rule-based and PID controllers provided progressively more adaptive alternatives. Results demonstrated that even relatively simple rule-based adjustments yielded substantial savings, while more advanced controllers offered improved responsiveness and stability under dynamic conditions. Although direct quantitative comparisons with other buildings are constrained by differences in occupancy patterns, HVAC configurations, and climatic conditions, the achieved 29% HVAC energy reduction aligns well with savings reported in comparable DT-enabled educational and office buildings in Europe and internationally (Section 4.1). This consistency suggests that the observed performance gains are not site-specific anomalies but indicative of transferable benefits under similar system architectures.

Overall, this full-scale pilot in a university teaching building demonstrates the tangible value of DT technology. By integrating real-time monitoring, adaptive control, and predictive modeling, the system continuously optimized performance, unlocking energy savings and advancing sustainability objectives. The DT functioned as a powerful decision-support platform, enabling scenario testing, outcome prediction, and the implementation of smarter control strategies. The success of this initiative highlights the potential for scaling DT solutions across diverse buildings and portfolios, offering a clear path toward smarter HVAC operations, reduced carbon footprints, and improved indoor environmental quality.

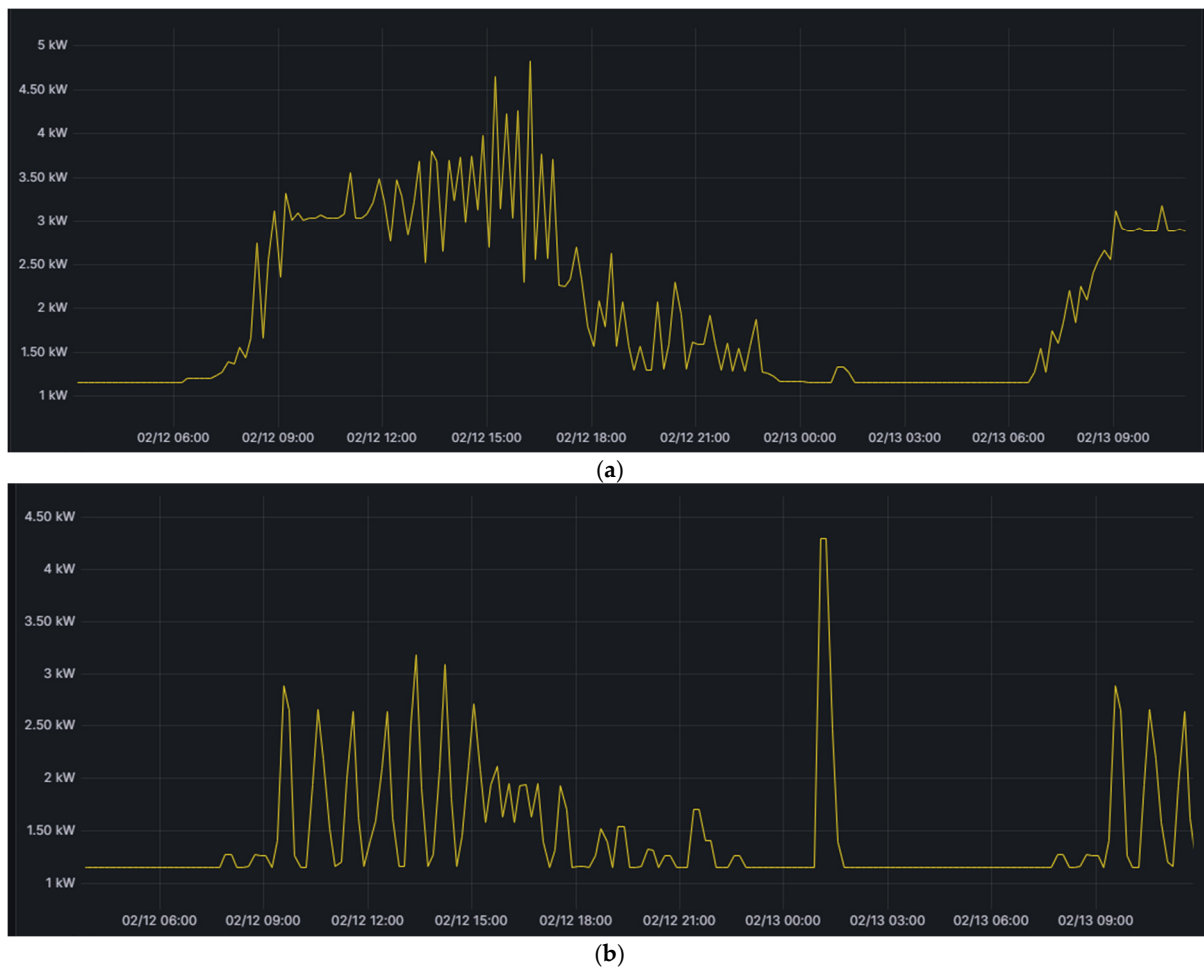


Figure 6. Ventilation system fan power consumption as reported in the (a) base case scenario, and (b) upgraded control strategy scenario.

4.3. Lessons Learned and Challenges

The full-scale implementation of the DT in the Danish teaching building reported above yielded important lessons that highlight both the opportunities and challenges in deploying DT technology in real-world settings. These insights, drawn from actual system performance, integration tasks, and stakeholder interaction, highlight practical considerations for scaling and replicating such solutions.

- Data Integration Difficulties

One of the most critical challenges encountered was the integration of data from heterogeneous sources. The building featured multiple systems, including legacy Building Management Systems (BMSs), room-level VAV controllers, and diverse sensors with varying communication protocols. Aligning these distinct systems to work cohesively with the DT required significant effort in terms of data standardization and system interoperability. The successful use of the SAREF ontology and containerized deployment using FastAPI v. 0.128.0 provided a consistent data structure and API access, but initial setup and mapping of device semantics posed technical hurdles. This demonstrates that standardized frameworks and interoperability protocols are essential for scalable DT deployments.

- Initial Investment and Resource Requirements

Although the long-term benefits of energy savings and system optimization were evident, with HVAC energy consumption reduced by 29%, the initial investment in modeling, system integration, and deployment was considerable. Smaller facilities or buildings

with limited digital infrastructure may find the upfront cost of sensor upgrades, software development, and model calibration to be a barrier. Therefore, cost-benefit analyses, supported by demonstrable pilot results like this one, are vital to justify the return on investment (ROI). The pilot building benefited from research funding and institutional support, which may not be universally available in all retrofit contexts.

- Operational Complexity and Skill Requirements

Developing a DT that includes dynamic control algorithms (e.g., PID, rule-based, and data-driven models) and scenario simulations introduced operational complexity. Building operators require training to interpret simulation results and implement control strategies effectively. It became evident that without sufficient user training and interface design, there is a risk that the system's capabilities may be underutilized or misapplied. Interdisciplinary collaboration, involving facility managers, IT staff, researchers, and building occupants, is essential to ensure proper deployment and value extraction.

- Stakeholder Engagement and Cultural Change

The case study highlighted that technical success must be matched by organizational engagement. In this case, active involvement of university facility managers and operations staff enabled smooth data access, validation of model results, and implementation of updated control strategies. Nevertheless, some hesitation was observed regarding automated control interventions, especially in rooms with fluctuating occupancy. Building trust in data-driven operations and promoting stakeholder ownership of the system were key to achieving long-term operational success. DT adoption must be accompanied by cultural change management strategies to ensure effective user participation.

- Scalability and Modularity

An important lesson was the value of modular and scalable architecture. The use of a containerized Python-based DT, built using the Twin4Build framework and SAREF ontology, enabled smooth updates, replication across similar systems, and flexible control logic testing. This modularity is essential for expanding DT use beyond a single system (ventilation) to other building subsystems such as lighting, heating, or renewable integration. Future implementations can leverage this design to avoid starting from scratch.

- Energy Savings through Adaptive and Occupancy-Based Control

A critical insight from the control strategy experiments was that simple adjustments, such as reactivating DCV and using relaxed CO₂ setpoints, can deliver significant energy savings. Importantly, the system identified rooms operating at unnecessarily high airflow levels despite low occupancy, and the updated control approach reduced HVAC energy use by 29% without compromising indoor comfort. This highlights the importance of occupancy-based optimization and real-time monitoring as low-hanging fruit for energy-efficient operation.

While the reported case studies in this paper demonstrate significant energy and operational benefits, it is important to acknowledge that DT performance is inherently context-dependent. Reported savings across the empirical cases range from approximately 20% to over 30% in energy reduction, reflecting variations in building age, system complexity, data availability, and baseline operational efficiency. Buildings with outdated HVAC infrastructure, limited sensor coverage, or rigid control architectures may experience lower initial gains or require higher upfront investments to realize comparable benefits. Scalability challenges may arise when extending DT implementations to large portfolios or heterogeneous building stocks. Increased system diversity amplifies data integration complexity and may necessitate partial rather than full-fidelity digital twins. Moreover, DTs may underperform in scenarios where occupancy patterns are highly irregular, operational data quality is poor, or organizational readiness for data-driven

control is limited. These findings highlight that DTs are not universal “plug-and-play” solutions, and their effectiveness depends on technical maturity and stakeholder engagement.

The lessons learned from this real-world deployment emphasize that while DTs offer transformative potential for building operations, their implementation is not without challenges. Addressing data integration, upfront investment, and stakeholder engagement is essential to unlocking the full value of DTs. Moreover, successful DT frameworks must be scalable, modular, and user-centric, ensuring they provide actionable insights while remaining accessible to building operators. The Danish pilot case demonstrates that with the right strategy, DTs can yield quantifiable improvements in both energy performance and operational transparency.

5. Challenges and Future Directions

While DT technologies show great promise, they face various implementation challenges, ranging from data silos to issues with interoperability. Table 5 summarizes these challenges along with practical strategies to overcome them, offering a roadmap for more effective and widespread adoption.

Table 5. Overview of Digital Twin implementation challenges and mitigation strategies.

Challenge	Description	Potential Mitigation Strategy
Data Interoperability	Incompatible formats between devices and systems	Adoption of open standards (e.g., NGS-LD, IFC, SAREF) [61]
High Initial Costs	Cost barriers for small and older buildings	Government subsidies; modular and phased implementation paths
Data Privacy and Security	Risks related to personal and operational data exposure	Use of data anonymization techniques; secure data protocols and encryption
Operator Skills Gap	Lack of technical expertise to manage digital tools	Development of targeted training programs; certification, and capacity building
Regulatory Misalignment	Absence of clear policy frameworks	Collaborative development of digital building codes

5.1. Data Availability and Interoperability

One of the major obstacles to the widespread use of DT technology is ensuring smooth interoperability between various building systems. DTs rely on real-time data from a wide range of devices such as sensors, BMS, and BIM, in addition to external data sources like weather forecasts or energy consumption trends. These data sources often come in different formats, standards, and protocols, making it challenging to integrate them into a unified system. The first hurdle is data availability. Building systems typically generate large amounts of data, but it is not always structured or easy to access for optimization purposes. Older buildings may not have advanced sensors, or they may use legacy BMS that are not designed to work with modern technologies. As a result, retrofitting existing systems to facilitate data sharing is necessary, while also ensuring that the data collected is relevant and of good quality.

Interoperability is another significant challenge. DT systems must work with existing infrastructure, which often involves connecting with various systems that were not designed to be interoperable. To overcome this, open standards and protocols are needed to ensure that different devices and platforms can communicate with each other. The adoption of universal communication frameworks, like the FIWARE platform used in smart cities or the NGS-LD API for IoT systems, can help bridge the gap and ensure compatibility across systems and vendors [63]. Data privacy and security concerns will continue

to be critical as buildings and infrastructure become more digitalized. With increasing amounts of sensitive data being generated and stored, robust cybersecurity measures will be essential. This includes complying with regulations such as the EU's General Data Protection Regulation (GDPR), which outlines strict guidelines for the collection, storage, and processing of personal data. Building operators must also ensure systems are protected from cyber threats, including breaches and attacks, which could disrupt building operations or violate privacy.

5.2. Scalability of Digital Twin Applications

While DT technology has shown promise in individual buildings, scaling it to cover entire districts or cities brings about a new set of challenges. Managing interconnected systems, like HVAC, lighting, water supply, and waste management, across a large network of buildings becomes exponentially more complex as the implementation expands. For successful scaling, technologies must be able to handle the vast amounts of data generated by numerous systems, requiring advanced data processing capabilities. Real-time data processing is one of the primary challenges for scalability. In large-scale applications, the sheer volume of data from multiple buildings, sensors, and systems can become overwhelming. Traditional cloud-based processing might struggle to keep up with this high data volume, leading to latency and delays in decision-making. Edge computing offers a solution by processing data locally on devices like sensors or gateways before transmitting it to the central server, reducing latency and enabling faster actions [64]. This is particularly crucial in real-time applications like building operation optimization, where delays could result in inefficient energy use or discomfort for occupants.

Furthermore, large-scale DT applications will require improved data storage, network infrastructure, and processing power to manage the growing amount of data. As the number of buildings and sensors increases, the need for efficient and secure data storage systems capable of handling high-frequency, high-volume data will become even more critical. Scalability also demands strong network protocols to handle communication between buildings and systems. The network needs to support both high-bandwidth and low-latency operations across diverse devices and platforms, while maintaining the security and integrity of the data being transmitted.

5.3. Regulatory and Policy Implications

The adoption of DT technology is heavily influenced by regulatory frameworks, and policies at both the national and EU levels will play a key role in driving its growth. To encourage widespread use of DTs in buildings and infrastructure, governments should offer financial incentives such as tax breaks, grants, or subsidies. These incentives would be especially valuable for retrofitting older buildings or implementing DT solutions in smaller buildings that might not have the budget for such technologies. Policy frameworks are crucial for scaling up DT technologies. Table 6 compares some initiatives, shedding light on regulatory trends and incentives that could accelerate adoption in the building sector.

Table 6. Comparison of some policies supporting digital twin adoption.

Policy or Initiative	Level	Relevance to Digital Twins	Description
EPBD (Energy Performance of Buildings Directive) [65]	EU	High	Mandates use of smart technologies and BACS
Danish National Energy Strategy [66]	National	Medium	Incentivizes energy efficiency and smart solutions

EU Green Deal [67]	EU	High	Promotes digitalization and decarbonization
Smart Readiness Indicator (SRI) [68]	EU	High	Framework for assessing digital building capabilities

Additionally, policies should be introduced to help incorporate DT technology into existing regulatory structures. For example, building codes and regulations could be updated to require the use of DTs in new constructions or major renovations for energy optimization. This would ensure that sustainability is a core part of the design process, allowing buildings to leverage DT technology for improved energy efficiency, reduced emissions, and enhanced occupant comfort right from the start. At the European level, clear regulatory guidelines are essential to align the standards and protocols used in DT projects across member states. This would foster cross-border cooperation and help reduce fragmentation in the market. The EU's Green Deal and the European Commission's Smart Cities initiative can serve as a roadmap for integrating DT technology into broader sustainability efforts. Additionally, data privacy, cybersecurity, and environmental standards should be harmonized to ensure that DT systems comply with EU regulations like the GDPR.

5.4. Future Research Opportunities

The future of DT technology in buildings is closely linked to developments in AI, circular economy practices, and smart grid systems. These emerging areas of research have the potential to greatly enhance the value that DTs can offer in terms of energy efficiency, sustainability, and operational optimization.

- **AI-Augmented Digital Twins:** Artificial intelligence (AI) and machine learning (ML) are rapidly evolving fields that will significantly expand the capabilities of DTs. Future research will likely focus on developing AI-driven models that can autonomously adjust building systems to achieve optimal performance. For example, AI could predict and address issues like energy inefficiencies or system failures before they happen. Additionally, AI could help fine-tune operations such as HVAC schedules or lighting levels based on real-time data from occupancy and environmental factors. By enabling more automation and faster decision-making, AI will be essential to unlocking the full potential of DTs in creating smart, energy-efficient buildings.
- **Circular Economy:** DTs can play a pivotal role in the circular economy by offering insights into material reuse, recycling, and the overall sustainability of a building's lifecycle. Research on integrating DTs with circular economy strategies will help track the carbon footprint of building materials over time and optimize resource usage throughout a building's life. For instance, by simulating how materials might be disassembled and recycled at the end of a building's lifecycle, DTs can help design structures that are easier to deconstruct, promoting the reuse of materials and minimizing construction waste and environmental impact.
- **Smart Grids:** The integration of DT systems with smart grid infrastructure will enable better coordination between buildings and the broader energy network. Smart grids can dynamically adjust electricity distribution based on real-time demand and supply, while DTs can optimize building energy usage to align with grid conditions. Future research can explore how DTs can enable demand-side management and demand-response capabilities, allowing buildings to better interact with smart grid systems. This would not only help reduce energy consumption during peak periods but also contribute to the overall stability and resilience of the energy network.

As these research areas develop, DTs will become an even more integral part of sustainable building and urban infrastructure, driving efficiency, reducing carbon emissions,

and helping create smart cities. Figure 7 highlights the roles and responsibilities of key actors, offering a forward-looking perspective on opportunities for collaboration across research, industry, and policy.

Based on the review and discussion presented in this work, Figure 8 provides a comprehensive overview of the key challenges hindering the widespread adoption of DT technologies in buildings. It also illustrates corresponding mitigation strategies and highlights future research directions aimed at enhancing scalability, interoperability, and sustainability in built environments.

Stakeholder	Role in Implementation	Required Support or Engagement
 Building Owners	Strategic investment and long-term planning	Financial incentives and ROI clarity
 Facility Managers	Daily operations, data interpretation	Training and digital tool familiarity
 Policymakers	Regulatory framework and funding	Develop and enforce supportive policy mechanisms
 Technology Providers	Hardware, software, and integration	Ensure compliance with standards and security
 Researchers & Consultants	Modeling, simulation, and strategy development	Support in best practices and knowledge transfer

Figure 7. Stakeholder roles in Digital Twin implementation.

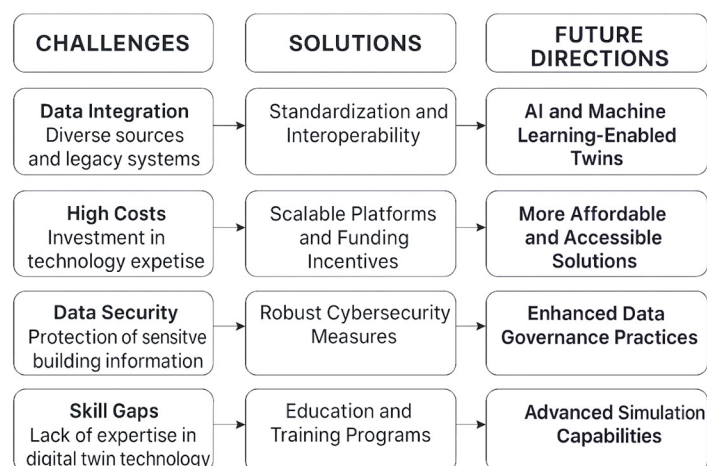


Figure 8. A comprehensive diagram of the current challenges in implementing Digital Twins in buildings, their proposed mitigation strategies, and future research opportunities.

6. Conclusions

This paper highlights the transformative potential of Digital Twin (DT) technology as a major enabler of the global transition toward a low-carbon, intelligent, and sustainable built environment. As the building sector remains a major contributor to global carbon emissions, the integration of DTs presents a critical pathway to decarbonization and climate resilience. By enabling real-time monitoring and control of energy systems, lifecycle carbon assessment, and the seamless incorporation of renewable energy sources, DTs provide a holistic approach to achieving net-zero energy buildings and fostering positive

energy communities. Through dynamic virtual replicas that merge data from sensors, building management systems, and external sources, DTs enhance operational awareness, support predictive maintenance, and deliver deep insights into performance and emission patterns across the building lifecycle.

The presented case study of a teaching building illustrates how DT implementation can yield substantial improvements in energy efficiency, operational reliability, and emission reductions. Specifically, the results demonstrate how DT-enabled optimization of HVAC systems not only minimizes operational costs but also reinforces the broader goals of sustainability and occupant well-being. Such outcomes provide compelling empirical evidence of the pivotal role that DTs can play in reducing energy consumption and advancing climate objectives.

The key findings of this paper are as follows:

1. This paper presents the architecture and functional layers of DTs, distinguishing between levels of fidelity and integration across sensor networks, Building Management Systems (BMSs), and cloud-based infrastructures. These elements are mapped within a broader framework of building performance optimization, lifecycle management, and carbon reduction.
2. The review of existing DT models reveals both their strengths and inherent limitations, particularly regarding interoperability and scalability. The analysis advances the discussion on how fragmented development efforts can be unified through standardized semantic data modeling and ontology-driven approaches such as SAREF.
3. A detailed exploration of challenges, ranging from data heterogeneity and the absence of interoperable protocols to cybersecurity vulnerabilities and cost constraints, provides a systematic categorization of barriers to adoption. These findings highlight the need for aligned technical innovation, policy reform, and institutional collaboration.
4. Beyond technological considerations, the study emphasizes the importance of coherent regulatory frameworks, financial incentives, and open data standards as catalysts for widespread deployment. Such mechanisms are particularly vital for retrofit projects and small- to medium-sized building owners, who often face financial and technical barriers to adoption.
5. The paper outlines a strategic research agenda emphasizing the integration of Artificial Intelligence (AI), machine learning, edge computing, and smart grid interconnectivity as critical drivers of future DT maturity. These innovations are positioned as enablers of predictive, autonomous, and adaptive building operations, serving as a basis for resilient, carbon-neutral urban ecosystems.

Despite these advancements, several implementation challenges must still be addressed. Data interoperability remains a major obstacle, with fragmented formats and communication protocols limiting seamless integration. Adopting open and standardized data frameworks is essential to overcoming this issue. Furthermore, the high initial investment costs associated with DT deployment present a barrier for smaller stakeholders and older building infrastructures. Targeted financial instruments, such as subsidies, tax incentives, and flexible financing schemes, can mitigate these constraints. Additionally, regulatory frameworks must evolve to encompass emerging issues surrounding data privacy, cybersecurity, and compliance standards, ensuring safe and transparent adoption across the sector.

Looking ahead, emerging advancements in AI-driven optimization, real-time edge analytics, and smart grid connectivity will significantly enhance the functional scope and scalability of DT applications. These technologies are expected to further expand the role of DTs from reactive monitoring tools to proactive, self-learning systems capable of autonomous decision-making and continuous performance improvement. As DT

technology matures and adoption widens, it will not only accelerate progress toward national and global climate targets but also reshape the foundation of modern cities, creating resilient, data-driven, and sustainable urban ecosystems for the future.

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