

Review

Digital Twin Technology for Structural Lifecycle Management and Health Monitoring

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Abstract

Digital twin (DT) technology is reshaping structural engineering by linking physical assets to dynamic and data-driven virtual counterparts. DTs enable monitoring, predictive analytics, and autonomous decisions across design, construction, operation, and maintenance. Additionally, DTs are updated with real-time streams continuously. This study focuses on the applications of DTs and the intersection between the Internet of Things (IoT), Building Information Modeling (BIM), and artificial intelligence (AI). Applications include structural health monitoring (SHM) and predictive maintenance for bridges and buildings, in addition to construction safety optimization and stewardship of architectural heritage. The paper also examines barriers to adoption, including data interoperability, cybersecurity, upfront cost, and workforce readiness, and discusses standardization needs. In addition, it highlights educational impacts and pathways for small and medium enterprises (SMEs) to adopt scalable DT solutions. By consolidating recent advances, the review shows how DTs can deliver more resilient, efficient, sustainable, and intelligent infrastructure and outlines the research priorities to overcome remaining gaps and fully realize their potential.

Keywords: Digital Twin (DT); structures; structural health monitoring (SHM); predictive maintenance; BIM; Internet of Things (IoT)

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1. Introduction

The digital revolution in the architecture, engineering, and construction (AEC) industry is driven by the integration of data-driven workflows and cyber-physical systems. Digital twin (DT), as the central technology in this shift, has transitioned from a manufacturing idea to a pillar of modern structural engineering [1–5]. While traditional models, for instance BIM, produce static snapshots, DT is a dynamic and virtual mirror of a physical asset [6]. The fundamental identification of a DT is its bi-directional data flow. The physical structure informs the digital model, and the virtual model, in turn, uses automated control systems to optimize the physical component. This difference is further explained in detail in Table 1 by comparing DT with BIM.

Table 1. Digital twin vs. BIM: definition and distinguishing traits.

Concept	Concise Definition	Differences
Digital Twin (DT)	Live, lifecycle-spanning digital representation updated from real-time data to support simulation/ML/reasoning.	Bi-directional data and control; “as-is” state; continuous monitoring; predictive and autonomous capabilities [6].
Building Information Modeling (BIM)	Structured geometry and semantics of a built asset (as-designed/as-built).	Largely static baseline; becomes dynamic when coupled with sensing/analytics in DT workflows [7].

In the context of structural engineering, this technology promises to shift the industry from reactive and prescriptive approaches to an initiative-taking and predictive paradigm. The traditional methods of structural design, construction oversight, and maintenance often rely on periodic inspections and idealized models that may not accurately reflect the true, evolving state of a structure under complex, real-world environmental and operational conditions. DTs address this gap by creating a living, breathing digital counterpart that mirrors in real time the behavior of the physical structure [8]. This capability is crucial for managing the entire lifecycle from initial design and construction to long-term operation and eventual decommissioning of infrastructure [9].

The development of specialized frameworks simplified the integration of DT technology in structural engineering to ensure structural integrity through autonomous interactions between physical and digital models [10]. This framework leverages IoT sensors and actuators to enhance the structural assessment process by facilitating real-time monitoring and self-adaptive responses [11,12]. Such innovations not only address the gaps in workflow modeling prevalent in current civil engineering practices but also enable automated decision-making capabilities, which are crucial for maintaining structural safety and performance. The implementation of this framework in a laboratory setting has demonstrated its potential for real-world applications, highlighting the transformative impact of digital twins in creating more resilient infrastructures. By offering an initiative-taking approach to engineering challenges and paving the way for more sustainable construction practices, these technologies promise to redefine the standards of structural integrity [10].

Numerous applications and challenges in DT implementation reflect the potential of DT technology in structural engineering [13]. According to recent studies, there are forty identified applications of DTs within construction, encompassing capabilities such as real-time simulation and lifecycle management. These applications allow engineers to address complex structural issues with unprecedented precision and efficiency. However, the integration of digital twins is not without its hurdles; practitioners have identified thirty-four challenges, ranging from technical constraints to the need for comprehensive data management strategies. Addressing these challenges requires a concerted effort from industry stakeholders to refine digital twin frameworks, ensuring they are robust, adaptable, and capable of meeting the evolving demands of modern construction practices [13].

This review will discuss future research directions and the overarching potential of digital twins to redefine the future of structural engineering, leading to smarter, safer, and more sustainable infrastructure. It will explore the fundamental components and enabling technologies that constitute a structural digital twin, including IoT, BIM, AI, and cloud computing. The paper will then delve into the diverse applications of DTs across various stages of a structure’s life, from design and construction to operation and maintenance, supported by specific case studies from the literature. A critical analysis of the implementation challenges, including technical, financial, and organizational, will be presented. Finally, this review paper aims to provide a systematic and exhaustive examination of the current state of digital twin technology in structural engineering.

This review is uniquely warranted to provide an integrated technical taxonomy that closes the research gap. The critical literature gap remains in understanding the unified operational integration across these layers, specifically how multi-layered digital twin architectures seamlessly bridge real-time data ingestion with lifecycle decision pipelines. Despite the growing volume of literature on independent cyber–physical concepts, existing surveys frequently treat sensor configurations, Building Information Modeling (BIM) protocols, and predictive algorithms as isolated silos.

To achieve this, the specific objectives and contributions of this review are to:

1. Systematically map out the technical interdependencies between physical IoT sensors, semantic BIM environments, and predictive algorithms.
2. Synthesize current practical deployments across specialized domains, including bridges, historical structures, and small and medium enterprise (SME) construction workflows.
3. Critically evaluate ongoing challenges regarding interoperability, data synchronization, and standard security protocols to establish a structured deployment roadmap.

2. Review Methodology

To ensure absolute transparency, reproducibility, and comprehensive coverage of the literature, a systematic methodology was employed to identify and filter the referenced studies.

- **Data Sources and Search Engines:** Primary literature searches were conducted across major academic databases, including Scopus, Web of Science, and Google Scholar.
- **Search Strings and Keywords:** The search configurations used Boolean operators combining terms such as: (“Digital Twin” OR “Cyber-Physical System”) AND (“Structural Health Monitoring” OR “BIM” OR “Predictive Maintenance”) AND (“Bridge” OR “Building” OR “Civil Infrastructure”).
- **Time Span:** The literature search focused on peer-reviewed articles, conference proceedings, and state-of-the-art industry white papers published within a definitive time span from 2015 to 2026.
- **Inclusion and Exclusion Criteria:** Articles were selected based on strict inclusion criteria (focus on multi-layered architectural loops, live sensory data ingestion, or concrete digital twin civil deployments). Papers were excluded if they were purely conceptual without framework validation, focused on non-civil engineering applications (e.g., manufacturing/aerospace), or represented duplicate preliminary studies.

3. Fundamental Concepts and Enabling Technologies

The seamless integration of several core technologies enables the effectiveness of the digital twin in structural engineering. Data flows from the physical world to the digital system, is processed and analyzed, and then insights are fed back to inform actions in the physical world. These components work together to create a closed-loop system.

3.1. The Core Digital Twin Framework

A structural DT is built upon a multi-layered architecture that connects the physical and virtual entities. Liu et al. describe a comprehensive layered framework for predicting the impact responses of prestressed steel structures, which is representative of many DT systems [14]. This framework, found in Table 2, typically comprises:

- **The Physical Layer:** The real structure and its interfaces with the environment. It includes the bridge or building itself and its members and components such as girders, decks, slabs, columns, walls, piers, bearings, supports, joints, connections, restraints, and expansion joints. From this layer come the raw, measurable responses such as strain, acceleration, displacement, temperature, humidity, loads, and reactions, as well as any actuation effects when devices are commanded.

- The Perception Layer: This layer converts real behavior into usable data streams by handling instrumentation and edge processing. Data acquisition (DAQ) units sample analog and digital sensors, edge gateways apply denoising, outlier removal, and drift checks, and precise time synchronization (PTP/NTP or GPS) aligns multi-sensor feeds. The result is clean, synchronized signals and lightweight features (for example, RMS, FFT components, or modal peaks) that are ready for downstream transport and analysis. Good perception design lowers bandwidth, reduces false alarms, and preserves temporal fidelity for modal and event-based studies.
- The Transmission Layer: This layer securely and reliably moves those prepared signals from edge to compute and storage with the latency and throughput the application needs. Connectivity may be used by 5G/LTE for high-rate or remote deployments, LoRaWAN for low-power long-range telemetry, and Wi-Fi or Ethernet on sites with stable backhaul. Transport is protected by TLS and device identity (certificates), often broken through gateways that handle protocol translation, buffering, retries, and quality of service. Its output is uninterrupted, tamper-resistant telemetry that reaches the analytics platforms without gaps.
- The Analysis Layer: This layer turns streams into insight by combining signal processing, physics, and machine learning. A time-series store holds high-rate histories for fast queries. For instance, digital signal processing performs filtering, spectral analysis, and modal identification; physics models such as FEM or reduced-order models (ROMs) compute expected responses and test “what-if” scenarios. And AI/ML detects anomalies, diagnoses damage, and estimates prognosis or remaining useful life. The outputs are actionable deviations versus baseline or physics expectations. For example, the output can be the identified location/type/severity of faults, risk-aware RUL trajectories, and simulated outcomes that inform interventions.
- The Service Layer: This layer is where insight becomes action for people and control systems. Dashboards and alerts present KPIs, thresholds, and trends to operators and engineers; CMMS integration creates and tracks work orders with priorities and due dates; and control policies (advisory or automated) translate analysis into operational changes such as temporary speed limits, lane closures, or actuator setpoints. Its outputs are concrete decisions, traceable maintenance tickets, and closed-loop control commands that can alter the physical asset and feed results back into the twin.

Table 2. Structural digital twin multi-layer architecture.

Layer	Purpose	Components/Examples	Outputs
Physical	The asset itself and interfaces	Bridge/building, members, boundary conditions	Real responses (strain, accel., temp.), actuation effects [10]
Perception	Acquire and pre-process data	DAQ, edge filtering, time sync	Clean, synchronized streams/features [15]
Transmission	Move data securely/reliably	5G/LTE, LoRaWAN, Wi-Fi; TLS; gateways	Low-latency, secure telemetry [11,12]
Analysis	Turn data into insight	Time-series store, DSP, physics (FEM/ROM), AI/ML	Anomalies, diagnosis, prognosis/RUL, simulations [16,17]
Service	Human and automated actions	Dashboards/alerts, CMMS/work orders, control policies	Decisions, tickets, closed-loop control [7,18]

A recent full-scale bridge study further illustrates how a structural digital twin can be organized as a layered and closed-loop SHM platform [19]. Nasim et al. proposed a hybrid DT framework for bridge infrastructures that combines physics-based finite element modeling, drone-based photogrammetry, and wireless IoT sensing within a continuous feedback loop for structural assessment and model updating. Their framework em-

phasizes that the practical value of a DT lies not only in representing geometry or storing sensor streams, but in continuously comparing field-measured responses with baseline model predictions, extracting modal characteristics, and updating the virtual model to maintain synchronization with the physical asset. The study is especially valuable because it demonstrates this concept on an operational railway bridge and shows how layered DT architectures can support anomaly detection, predictive maintenance, and scalable infrastructure management in real-world conditions [19].

Chiachío et al. introduced a structural digital twin framework specifically tailored for structural applications, enabling autonomous interactions between physical and digital components, which is a critical advantage over traditional methodologies [10]. This framework addresses a notable gap in current civil and structural engineering practices by seamlessly integrating workflow modeling into the digital twin paradigm. By utilizing IoT sensors and actuators, this approach allows for real-time monitoring and self-adaptive responses, thereby facilitating automated decision-making processes to uphold structural integrity [10].

Sun et al. proposed a hybrid monitoring methodology in which a digital twin for bridge SHM is established by integrating the physical entity, finite element models as the mechanical twin, bridge information modeling (BRIM) as the information twin, and IoT systems [20]. Their framework is particularly important because it enables the conversion, expansion, and fusion of monitored data, allowing spatially discrete measurements to be extended to full-field virtual sensing and heterogeneous information to be visualized in a unified environment. This study further demonstrates how model–data integration can improve data management, response reconstruction, and damage identification in bridge digital twins.

While these frameworks demonstrate the versatility of structural DTs, their practical implementation highlights distinct architectural differences and individual limitations. Furthermore, discrepancies reported across the literature regarding system accuracy and damage localization performance often stem from heterogeneous factors: variations in sensor synchronization accuracy (e.g., microsecond-level GPS time-stamping versus delayed network time protocols), the discrete placement density of monitoring arrays relative to stress-concentration zones, and localized micro-environmental fluctuations (such as thermal gradients and moisture cycles) that are often oversimplified or omitted during initial model baseline calibration. Hybrid architectures that fuse finite element modeling (FEM) with wireless IoT data provide high mechanical fidelity but are bounded by the steep computational expense of running real-time, non-linear simulations on complex infrastructure. Conversely, purely data-driven architectures rely exclusively on high-frequency stream filtering and edge analytics; while computationally lightweight and scalable, they lack the underlying physics constraints necessary to accurately diagnose unprecedented structural failure modes.

3.2. The Role of the IoT and Sensing Technologies

IoT sensors are the sensory organs of the digital twin, providing real-time data that animates the virtual model. The type and placement of sensors are critical for accurate representation. Liu et al. emphasizes that effective implementation of a structural digital twin (SDT) necessitates careful planning of sensor placement, data acquisition, and analytic models, ensuring that the system aligns with specific business objectives and expectations [15]. Advanced SHM sensor techniques such as electric resistance strain gauges, fiber Bragg grating strain gauges, accelerometers, and pressure transducers are commonly employed to offer detailed insights into the current state of infrastructure [15].

Distributed sensing represents a significant advancement in this area. Bado et al. highlight that by integrating geometric data with semantic and operational information, digital twins can accurately simulate and assess the structural health of assets over their entire service life [21]. This comprehensive approach not only supports infrastructure

managers in decision-making but also enhances the reliability of maintenance strategies by mapping temperature, strain, and vibration distributions with high accuracy. As the deployment of distributed sensing becomes more feasible, the ease of installation and high sampling frequency further empower digital twins to deliver real-time insights, ultimately refining the resilience and sustainability of infrastructure systems [21].

Furthermore, the application of fiber-optic sensors (FOSs) in conjunction with deep neural networks demonstrates the high precision achievable. Hielscher et al. developed a neural network-based digital twin for reinforced concrete bridges that transforms strain outputs into comprehensive digital twin visualizations, enabling real-time structural analytics [22]. The model's precision is evidenced by its ability to maintain an average error of less than 2 kNm for bending moments, and an absolute error below 0.15 mm for deflections, highlighting its capability to enhance accuracy in structural assessments [22]. Table 3 lists the major sensing options with placements, measurements, and DT value.

Table 3. SHM sensing modalities for DTs.

Modality	Placement	Measures	Benefit
Electrical resistance strain gauges	Girders, decks, columns	Local strain	Crack initiation/trends; load paths [15]
Fiber Bragg gratings (FOSs)	Tendons, rebar, long spans	Distributed strain/temperature	Dense coverage; drift-resistant; multiplexing [21]
Accelerometers	Decks, towers, floors	Vibration/ambient response	Modal ID, damage localization [15]
Thermo-hygro sensors	Enclosures, bearings	Temperature/humidity	Thermal effects, compensation [21]
Pressure/load cells	Bearings, cables	Loads/reactions	Load redistribution, overload flags [21]
FOS + DNN (bridge example)	RC bridges	Strain → responses	High-precision DT inference (deflection, moments) [22]

3.3. Integration with BIM

BIM creates a comprehensive digital representation of physical structures. It allows stakeholders to effectively manage and visualize the entire lifecycle of a project. For many structural DTs, BIM is the foundational geometric and semantic backbone. While a traditional BIM model is a rich, static repository of a building's physical and functional characteristics, it becomes the initial, as-designed state of the digital twin. Girmay Mengesha Azanaw states that incorporating BIM alongside digital twin technology significantly enhances design coordination and collaboration within structural engineering projects [7].

These models can be continuously updated with real-time data when paired with DTs to enable predictive analysis and proactive maintenance strategies. This integration underscores the importance of establishing standardized data integration protocols, which are crucial for maximizing the efficacy of these technologies in monitoring structural health. The evolution of digital twins with sensor inputs underscores the importance of continual data flow in optimizing structural performance and preemptively addressing maintenance needs [23]. As a result, the implementation of digital twin–BIM technologies not only facilitates superior asset management but also sets a precedent for innovative, data-driven solutions in the broader field of structural engineering [23]. Figure 1 explains the two-way exchange between BIM and the live twin. BIM-to-DT flows provide identity, geometry, and semantics for analysis; DT-to-BIM flows push back change sets and condition states, keeping BIM “as-is.” It motivates why asset IDs and data alignment (the digital thread) matter for lifecycle management.

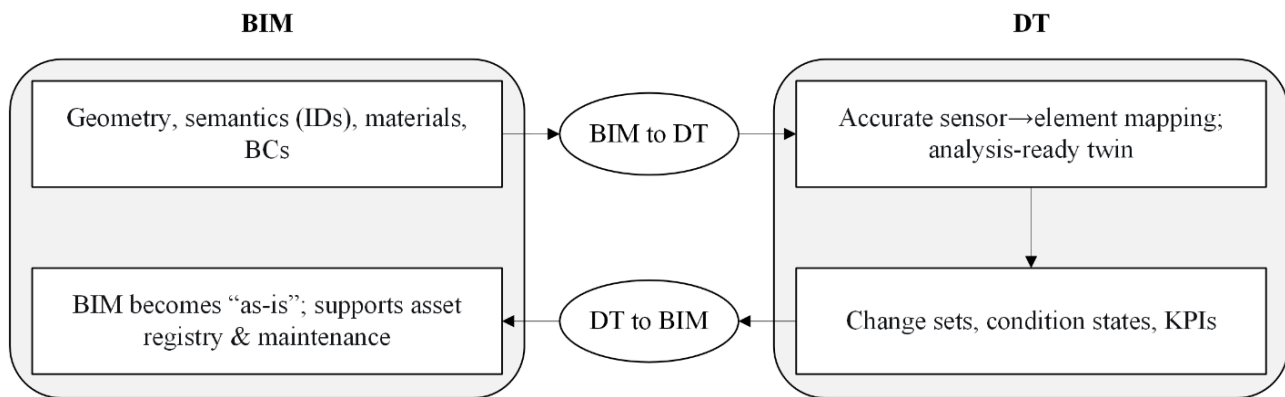


Figure 1. BIM and DT integration closed loops.

3.4. The Power of Integrating Machine Learning (ML) and Artificial Intelligence (AI)

The integration of deep learning (DL) with digital twin (DT) technology represents a significant stride towards advancing Construction 4.0, with implications for both automation and enhanced decision-making capabilities within structural engineering [24]. Construction 4.0 is a concept in which digital tools like BIM and digital twins, IoT sensors, robotics, automation, and AI are integrated across the project lifecycle to create connected, data-driven, and highly automated construction processes, with the goals of improving productivity, safety, quality, and sustainability. By leveraging cognitive abilities, this synergy allows for the detection of complex actions and the optimization of dynamic processes, thereby streamlining operational workflows and improving real-time decision support. AI and ML are the cognitive engines of the digital twin, turning vast streams of data into actionable intelligence. They enable prediction, optimization, and autonomous decision-making that distinguish a digital twin from a simple monitoring system. Researchers are utilizing multiple back-propagation artificial neural networks (BP-ANNs) to enhance the “cognitive” layer of the DT and reconstruct structural responses under vehicular loading, which reduces the requirement for exhaustive baseline data and precise damage localization [25].

Specific applications are numerous; for instance, Liu et al. demonstrated the application of DT in predicting the impact responses of prestressed steel structures by integrating machine learning (ML) with high-fidelity DTs [14]. This approach not only improves the understanding of how key structural components respond to various impacts but also facilitates data-driven strategies for maintenance and resilience. Similarly, Zhu and Wang showcased the innovative fusion of digital twins with random forest algorithms to transform the safety analysis of prestressed steel structures [26]. This method allows for real-time extraction and analysis of critical design and mechanical parameters, enhancing the accuracy of structural safety assessments and underpinning an intelligent control strategy for maintaining structural safety. The current state-of-the-art approaches are transitioning from purely data-driven black-box models to Physics-Informed Neural Networks (PINNs), which embed structural mechanics and governing physical laws directly into the learning process to improve predictive reliability [27].

Despite the expanded integration of these AI/ML models, their deployment in practical structural twins faces stringent training data requirements, rigorous model validation procedures, and clear operational limitations. To prevent predictive drift and false alarms, deep architectures require vast, multimodal training datasets that encompass balanced distributions of both pristine states and structural damage scenarios. In terms of practical implementation, the primary limitations include the extreme computational latency encountered when executing large neural networks on low-power edge gateways,

the lack of interpretability inherent in data-driven “black-box” models which impedes engineering trust, and the vulnerability of the predictive engines to sensor drifting or packet loss, requiring automated data-cleansing and data-imputation protocols to maintain decision-making continuity. Because structural damage data from operational assets is inherently scarce, models must often rely on synthetic data generated via validated high-fidelity FEM simulations, introducing structural-domain-gap challenges. Consequently, model validation cannot depend solely on standard statistical metrics (e.g., R^2 or Root Mean Square Error); it demands split-sample cross-validation using blind experimental data, combined with long-term field benchmarking to verify the model’s robust sensitivity under varying ambient noise levels.

Cloud-based platforms further amplify this capability. Dang et al. proposed a cloud-based digital twinning framework for structural health monitoring that integrates deep learning [17]. These frameworks leverage cloud computing to seamlessly link structural components with digital models, enhancing the interaction between physical structures and human interventions. By utilizing advanced algorithms and a user-friendly interface, they enable precise damage detection, achieving an impressive accuracy rate of 92% in case studies involving both model and real bridge structures [17]. Figure 2 outlines the core analytics tasks, anomaly detection, diagnosis, prognosis (RUL), impact prediction, and safety factor analysis, along with inputs and outputs. It shows how physics and ML complement each other and where to introduce more advanced models over time.

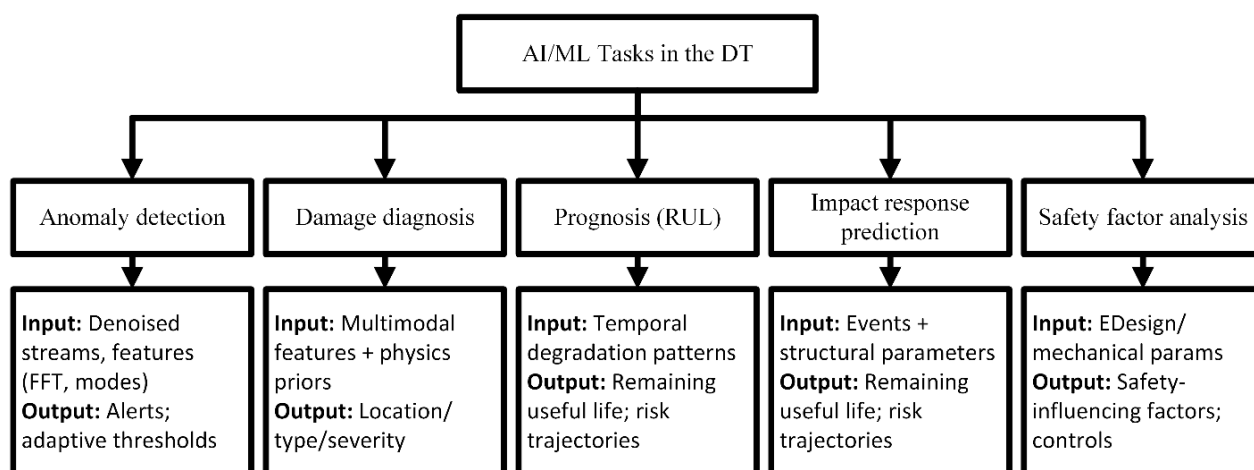


Figure 2. AI/ML tasks in digital twin.

Sarasin et al. further highlighted the role of AI-enabled and physics-based digital twin architectures in SHM through a framework developed for next-generation landing-gear systems. Their study proposed an SHM-based DT architecture that integrates high-fidelity FE models, sensor data, connectivity, AI, and physics-informed AI simulation models within an MBSE environment to support fatigue analysis and condition-based maintenance. The framework is significant because it shows how DT-SHM systems can be designed from the early development stage to support predictive maintenance, reduce downtime, and improve reliability in safety-critical structures [28].

3.5. Data Management and Interoperability: The Digital Thread

DT is increasingly valued as an emerging technology for its potential to optimize asset operation and maintenance in bridge management. However, existing DT applications and traditional bridge management systems typically rely on standalone BIM or GIS platforms, with limited integration between BIM and GIS [29].

By seamlessly connecting data across the design, construction, and operational phases, DTs can offer real-time insights that enhance decision-making and performance optimization. This interconnected approach addresses a critical challenge in maximizing the potential of digital twins, as it ensures that the flow of information is continuous and coherent throughout the entire process [30]. The concept of the “digital thread” is critical for a coherent DT. It refers to the seamless flow of data across the entire lifecycle of a structure from design and construction to operation and maintenance. Iranshahi et al. stated that the integration of DT in structural engineering projects with the digital thread presents a transformative opportunity for advancing lifecycle management [30].

Recent work has also emphasized that the effectiveness of digital twins depends not only on sensing and simulation capabilities, but also on the standardized management, exchange, and contextualization of as-built and as-is data within an interoperable digital environment. Bornholdt et al. demonstrated this in a digital twin-based SHM framework for dikes, where a standard-compliant BIM model, linked with sensor streams through a customized webform and communication protocols based on the OGC SensorThings API, enabled model-based visualization and condition assessment. Their study further highlighted the need to structure DT workflows around requirements such as integrating geometry, material and condition data, filtering and aggregating sensor inputs, localizing damage in relation to structural elements, and providing customizable visualization for stakeholders. This contribution is important because it shows that interoperability is not merely a software concern, but a foundational requirement for scalable predictive maintenance and resilient infrastructure management across different structure types [31].

However, due to the heterogeneity of data sources and models, achieving this seamless flow is a significant challenge. Bordeleau et al. suggest that incorporating Model-Driven Engineering (MDE) techniques into Dt offers promising solutions [32]. MDE facilitates the management of heterogeneous models that are crucial for accurately reflecting the complexities of real-world construction projects. This approach ensures that DTs remain synchronized with their physical counterparts to enhance the precision and reliability of simulations and analyses.

3.6. Emerging Frontiers: Edge-AI and Vision-Based Digital Twins

The traditional DT frameworks heavily rely on centralized cloud-based processing. Recently, to manage the massive high-frequency data streams required for modern SHM, the field has been rapidly shifting toward a decentralized and intelligent architecture. Two technological synergies primarily drive this evolution:

- **Edge Computing and Real-Time Processing:** To overcome the inherent latency and bandwidth bottlenecks of cloud-only systems, modern DTs are adopting Edge-AI. By moving computational tasks such as signal denoising, FFT-based feature extraction, and initial anomaly detection directly to the sensor gateway, the system can trigger near-instantaneous safety alerts for dynamic events such as seismic shifts or vehicle impacts. This decentralized approach significantly reduces the data volume transmitted to the cloud while preserving the high temporal fidelity essential for modal analysis. This technology has been considered in recent research as a novel solution for structural damage monitoring and detection [33]. Due to high installation costs and complexity, traditional wired systems are limited. On the other hand, existing wireless systems still face cost, synchronization, and reliability issues. Furthermore, cloud-based methods struggle to meet real-time and bandwidth constraints for extreme event detection in edge environments. To resolve these barriers, the SHM system based on edge computing can achieve less than 1% accuracy loss and 35% reduction in power consumption [34].

- **Vision-Based and Non-Contact Sensing:** To monitor critical bridge components, modern IoT-driven systems are now incorporating cloud-based computer vision for long-term health assessment by providing a non-contact alternative to traditional displacement sensors [35]. The integration of computer vision (CV), unlike traditional physical sensors, is transforming how DTs maintain “as-is” geometric accuracy. Engineers can now automate the detection of surface cracks or corrosion using high-resolution cameras and Unmanned Aerial Vehicles (UAVs). This technology preserves the structural features of crack edges and enhances the image contrast. This provides a high-quality data foundation for the detection network. It also reduces parameter count and computation [36].

4. DT Applications in Structural Engineering

Integrating DT technologies into structural engineering enables a vast array of applications that are revolutionizing practices. These applications span the entire lifecycle of a structure and offer tangible benefits in safety, efficiency, and cost-effectiveness. Figure 3 maps representative DT use cases to each lifecycle phase, including design, construction, operations, maintenance, and end of life (EOL). With clear, measurable benefits such as Operating Expenditure (OPEX).

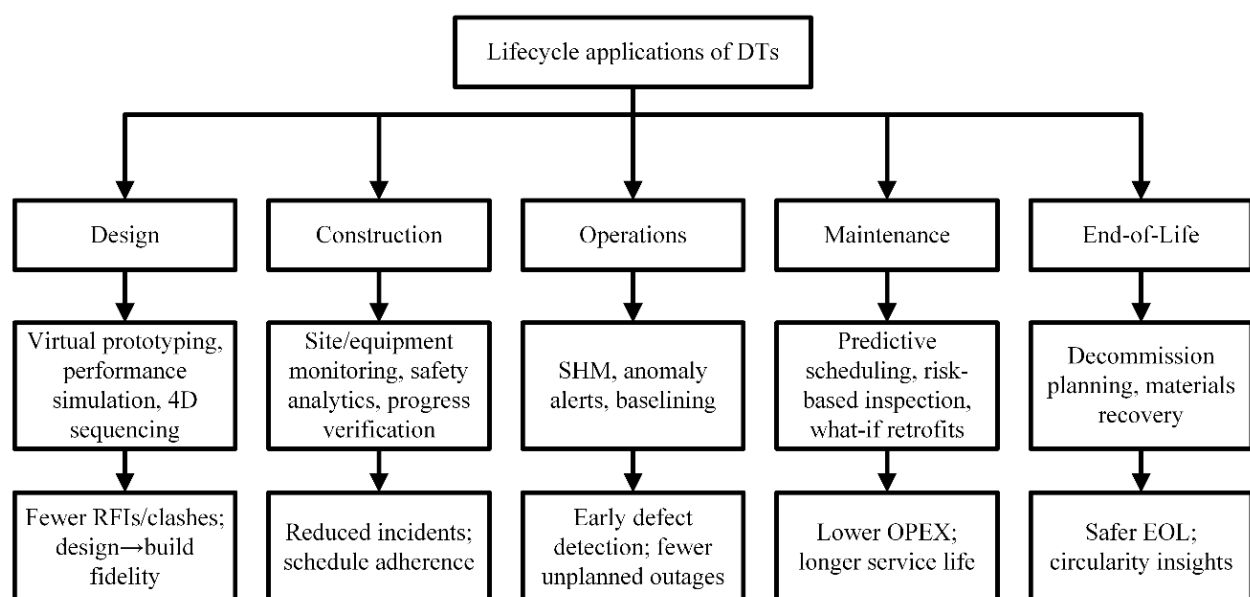


Figure 3. Digital twin application over the lifecycle of structures.

4.1. Structural Health Monitoring (SHM) and Predictive Maintenance

SHM is one of the most prominent and impactful applications of DTs. Engineers can detect anomalies, assess damage, and predict remaining useful life by continuously comparing real-time sensor data with the expected behavior simulated by the digital model. Liu et al. detail the application of structural health monitoring (SHM) for structural digital twins, utilizing advanced SHM sensor techniques to offer detailed insights into the current state of infrastructure [15]. This approach allows for real-time data processing and analysis. It provides critical information to preemptively address structural deficiencies and extend the lifespan of engineering assets.

An intelligent BIM-DT framework for real-time SHM integrated with wireless IoT sensing and digital signal processing was introduced by Hu et al. [18]. This framework enhances existing BIM-based SHM systems by leveraging IoT for continuous sensor data collection and applying DSP techniques to refine sensor inputs, thereby improving the

accuracy of structural analysis and visualization. Tested on a prototype structural frame, this approach demonstrated a high update frequency for digital twins, showcasing its potential to transform civil infrastructure asset management through enhanced real-time monitoring capabilities [18].

The application extends to specific structure types with high precision. Hielscher et al. demonstrated a neural network-based digital twin for reinforced concrete bridges that provides exceptionally reliable baseline data, fostering trust in predictive maintenance strategies [22]. With a predictive mean absolute error under $1 \mu\epsilon$ during testing, these digital twins optimize the monitoring of structural integrity and facilitate proactive decision-making, ensuring sustainable and resilient infrastructure management in dynamic environments [22].

Xu et al. also demonstrated that digital twins can improve SHM by enabling time-evolving reliability estimation under changing environmental conditions. Their framework used installed SHM measurements to update a digital twin model in real time and account for temperature variations, transducer performance, and noise, thereby supporting more accurate probability-of-detection assessments than static MAPOD approaches. This work is important because it shows that DTs can support not only damage detection, but also continuous performance verification of SHM systems throughout their service life [37].

Crucial to long-term predictive maintenance within the DT framework is the explicit accounting for slow-acting degradation processes, such as concrete carbonation, reinforcement corrosion, and microstructural material decay. Concrete carbonation alters the internal chemical baseline, lowering the pH and destroying the passive protective layer around the reinforcing steel, which subsequently triggers localized or generalized reinforcement corrosion. These electrochemical changes cause sub-surface volumetric expansion, leading to concrete spalling, microstructural degradation, and a progressive reduction in the effective cross-sectional area of load-bearing steel rebars. In future digital twin systems, these degradation processes must be integrated not merely as static environmental multipliers, but as time-dependent, coupled multi-physics modules. Real-time inputs from specialized non-destructive sensors (such as relative-humidity probes, embedded corrosion-rate sensors, and electrochemical impedance spectroscopy arrays) can continually update the microstructural state variables within an information twin environment. By directly feeding these live corrosion rates into parallel reduced-order mechanical models, future DTs can dynamically adjust local stiffness matrices and element capacities, enabling highly accurate, risk-aware long-term predictions of structural durability and remaining service life under actual aggressive environmental exposure.

4.2. Design, Construction, and Project Management

By combining augmented reality (AR) and virtual reality (VR) with digital twins, practitioners can achieve real-time monitoring and optimization of construction processes, thereby enhancing precision and reducing errors. This technological synergy is projected to result in substantial cost savings, with validated 2026 economic assessments indicating potential reductions of US\$950 million in design and construction, and US\$400 million in operation and maintenance [38]. DTs are not only for existing structures and are increasingly used during the phases of design and construction. They enable virtual prototyping, clash detection, and construction process simulation. The integration of Virtual Design and Construction (VDC) with digital twin technologies presents a promising avenue for revolutionizing the architecture, engineering, and construction (AEC) industry [38]. While optimizing for modern occupancy requirements, DT applications in heritage conservation are evolving to include social dynamics and environmental stressors, ensuring that historical integrity is maintained [39].

For small and medium enterprises (SMEs), this technology is particularly transformative. Digital twin technology is particularly beneficial for SMEs within structural engineering, as it provides a cost-effective means to simulate and predict the behavior of structures before they are physically built [40]. By leveraging digital twins, SMEs can explore various design scenarios, identify potential issues, and optimize solutions without the need for expensive prototypes. This synergy allows SMEs to compete with larger firms by offering sophisticated engineering solutions that optimize resource use and mitigate risks [40].

Real-time monitoring of construction sites is another critical application. Talmaki and Kamat focused on real-time monitoring within DTs to significantly enhance the safety and operational efficiency of articulated construction equipment. By employing a scalable technical approach, sensor data from real-world equipment can be seamlessly integrated into 3D digital models, facilitating concurrent visualization and monitoring of construction activities. This capability not only aids accident prevention by providing real-time alerts to operators but also enhances decision-making during critical operations [41].

4.3. Lifecycle Management and Operational Optimization

DTs provide a unified platform for managing a structure throughout its entire operational life. Gao et al. explored the application of digital twin technology in transportation infrastructure, underscoring its transformative potential in structural engineering, particularly in addressing design and maintenance challenges [42]. By creating a virtual space with enhanced real-time state assessment and prediction, DT technology mirrors real-world infrastructure through advanced sensor and computing technologies. By managing substantial volumes of monitoring data, digital twins provide engineers with critical insights into the performance and longevity of structures like railways, bridges, and tunnels [42].

The integration of digital twins, BIM, and AI in structural engineering is poised to significantly enhance infrastructure lifecycle management by enabling real-time data monitoring and predictive analysis [7]. From design to demolition, DTs exploration within construction, according to Yang et al., highlights their broad applicability across the entire lifecycle of a construction project [43]. This comprehensive approach ensures that digital twins are not only tools for monitoring but also pivotal in optimizing every phase of construction. By integrating data and model automation, digital twins facilitate intelligent system control, ultimately enhancing decision-making processes and improving project outcomes [43].

4.4. Risk, Safety, and Resilience Analysis

DTs enable engineers to test structures against extreme events and evolving conditions in a safe, virtual environment. Zhu and Wang demonstrated this for prestressed steel structures, where their digital twin and random forest integration provides an intelligent analysis model that effectively correlates design and mechanical parameters, delivering insights into safety-influencing factors [26]. This sophisticated approach not only identifies the key design parameters impacting structural integrity but also underpins an intelligent control strategy for maintaining structural safety.

In managing engineering dynamics, Wagg et al. discussed the use of DTs by offering innovative solutions to longstanding challenges such as system identification and data-augmented modeling. This capability is exemplified using DTs in the management of wind turbine assets, where complex dynamic behaviors are modeled and monitored to enhance operational efficiency and reliability. Moreover, digital twins facilitate the integration of uncertainty management and trust quantification, which are essential for establishing robust and reliable models in engineering [16].

The integration of environmental factors is crucial for accurate resilience analysis. Hu et al. noted that by considering these factors, DTs can better replicate the dynamic inter-

play between structures and their surroundings, leading to more precise simulations and predictions [8]. This integration addresses the limitation of traditional models that often overlook the environmental conditions' impact on the structural integrity. As engineers advance these capabilities, the potential to develop more accurate virtual components that account for real-world interactions becomes a reality, facilitating improved lifecycle management of infrastructure [8].

4.5. Sustainability and Heritage Preservation

Digital twins are powerful tools for promoting sustainability in the built environment. Zhang et al. highlighted that digital twin technology's capacity to transform structural engineering extends to enhancing sustainability by integrating Building Information Modeling (BIM) methodologies [44]. This integration facilitates the development of sustainable building designs by addressing current gaps and difficulties in embedding sustainability concepts into structural engineering practices. The combination of digital twins and BIM not only streamlines the design process but also promotes a more comprehensive approach to sustainability, ensuring that both environmental and structural integrity are maintained [44].

Petri et al. further showed that digital twins can support sustainability by enabling dynamic lifecycle assessment (LCA) based on real-time data rather than static assumptions. Their BLDT framework combined IoT data, machine learning, and semantic interoperability to deliver continuous environmental assessment and predictive sustainability insights in the built environment. This study highlights the potential of DTs to improve environmental decision-making, decarbonisation planning, and lifecycle-based performance evaluation [45].

DTs offer a non-invasive means to protect culturally significant structures. Vuoto et al. underscored the application of DT technology in preserving architectural heritage [46]. By enabling real-time monitoring and predictive analytics, DTs offer a sophisticated means of protecting the structural integrity of historic buildings. This capability is especially crucial in addressing the uncertainties related to material properties and environmental interactions, which are inherent in heritage structures. As DTs are integrated into the AECO domain, they move beyond traditional geometric models to facilitate a deeper understanding of a building's performance over time [46].

Aroquipa et al. further expanded this direction by proposing an SHM–digital twin methodology for heritage buildings within a smart-city and disaster-risk-reduction context. Their framework introduced the concept of Intelligent Circular Resilience (ICR) and outlined a six-stage process including building characterization, virtualization, sensor-based data retrieval and analysis, DT model updating, result generation, and feedback. The study is especially relevant because it emphasizes how DTs can support seismic damage assessment, BIM/FEM integration, sensor planning, and long-term resilience strategies for heritage structures under limited-data conditions [47].

4.6. Education and Training

The immersive nature of digital twins makes them ideal for educational purposes. Maksimović and Davidović detailed the role of DT in transforming engineering education by providing students with interactive and immersive learning experiences, particularly in structural engineering [48]. The use of digital twins in educational settings enables learners to engage with complex engineering concepts through realistic simulations, thereby enhancing their understanding and retention of knowledge. This innovative approach prepares future engineers to tackle real-world challenges with greater competence and confidence by bridging the gap between theoretical knowledge and practical application [48].

4.7. Comparative Synthesis and Empirical Boundaries of Core Reviewed DT Domains

To transform the compiled review of DT approaches from an isolated descriptive summary into an evaluative engineering framework, the core operational application domains and technical components reviewed in this study must be critically cross-examined. Table 4 synthesizes these paradigms across their enabling architectures, explicit performance indicators, structural parameters, and data integration boundaries directly established in the analyzed literature.

Table 4. Synthesis and critical performance evaluation of core reviewed digital twin environments.

Target Infrastructure/Domain	Core Enabling Technologies	Quantified Performance Indicators	Monitored Structural Parameters	Primary Technical Limits	Representative Case Frameworks Reviewed
Bridge Engineering and SHM Platforms	Neural Networks, Wireless IoT Sensing, and Fiber-Optic Sensors (FOSs)	- Maintain an average error of less than 2 kNm for bending moments. - Capable of maintaining an absolute error below 0.15 mm for deflections. - Achieving a predictive mean absolute error under 1 $\mu\epsilon$ during testing.	Dynamic structural health tracking, localized strains, bending moments, and geometric deflection fields.	Strict edge-to-cloud data synchronization bandwidth; vulnerability to time-evolving environmental noise and transducer drift.	The Twinway operational railway bridge and Iowa bridge asset management systems.
Cloud-Based SHM Analytics	Centralized Deep Learning (DL) Frameworks	- Automated damage detection networks achieve a 92% precision/accuracy rate. - Back-propagation artificial neural networks (BP-ANNs) reconstruct traffic loading states.	Structural fault anomalies, load-induced time-series anomalies, damage type, and severity localization.	Blind to localized edge dynamics without stable backhaul; substantial high-frequency bandwidth consumption.	Multi-bridge data-driven fault diagnosis and structural frame models.
Decentralized Intelligent Gateways	Edge Computing and Edge-AI Processing	- Optimization results in less than 1% accuracy loss. - Prompts a substantial 35% reduction in asset power consumption.	Real-time signal denoising, FFT feature extraction, and instantaneous dynamic event-trigger thresholds.	Local processing power constraints; structural boundaries limited to surface-level edge triggers.	Extreme dynamic events, seismic shifts, and vehicle impact tracking.
Design, Construction and Management	Virtual Reality (VR), Augmented Reality (AR), and Virtual Design and Construction (VDC)	- Projected lifecycle cost reductions of US\$950 million in design and construction. - Indicated potential savings of US\$400 million in operations and maintenance.	4D sequencing, real-time worker tracking, asset clash detection, and historic structural weathering.	High upfront capital technology costs; profound workforce digital readiness and technical training barriers.	Small and medium enterprise (SME) construction site and historic heritage models.

Furthermore, a persistent technical gap across these reviewed digital twin architectures is their heavy focus on the digital, systemic, and macro-structural layers (such as geometric alignment, spatial data mapping, and macro-deflection tolerances) while marginally addressing the microstructural, physicochemical degradation processes occurring within core construction materials. For long-term lifecycle management, digital twins must expand past macro-telemetry to actively incorporate material kinetics laws that track concrete carbonation depths, reinforcing-steel rebar electrochemical corrosion rates, and microstructural matrix degradation under cyclic environmental stressors. Bridging the gap between macro-level digital tracking and micro-level physical degradation laws remains a critical next step for establishing long-term structural resilience forecasting.

5. Implementation Challenges and Barriers

The widespread adoption of DTs is hindered by a series of significant challenges in structural engineering despite their immense potential. These barriers are multifaceted, spanning technical, financial, and organizational domains.

5.1. Technical and Data-Related Challenges

The most frequently cited challenges revolve around data. Madubuike et al. reported that despite the clear benefits, such as improved planning and construction processes through virtual representations, the industry must address limitations related to data interoperability and system integration [49]. To ensure accuracy and reliability, the use of DTs underscores the need for robust data management frameworks to automatically update virtual models with real-time data from physical assets [49].

According to Omrany et al., it is crucial to address challenges such as data integration and scalability to fully capitalize on the benefits of DTs, which can hinder widespread deployment [50]. The essential steps towards overcoming these barriers and unlocking the full potential of DTs include establishing standardized data formats and exploring semantic data modeling [50]. The integration of interoperable systems and effective data management practices is cited as a critical requirement for the successful deployment of digital twins in structural engineering [51]. Cybersecurity is another paramount technical concern. Mousavi et al. pointed out that cybersecurity concerns and the necessity for standardized data protocols underscore the importance of interdisciplinary collaboration to ensure reliable and secure use of digital twins [52]. As these systems often manage critical infrastructure, the consequences of a cyber-attack could be severe. Table 5 pairs each commonly reported barrier with pragmatic mitigations.

Xiao et al. also showed that digital twin implementation challenges extend to other complex infrastructure systems beyond civil structures. In a power grid data center application, they used a 5D digital twin architecture and integrated heterogeneous data sources, including metrics, logs, and traces, to support anomaly detection and root cause analysis. Their work highlights that a major barrier to effective DT deployment is not only model development, but also the integration and interpretation of large, multi-source datasets for reliable maintenance decision-making [53].

Table 5. Adoption challenges and actionable mitigations.

Challenge	Impact	Practical Mitigation
Data quality	Fragmented schemas; hard to fuse	Open standards/ontologies; digital-thread IDs; QA pipelines
Cybersecurity	Critical infra at risk	Zero-trust IAM; secure onboarding; network segmentation; monitoring
Upfront cost	Sensors/integration seen as expensive	Narrow pilots with KPIs; modular scale-out; value tracking
Skills and culture	Siloed orgs; lack of data/OT skills	Cross-disciplinary teams; playbooks; upskilling
Maturity/TRL	Not fully off-the-shelf	Start with proven patterns; vendor-neutral architectures

5.2. Financial and Resource Barriers

The high initial cost of implementation is a major deterrent, especially for smaller firms. Girmay Mengesha Azanaw noted that despite the advantages of integrating AI with digital twins and BIM, the implementation of such technologies faces challenges, including concerns over high initial costs and the necessity for skilled labor to manage these complex systems [7]. This is echoed by Yang et al. [43], who identified the need for skilled technical personnel as a significant concern that must be addressed to fully leverage the potential of digital twins.

5.3. Organizational and Collaboration Hurdles

In their study on modular integrated construction, Xie and Pan highlighted that challenges such as the need for interdisciplinary collaboration and the development of standardized frameworks remain critical for the widespread adoption of DTs [54]. The successful implementation of a DT requires a cultural shift and close collaboration between disciplines. Ammar et al. identified thirty-four challenges from a practitioner's perspective, many of which are organizational, ranging from resistance to change to a lack of clear standards and protocols [13].

The current maturity of this technology also presents a barrier. Iranshahi et al. reported that the current Technology Readiness Level of digital twins, assessed at 4.8 out of nine, highlights both the progress made and the remaining potential for further development and integration with other digital technologies [30]. This indicates that while the technology is promising, it is not yet fully mature for off-the-shelf deployment in all structural engineering contexts.

6. Real-World Implementations and Case Studies

The theoretical potential of DTs is being realized in a growing number of real-world projects and research implementations. These case studies provide valuable insights into practical workflows and serve as proof of concept.

6.1. Bridge Digital Twins

Bridges are a common subject for digital twin development due to their critical role in infrastructure and their exposure to dynamic loads. Gürdür Broo et al. presented a case study involving a bridge digital twin implementation that illustrates the multi-layered approach necessary for successful deployment, emphasizing the critical role of systems, information, and organizational perspectives [51]. This implementation highlights the critical role of integrating physical, cyber, and service layers to create smart infrastructure systems [51].

Pregolato et al. provided a seminal example with the digital twin of the Clifton Suspension Bridge; see Figure 4. They proposed a step-by-step workflow process that highlights the transition from prototype to practical application. This approach is exemplified by the digital twin of the Clifton Suspension Bridge, demonstrating the method's potential to enhance existing infrastructure management by integrating physical and virtual architectures. The adoption of this methodology is essential for addressing the knowledge challenges inherent in digital twin development and realizing its value proposition [55].

Tita et al. elaborated on a DT-BIM technology for bridge management, highlighting its potential to revolutionize structural engineering through advanced monitoring and centralized data integration. By seamlessly merging cyber and physical environments, this technology enables real-time updates and comprehensive health monitoring of bridge structures, which is crucial for maintaining infrastructure longevity and safety [23].

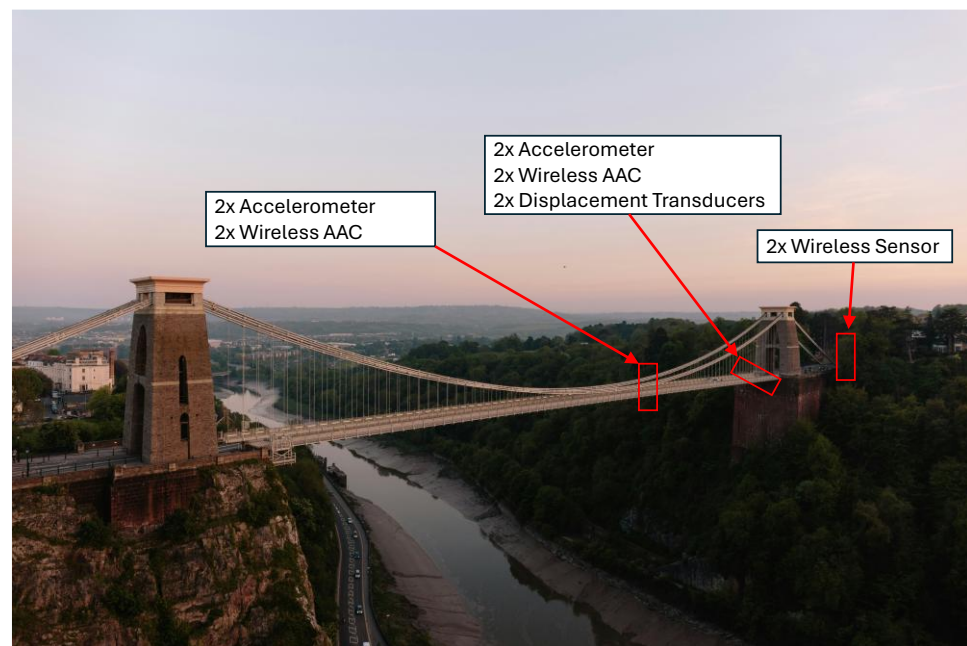


Figure 4. Illustration of the sensor deployment as part of the Dashboard project for the Clifton Suspension Bridge. Base image from <https://unsplash.com/>.

A recent study further strengthens the bridge-DT literature by demonstrating a digital twin-based SHM framework for a balanced cantilever bridge, a structurally complex bridge type for which accurate monitoring is particularly challenging [56]. In that work, the twin was updated using 3D-LiDAR scanning to capture the as-is geometry, Ultrasonic Pulse Velocity (UPV) testing to estimate the in-service concrete elastic modulus, and accelerometer and piezo-resistive strain gauge measurements to extract modal and strain-based response characteristics. The study showed that the updated as-is model provided better agreement with measured bridge behavior than the original design model, while dynamic strain patterns and neutral axis depth served as sensitive indicators for local condition assessment and future damage detection. This case study is important because it illustrates how geometric deviations, material-property evolution, and field-measured dynamic response can be fused into a validated DT workflow for predictive maintenance and long-term bridge management [56].

6.2. Industrial and Other Infrastructure Applications

Beyond bridges, digital twins are being applied to a variety of other structures. Mahmoodian et al. demonstrated the application of a novel digital twin architecture at the Dalrymple Bay Coal Terminal, showcasing its capability to monitor structural performance in real time, enabling timely interventions and predictive maintenance strategies. This approach not only enhances the operational efficiency of infrastructures but also prolongs their service life by preemptively addressing potential issues [57].

Shi et al. reviewed the development and application of digital twin techniques in steel structures, highlighting global contributions that have enriched the application scope of digital twins, fostering innovations in material deformation and structural monitoring [58]. By integrating digital twins with infrastructure maintenance and fatigue assessment, engineers can achieve superior precision and efficiency in managing steel structures [58].

7. Future Directions and Emerging Trends

The evolution of digital twin technology is rapid, with several emerging trends pointing towards an even more integrated and intelligent future for structural engineering.

7.1. Advanced Integration with AI and Cognitive Capabilities

The development of a conceptual framework model facilitates interoperable functionality, enabling autonomous interpretation and control throughout the project lifecycle. This integration not only enhances the efficiency of construction processes but also supports adaptive learning systems that can evolve in response to environmental and project-specific changes [24]. The fusion of AI with digital twins is expected to deepen. Kor et al. suggested that the integration of deep learning (DL) with digital twin (DT) technology will drive innovation in Construction 4.0 [24].

7.2. Cloud Computing, Edge Computing, and Metaverse

As models become more complex and data rates increase, edge computing will process data closer to the source to reduce latency, while cloud platforms will handle large-scale analytics and storage. The computational demands of DTs make cloud and edge computing essential. Dang et al. already demonstrated the power of cloud-based DT for SHM [17].

Furthermore, integration with extended reality (XR) and the metaverse offers exciting possibilities. Yao et al. discussed how DT offers exciting possibilities for structural engineering when integrating with extended reality (XR) and the metaverse. This enables more immersive and interactive project visualization [59]. Engineers can conduct virtual simulations that enhance the understanding of complex systems and facilitate more effective decision-making processes by leveraging these advanced technologies. This fusion allows for real-time collaboration among stakeholders, irrespective of their physical location [59].

7.3. Standardization and Maturation of Frameworks

Standardized frameworks and protocols are essential for DTs to become mainstream. Future efforts will likely focus on developing these standards to ensure interoperability between different systems and vendors. The work by Bordeleau et al. on Model-Driven Engineering (MDE) and by Iranshahi et al. on the digital thread points towards a future where data flow is more structured and automated [30,32]. As technology matures, its Technology Readiness Level is expected to increase, making it more accessible and reliable for a broader range of applications [30].

7.4. Human-Centric and Socio-Technical Systems

DT's future will not be purely technological. It will increasingly focus on human-in-the-loop models. Rafsanjani and Nabizadeh indicated that as the industry moves towards automation, the synergy of VDC, AR/VR, and DTs with artificial intelligence presents opportunities for developing human-centered approaches. These approaches will not only streamline work progress, but will also improve safety standards [38]. This human-centric focus will ensure that technology augments human expertise rather than replacing it.

8. Conclusions

DT technology has moved the structural engineering industry from static to dynamic and predictive. This review has synthesized a vast body of literature to demonstrate that by creating a living digital counterpart of a physical structure, engineers can achieve unprecedented levels of insight into structural behavior, performance, and health. The core of this capability lies in the integration of technologies that form a closed-loop system for continuous monitoring, analysis, and optimization, such as BIM, AI, ML, IoT sensing, and cloud computing.

However, the path to widespread adoption is not without significant obstacles. Challenges related to data interoperability, cybersecurity, high initial investment, and the need for a skilled workforce and interdisciplinary collaboration remain substantial barriers that

the industry must collectively address. The current Technology Readiness Level indicates that while progress is impressive, further development is needed to mature the technology for universal application.

The applications are profound and wide-ranging. From enabling predictive maintenance and extending the lifespan of critical infrastructure like bridges and tunnels, to optimizing construction processes, enhancing safety on-site, preserving cultural heritage, and revolutionizing engineering education, digital twins are proving their value across the entire project lifecycle. Real-world case studies, such as those on the Clifton Suspension Bridge and the Dalrymple Bay Coal Terminal, provide tangible evidence of the benefits, including improved safety, reduced costs, and enhanced sustainability.

By overcoming these challenges, the structural engineering community can fully harness the transformative power of DT technology, ushering in a new era of resilient, efficient, sustainable, and intelligent infrastructure that can meet the demands of the 21st century and beyond. DT's future is exceptionally promising in structural engineering. The ongoing integration with advanced AI, cloud platforms, and immersive technologies like Metaverse will unlock even greater capabilities for autonomous decision-making and collaborative design. The focus must now be on developing robust standards, addressing security concerns, lowering implementation barriers, and fostering the necessary cultural and educational shifts within the industry.

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References

1. Moghadam, H.M.; Foroozan, H.; Gheisarnejad, M.; Khooban, M.H. A Survey on New Trends of Digital Twin Technology for Power Systems. *J. Intell. Fuzzy Syst.* **2021**, *41*, 3873–3893.
2. UU Republik Indonesia; Munawir, M.; Nasional, B.S.; Susanta, G.; Jatimnet.com; MajaMojokerto.net; Radarmojokerto.jawapos.com; Wijayakusuma, D.M.S.; Nahman, A.; Godfrey, L.; et al. Penentuan Alternatif Lokasi Tempat Pembuangan Akhir (TPA) Sampah Di Kabupaten Sidoarjo. *Energies* **2022**, *15*.
3. Gervasi, M.; Bove, L.; Corallo, A.; Miglietta, M.; Negro, L.; Pellegrino, G.; Ria, F.; Visaggio, C.A. Systems of Digital Twins: A Systematic Literature Review and a Formal Framework. *Digit. Eng.* **2026**, *9*, 100100. <https://doi.org/10.1016/j.dte.2026.100100>.
4. Rabaia, M.K.H.; Semeraro, C.; Soudan, B.; Salameh, T.S.Z.; Abdelkareem, M.A.; Olabi, A.G. Digital Twin-Driven Sustainable Energy Life Cycles: Technical Review and Guidelines. *Energy Nexus* **2025**, *19*, 100482.
5. Ramirez, C.A.; Agrawal, P.; Thompson, A.E. An Approach Integrating Model-Based Systems Engineering, IoT, and Digital Twin for the Design of Electric Unmanned Autonomous Vehicles. *Systems* **2025**, *13*, 73. <https://doi.org/10.3390/systems13020073>.
6. Mihai, S.; Yaqoob, M.; Hung, D.V.; Davis, W.; Towakel, P.; Raza, M.; Karamanoglu, M.; Barn, B.; Shetve, D.; Prasad, R.V.; et al. Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 2255–2291. <https://doi.org/10.1109/COMST.2022.3208773>.
7. Azanaw, G.M. Revolutionizing Structural Engineering: A Review of Digital Twins, BIM, and AI Applications. *Indian J. Struct. Eng.* **2024**, *4*, 1–8. <https://doi.org/10.54105/ijse.B1321.04021124>.
8. Hu, W.; Zhang, T.; Deng, X.; Liu, Z.; Tan, J. Digital Twin: A State-of-the-Art Review of Its Enabling Technologies, Applications and Challenges. *J. Intell. Manuf. Spec. Equip.* **2021**, *2*, 1–34. <https://doi.org/10.1108/jimse-12-2020-010>.
9. Yang, D.; Karimi, H.R.; Kaynak, O.; Yin, S. Developments of Digital Twin Technologies in Industrial, Smart City and Healthcare Sectors: A Survey. *Complex Eng. Syst.* **2021**, *1*, 3.

10. Chiachío, M.; Megía, M.; Chiachío, J.; Fernandez, J.; Jalón, M.L. Structural Digital Twin Framework: Formulation and Technology Integration. *Autom. Constr.* **2022**, *140*, 104333. <https://doi.org/10.1016/j.autcon.2022.104333>.
11. Feng, H.; Chen, Q.; de Soto, B.G. Application of Digital Twin Technologies in Construction: An Overview of Opportunities and Challenges. In Proceedings of the International Symposium on Automation and Robotics in Construction, Dubai, United Arab Emirates, 2–4 November 2021.
12. Madni, A.M.; Madni, C.C.; Lucero, S.D. Leveraging Digital Twin Technology in Model-Based Systems Engineering. *Systems* **2019**, *7*, 7. <https://doi.org/10.3390/systems7010007>.
13. Ammar, A.; Nassereddine, H.; AbdulBaky, N.; AbouKansour, A.; Tannoury, J.; Urban, H.; Schranz, C. Digital Twins in the Construction Industry: A Perspective of Practitioners and Building Authority. *Front. Built Environ.* **2022**, *8*, 834671. <https://doi.org/10.3389/fbuil.2022.834671>.
14. Liu, Z.; Yuan, C.; Sun, Z.; Cao, C. Digital Twins-Based Impact Response Prediction of Prestressed Steel Structure. *Sensors* **2022**, *22*, 1647. <https://doi.org/10.3390/s22041647>.
15. Liu, X.; Liu, H.; Serratella, C. Application of Structural Health Monitoring for Structural Digital Twin. In Proceedings of the Offshore Technology Conference Asia 2020, OTCA 2020, Kuala Lumpur, Malaysia, 24–27 March 2020.
16. Wagg, D.J.; Worden, K.; Barthorpe, R.J.; Gardner, P. Digital Twins: State-of-The-Art and Future Directions for Modeling and Simulation in Engineering Dynamics Applications. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* **2020**, *6*, 030901. <https://doi.org/10.1115/1.4046739>.
17. Dang, H.; Tatipamula, M.; Nguyen, H.X. Cloud-Based Digital Twinning for Structural Health Monitoring Using Deep Learning. *IEEE Trans. Ind. Inform.* **2022**, *18*, 3820–3830. <https://doi.org/10.1109/TII.2021.3115119>.
18. Hu, X.; Olgun, G.; Assaad, R.H. An Intelligent BIM-Enabled Digital Twin Framework for Real-Time Structural Health Monitoring Using Wireless IoT Sensing, Digital Signal Processing, and Structural Analysis. *Expert Syst. Appl.* **2024**, *252*, 124204. <https://doi.org/10.1016/j.eswa.2024.124204>.
19. Nasim, M.; Rajabifard, A.; Chen, Y.; Samali, B. A Demonstration of a Digital Twin Framework for Structural Health Monitoring: Application to Bridge Infrastructures. *J. Infrastruct. Intell. Resil.* **2026**, *5*, 100184. <https://doi.org/10.1016/j.iintel.2025.100184>.
20. Sun, L.; Sun, H.; Zhang, W.; Li, Y. Hybrid monitoring methodology: A model-data integrated digital twin framework for structural health monitoring and full-field virtual sensing. *Adv. Eng. Inform.* **2024**, *60*, 102386. <https://doi.org/10.1016/j.aei.2024.102386>.
21. Bado, M.F.; Tonelli, D.; Poli, F.; Zonta, D.; Casas, J.R. Digital Twin for Civil Engineering Systems: An Exploratory Review for Distributed Sensing Updating. *Sensors* **2022**, *22*, 3168.
22. Hielscher, T.; Khalil, S.; Virgona, N.; Hadigheh, S.A. A Neural Network Based Digital Twin Model for the Structural Health Monitoring of Reinforced Concrete Bridges. *Structures* **2023**, *57*, 105248. <https://doi.org/10.1016/j.istruc.2023.105248>.
23. Tita, E.E.; Watanabe, G.; Shao, P.; Arii, K. Development and Application of Digital Twin–BIM Technology for Bridge Management. *Appl. Sci.* **2023**, *13*, 7435. <https://doi.org/10.3390/app13137435>.
24. Kor, M.; Yitmen, I.; Alizadehsalehi, S. An Investigation for Integration of Deep Learning and Digital Twins towards Construction 4.0. *Smart Sustain. Built Environ.* **2023**, *12*, 461–487. <https://doi.org/10.1108/SASBE-08-2021-0148>.
25. Lu, X.; Wei, C.; Sun, L.; Zhang, W. Bridge Damage Localization Through Response Reconstruction with Multiple BP-ANNs Under Vehicular Loading. *Appl. Sci.* **2024**, *14*, 10226. <https://doi.org/10.3390/APP142210226>.
26. Zhu, H.; Wang, Y. Intelligent Analysis for Safety-Influencing Factors of Prestressed Steel Structures Based on Digital Twins and Random Forest. *Metals* **2022**, *12*, 646. <https://doi.org/10.3390/met12040646>.
27. Gupta, V.; Marsili, F.; Kessler, S.; Maleshkova, M. Physics-Informed Neural Networks Used for Structural Health Monitoring in Civil Infrastructures: State of Art and Current Challenges. In Proceedings of the 35th European Safety and Reliability Conference (ESREL 2025) and the 33rd Society for Risk Analysis Europe Conference, Stavanger, Norway, 15–19 June 2025. https://doi.org/10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P6507-cd.
28. Sarasin, A.; Deng, K.; Zhao, Y.; Ompusunggu, A. Architectural Design of Structural Health Monitoring (SHM) Based Digital Twin for the next-Generation Landing Gear. *Procedia CIRP* **2025**, *136*, 552–557.
29. Gao, Y.; Xiong, G.; Hu, Z.; Chai, C.; Li, H. Bridge Digital Twin for Practical Bridge Operation and Maintenance by Integrating GIS and BIM. *Buildings* **2024**, *14*, 3731. <https://doi.org/10.3390/BUILDINGS14123731>.
30. Iranshahi, K.; Brun, J.; Arnold, T.; Sergi, T.; Müller, U.C. Digital Twins: Recent Advances and Future Directions in Engineering Fields. *Intell. Syst. Appl.* **2025**, *26*, 200516. <https://doi.org/10.1016/j.iswa.2025.200516>.
31. Bornholdt, M.; Herbrand, M.; Smarsly, K.; Zehetmaier, G. Digital-Twin-Based Structural Health Monitoring of Dikes. *CivilEng* **2025**, *6*, 39. <https://doi.org/10.3390/civileng6030039>.

32. Bordeleau, F.; Combemale, B.; Eramo, R.; van den Brand, M.; Wimmer, M. Towards Model-Driven Digital Twin Engineering: Current Opportunities and Future Challenges. In *Systems Modelling and Management; Communications in Computer and Information Science (CCIS)*; Springer: Cham, Switzerland, 2020; Volume 1262.
33. Hidalgo-Fort, E.; Blanco-Carmona, P.; Muñoz-Chavero, F.; Torralba, A.; Castro-Triguero, R. Low-Cost, Low-Power Edge Computing System for Structural Health Monitoring in an IoT Framework. *Sensors* **2024**, *24*, 5078. <https://doi.org/10.3390/S24155078>.
34. Wang, Y.; Tang, Z.; Qian, G.; Xu, W.; Huang, X.; Fang, H. A Prototype of a Lightweight Structural Health Monitoring System Based on Edge Computing. *Sensors* **2025**, *25*, 5612. <https://doi.org/10.3390/S25185612>.
35. Kim, G.; Shin, J.; Won, J.; Park, J. Cloud-Based Internet-of-Things System for Long-Term Bridge Bearing Monitoring Using Computer Vision. *Appl. Sci.* **2025**, *15*, 1622. <https://doi.org/10.3390/AP15031622>.
36. Wang, T.; Huo, J.; Wu, X. A Real-Time Detection Approach for Bridge Crack. *Algorithms* **2026**, *19*, 247. <https://doi.org/10.3390/A19040247>.
37. Xu, P.; Sarris, G.; Jones, R.; Huthwaite, P. A Digital Twin-Based Framework for Reliability Estimation in Ultrasonic Guided Wave Structural Health Monitoring Systems with Temperature Variations. *Mech. Syst. Signal Process.* **2025**, *235*, 112848. <https://doi.org/10.1016/j.ymssp.2025.112848>.
38. Rafsanjani, H.N.; Nabizadeh, A.H. Towards Digital Architecture, Engineering, and Construction (AEC) Industry through Virtual Design and Construction (VDC) and Digital Twin. *Energy Built Environ.* **2023**, *4*, 169–178. <https://doi.org/10.1016/j.enbenv.2021.10.004>.
39. Karatzas, S.; Lazari, V.; Fouseki, K.; Pracchi, V.N.; Balaskas, E. Digital Twins-Enabled Heritage Buildings Management through Social Dynamics. *J. Cult. Herit. Manag. Sustain. Dev.* **2026**, *16*, 150–166. <https://doi.org/10.1108/JCHMSD-08-2023-0136>.
40. Marino, A.; Pariso, P.; Picariello, M. Digital Twin in SMEs: Implementing Advanced Digital Technologies for Engineering Advancements. *Macromol. Symp.* **2024**, *413*, 2300176. <https://doi.org/10.1002/masy.202300176>.
41. Talmaki, S.A.; Kamat, V.R. Sensor Acquisition and Allocation for Real-Time Monitoring of Articulated Construction Equipment in Digital Twins. *Sensors* **2022**, *22*, 7635. <https://doi.org/10.3390/s22197635>.
42. Gao, Y.; Qian, S.; Li, Z.; Wang, P.; Wang, F.; He, Q. Digital Twin and Its Application in Transportation Infrastructure. In Proceedings of the 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence, DTPI 2021, Beijing, China, 15 July–15 August 2021.
43. Yang, Z.; Tang, C.; Zhang, T.; Zhang, Z.; Doan, D.T. Digital Twins in Construction: Architecture, Applications, Trends and Challenges. *Buildings* **2024**, *14*, 2616. <https://doi.org/10.3390/buildings14092616>.
44. Zhang, J.; Zhao, L.; Ren, G.; Li, H.; Li, X. Special Issue “Digital Twin Technology in the AEC Industry”. *Adv. Civ. Eng.* **2020**, *2020*, 8842113. <https://doi.org/10.1155/2020/8842113>.
45. Petri, I.; Amin, A.; Ghoroghi, A.; Hodorog, A.; Rezgui, Y. Digital Twins for Dynamic Life Cycle Assessment in the Built Environment. *Sci. Total Environ.* **2025**, *993*, 179930. <https://doi.org/10.1016/j.scitotenv.2025.179930>.
46. Vuoto, A.; Funari, M.F.; Lourenço, P.B. On the Use of the Digital Twin Concept for the Structural Integrity Protection of Architectural Heritage. *Infrastructures* **2023**, *8*, 86. <https://doi.org/10.3390/infrastructures8050086>.
47. Aroquipa, H.; Hurtado, A.; Murga, C.; De La Cruz, R.; Tarque, N. Towards Smart Cities: Foundational Methodology for Implementing Intelligent Circular Resilience in Heritage Buildings through Structural Health Monitoring and Digital-Twins—Part A. *Int. J. Disaster Risk Reduct.* **2025**, *128*, 105749. <https://doi.org/10.1016/j.ijdr.2025.105749>.
48. Maksimović, M.; Davidović, N. The Role of Digital Twin Technology in Transforming Engineering Education. In Proceedings of the 9th International Scientific Conference Technics and Informatics in Education, Čačak, Serbia, 22–24 September 2022.
49. Madubuike, O.C.; Anumba, C.J.; Khallaf, R. A Review of Digital Twin Applications in Construction. *J. Inf. Technol. Constr.* **2022**, *27*, 145–172. <https://doi.org/10.36680/j.itcon.2022.008>.
50. Omrany, H.; Al-Obaidi, K.M.; Husain, A.; Ghaffarianhoseini, A. Digital Twins in the Construction Industry: A Comprehensive Review of Current Implementations, Enabling Technologies, and Future Directions. *Sustainability* **2023**, *15*, 10908.
51. Gürdür Broo, D.; Bravo-Haro, M.; Schooling, J. Design and Implementation of a Smart Infrastructure Digital Twin. *Autom. Constr.* **2022**, *136*, 104171. <https://doi.org/10.1016/j.autcon.2022.104171>.
52. Mousavi, Y.; Gharineiat, Z.; Karimi, A.A.; McDougall, K.; Rossi, A.; Gonizzi Barsanti, S. Digital Twin Technology in Built Environment: A Review of Applications, Capabilities and Challenges. *Smart Cities* **2024**, *7*, 2594–2615. <https://doi.org/10.3390/smartcities7050101>.
53. Xiao, M.; Cui, S.; Wang, L. Digital Twin-Based Integrated Modeling and Maintenance Framework in the Power Grid Data Center Scenario. *Cyber-Phys. Energy Syst.* **2026**, *2*, 73–89. <https://doi.org/10.1016/j.cpes.2026.01.001>.

54. Xie, M.; Pan, W. Opportunities and Challenges of Digital Twin Applications in Modular Integrated Construction. In *Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC), Kitakyushu, Japan, 27–28 October 2020*; Hisashi, O., Hiroshi, F., Kazuyoshi, T., Eds.; International Association for Automation and Robotics in Construction (IAARC): Philadelphia, PA, USA, 2020; pp. 278–284.
55. Pregnotato, M.; Gunner, S.; Voyagaki, E.; De Risi, R.; Carhart, N.; Gavriel, G.; Tully, P.; Tryfonas, T.; Macdonald, J.; Taylor, C. Towards Civil Engineering 4.0: Concept, Workflow and Application of Digital Twins for Existing Infrastructure. *Autom. Constr.* **2022**, *141*, 104421. <https://doi.org/10.1016/j.autcon.2022.104421>.
56. Jirawattanasomkul, T.; Hang, L.; Srivaranun, S.; Likitlersuang, S.; Jongvivatsakul, P.; Yodsudjai, W.; Thammarak, P. Digital Twin-Based Structural Health Monitoring and Measurements of Dynamic Characteristics in Balanced Cantilever Bridge. *Resilient Cities Struct.* **2025**, *4*, 48–66. <https://doi.org/10.1016/j.rcns.2025.08.001>.
57. Mahmoodian, M.; Shahrivar, F.; Setunge, S.; Mazaheri, S. Development of Digital Twin for Intelligent Maintenance of Civil Infrastructure. *Sustainability* **2022**, *14*, 8664. <https://doi.org/10.3390/su14148664>.
58. Shi, L.; Ding, Y.; Cheng, B. Development and Application of Digital Twin Technique in Steel Structures. *Appl. Sci.* **2024**, *14*, 11685. <https://doi.org/10.3390/app142411685>.
59. Yao, J.-F.; Yang, Y.; Wang, X.-C.; Zhang, X.-P. Systematic Review of Digital Twin Technology and Applications. *Vis. Comput. Ind. Biomed. Art* **2023**, *6*, 10. <https://doi.org/10.1186/s42492-023-00137-4>.

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