Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 5, 2026

PREDICTIVE MAINTENANCE OF CIVIL INFRASTRUCTURE USING DIGITAL TWIN TECHNOLOGY AND AI-BASED STRUCTURAL PERFORMANCE MODELING TECHNIQUES

Ahsan Ali[1], Shuban Ali[2,3,4], Mutahar Ali[2,3], Faryal Ahmed[4], Mohamed Ismail[5], Sagar Ali[*6]

[*1]Embry-Riddle Aeronautical University, Daytona Beach, FL, USA
[2]College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518060, China
[3]College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518060, China
[4]Department of Civil Engineering, Aror University of Art, Architecture, Design and Heritage, RCW Rohri Bypass, Sukkur 65170, Pakistan
[4]Peoples University of Medical and Health Sciences for Women (PUMHSW), Nawabshah, Sindh, Pakistan
[5]Embry-Riddle Aeronautical University, Daytona Beach, FL, USA
[6]G3 Engineering Consultants Pvt. Ltd., Sindh, Pakistan

[*1]alia7@my.erau.edu, [2]alishuban2025@email.szu.edu.cn, [3]mutaharali2025@mails.szu.edu.cn, [4]ahsanfaryal29@gmail.com, [5]ismailm6@my.erau.edu, [6]sagar.civil.078981@gmail.com

DOI: https://doi.org/10.5281/zenodo.20267312

Keywords
Digital Twin; Predictive maintenance; Civil infrastructure; Artificial intelligence; Structural health monitoring; Physics-informed neural networks; Internet of Things; Building Information Modeling; Remaining Useful Life; Smart infrastructure.

Article History
Received: 21 March 2026
Accepted: 01 May 2026
Published: 18 May 2026

Corresponding Author: *
Sagar Ali
sagar.civil.078981@gmail.com

Abstract

The growing complexity, aging, and environmental vulnerability of civil infrastructure systems have accelerated the transition from traditional maintenance approaches toward predictive and intelligent asset management strategies. This review paper explores the integration of Digital Twin (DT) technology with Artificial Intelligence (AI)-based structural performance modeling techniques for predictive maintenance of civil infrastructure. The study critically examines the evolution from static Building Information Modeling (BIM) toward dynamic Digital Twin systems capable of real-time monitoring, simulation, and decision-making throughout an infrastructure asset's lifecycle. Key architectural components including IoT-enabled sensing systems, cloud-edge communication networks, semantic synchronization frameworks, and cybersecurity mechanisms are discussed in relation to structural health monitoring applications. The review further analyzes advanced AI methodologies such as deep learning, Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), Transformers, and Physics-Informed Neural Networks (PINNs) for anomaly detection, Remaining Useful Life (RUL) prediction, and real-time structural performance assessment. Digital Twin-enabled predictive maintenance frameworks demonstrate substantial operational benefits, including reduced maintenance costs, minimized infrastructure downtime, improved fault detection accuracy, and enhanced lifecycle sustainability. The paper also highlights the role of reduced-order modeling, federated learning, edge computing, and AI-native 6G connectivity in achieving computational efficiency and real-time system responsiveness. Case studies involving bridges, dams, tunnels, healthcare facilities, and urban infrastructure systems demonstrate the practical *effectiveness of AI-driven Digital Twins in extending service life and improving resilience. Despite significant advancements, challenges related to interoperability, high implementation costs, cybersecurity, and data governance remain critical barriers to widespread adoption. Overall, the integration of Digital Twin technology and AI-based predictive analytics represents a transformative approach for developing resilient, sustainable, and intelligent infrastructure management systems in future smart cities.*

1. Introduction

The paradigm of civil infrastructure management is undergoing a fundamental shift from reactive and preventive strategies toward a predictive, data-driven framework. This transition is necessitated by the increasing complexity, age, and environmental exposure of critical assets such as bridges, tunnels, dams, and high-rise buildings (Liu et al., 2023). As global infrastructure systems face escalating environmental, social, and operational challenges, enhancing their resilience through digital and intelligent technologies has become a strategic priority (Ajayi et al., 2025). The integration of Digital Twin (DT) technology with Artificial Intelligence (AI) and the Internet of Things (IoT) offers transformative capabilities for monitoring, predicting, and optimizing infrastructure performance under stress (Kaveh & Alhajj, 2025).

2. Evolution from Building Information Modeling to Digital Twin Systems

A critical foundation for understanding modern predictive maintenance is the distinction and transition from Building Information Modeling (BIM) to Digital Twin systems. BIM has long served as a collaborative process for creating and managing information throughout the design and construction phases of a project, Table 1, However, BIM models typically contain static or semi-static data representing design intent (Zabadi et al., 2025). By contrast, a Digital Twin is a live virtual replica that persists throughout the asset's lifecycle, continuously updated with real-time data from IoT sensors and simulations (Yousef Zabadi et al., 2026).

The primary difference between these two technologies is temporal and functional. BIM focuses on "What did we plan?" whereas the Digital Twin addresses "What is happening now and what will happen next?" By 2025, over 70% of large commercial and industrial projects in North America are expected to require BIM deliverables as a standard, serving as the "seed" for future digital twins. This integration ensures that data captured during construction is leveraged for ongoing facility management, enabling proactive maintenance and optimized asset performance (Xie et al., 2023).

Table 1. Functional Differences between Building Information Modeling (BIM) and Digital Twins (DT)

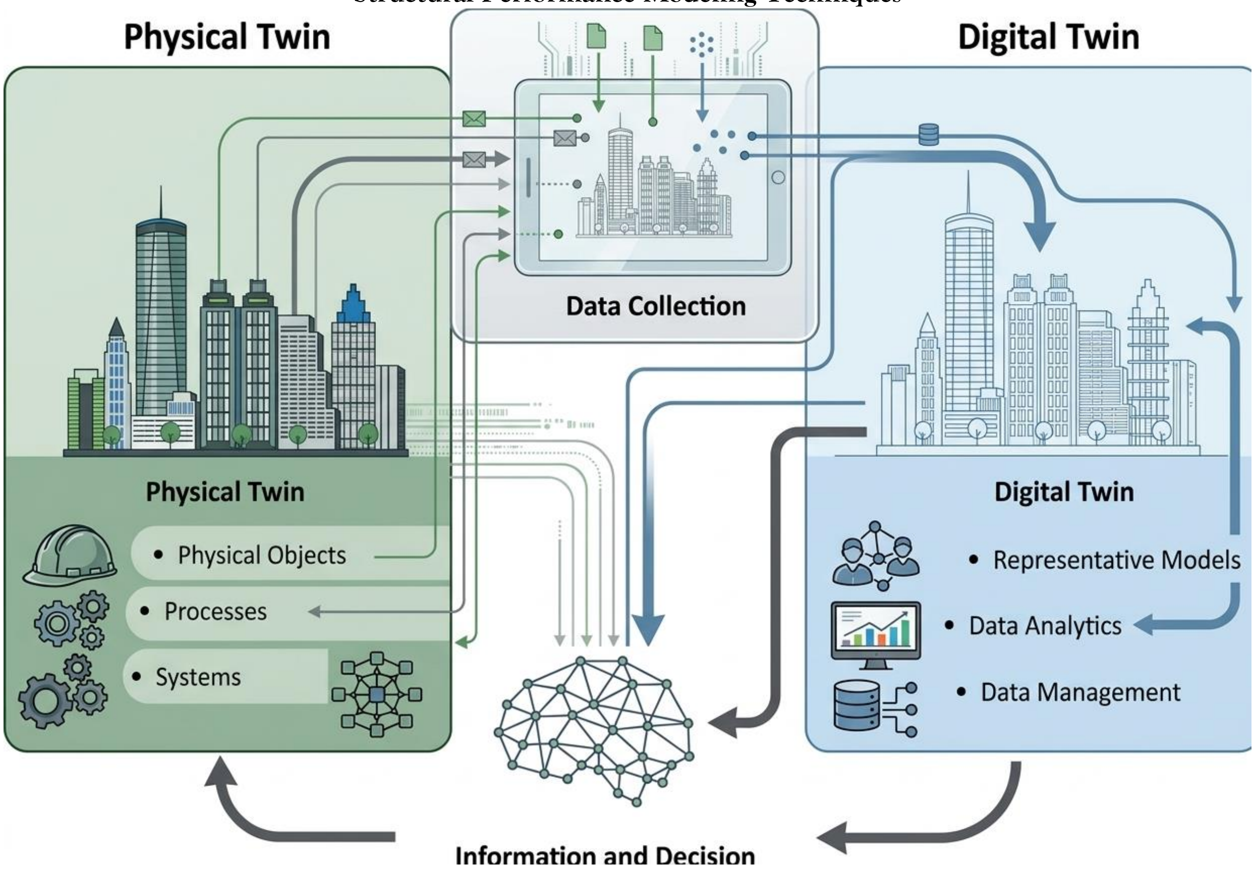
Feature	Building Information Modeling (BIM)	Digital Twin (DT)
Lifecycle Phase	Design and Construction focus	Operations and Maintenance focus
Data Nature	Static/Semi-static (Design Intent)	Dynamic (Real-time physical state)
Primary Goal	Planning, Coordination, Construction	Optimization, Prediction, Monitoring
Data Source	Architectural/Engineering inputs	IoT Sensors, AI, Real-time telemetry
Temporal Context	Historical/Planned	Real-time and Future (Predictive)

The transition toward Digital Twins allows for the evaluation of "what-if" simulations, assessing how various load scenarios, temperature fluctuations, or material defects might accelerate failure. This facilitates a move toward condition-based maintenance, which has been shown to reduce unplanned bridge closures by up to 40% in pilot studies (Mousavi et al., 2024).

3. Architectural Layers of Digital Twin Systems in Civil Engineering

The implementation of a Digital Twin for predictive maintenance requires a multi-layered integration framework that emphasizes interoperability, cybersecurity, and semantic data synchronization. This architecture typically consists of several distinct layers that facilitate the flow of information from the physical asset to the digital environment and back to the decision-makers (Deng et al., 2021).

Figure: 1 Predictive Maintenance of Civil Infrastructure Using Digital Twin Technology and AI-Based Structural Performance Modeling Techniques



3.1. The Physical and Sensing Layers

At the base of the architecture is the physical asset instrumented with a distributed network of IoT sensors. These sensors collect high-frequency data on strain, vibration, displacement, humidity, and corrosion potential. Modern sensing technologies have moved beyond traditional settlement plates and inclinometers to include distributed Fiber Bragg Grating (FBG) sensors, terrestrial laser scanning (TLS), and Unmanned Aerial Vehicles (UAVs) for vision-based inspection (Boje et al., 2022)

3.2. Data Transmission and Network Layers

The connectivity layer is responsible for transmitting vast amounts of sensor data to the cloud-connected DT environment. This layer must maintain low latency to ensure real-time alignment between the physical and digital states (Uddin & Koo, 2024). Edge-level preprocessing and LoRaWAN optimization have enabled average data latencies of 2.6 seconds, well within the operational thresholds required for real-time structural health monitoring (SHM). The emergence of 6G technology is expected to further revolutionize this layer by providing AI-native networks that can self-learn, self-heal, and self-optimize, supporting the high data rates and ultra-low latency required for massive device connectivity in smart city frameworks (Sepasgozar et al., 2023).

3.3. Middleware and Semantic Synchronization

To address information fragmentation and data duplication, digital twins utilize semantic web technologies and standardized data formats like Industry Foundation Classes (IFC) (Pan & Zhang, 2021). Converting BIM models to a linked data version, such as ifcJSON, allows for the effective federation of building information with IoT sensor data and ontologies like the Brick ontology or ifcOWL. This semantic synchronization ensures that the digital twin correctly handles structural constraints and different types of particles, such as identifying fixed joints versus free nodes in a structural simulation (Sakr & Sadhu, 2023).

4. AI-Based Structural Performance Modeling Techniques

The analytical power of a Digital Twin is derived from the integration of advanced Artificial Intelligence (AI) and Machine Learning (ML) models, Fig 1. These technologies can process large datasets to recognize patterns, predict failures, and optimize decisions under uncertainty (Kone & Mahesh, 2025).

4.1. Deep Learning and Time-Series Analysis

Deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), are widely used to analyze structural response data. CNNs excel at extracting features directly from raw vibration and acoustic data, while Long Short-Term Memory (LSTM) networks are effectively used to predict strain distribution and fatigue crack evolution. In some frameworks, hybrid FEM–LSTM models have achieved predictive accuracy with an R^2 of 0.93, significantly outperforming baseline regression models (Merino et al., 2022).

4.2. Graph Neural Networks for Infrastructure Networks

Infrastructure systems are inherently networked and interdependent. Graph Neural Networks (GNNs) represent an advanced approach for modeling these interdependencies, enabling simulations of cascading failures or the optimization of recovery routes in transportation and power grids. GNNs represent the structure as a graph where nodes signify mass and edges represent structural components like beams and columns. This spatiotemporal structural response modeling allows for the prediction of displacement and acceleration by effectively integrating spatial positions with temporal correlations. (Raissi et al., 2019).

4.3. Physics-Informed Neural Networks (PINNs)

A significant challenge in applying artificial intelligence to structural engineering is ensuring both physical consistency and model interpretability. Artificial Intelligence Structural Engineering Physics-Informed Neural Networks (PINNs) address this challenge by embedding established physical laws—such as the conservation of mass, momentum, and energy—directly into the neural network loss function (Kilic et al., 2025). This mesh-free framework enables PINNs to solve the partial differential equations (PDEs) that govern structural behavior, producing solutions that are more accurate, physically consistent, and data-efficient than conventional black-box models (Biau et al., 2024).

In structural dynamics, the PINN is typically trained by minimizing a composite global loss function:

$$L = w_{\text{data}} L_{\text{data}} + w_{\text{physics}} L_{\text{physics}} + w_{\text{bc}} L_{\text{bc}}$$

where L_{data}denotes the data-driven loss, L_{physics}represents the residual of the governing differential equations, and L_{bc}enforces boundary and initial conditions. The coefficients w_{data}, w_{physics}, and $w_{\text{bc}}$are weighting parameters that balance the relative contributions of each loss component. In structural applications, L_{physics}may be defined using the residual of governing equations such as the Euler–Bernoulli beam equation, which describes the bending behavior of slender beams. Recent developments in Auxiliary Physics-Informed Neural Networks

(A-PINNs) have further improved the robustness of this framework by incorporating balanced adaptive optimizers and additional auxiliary loss terms to control error propagation and enhance numerical stability in complex real-world dynamical systems (Nuugulu et al., 2025).

5. Predictive Maintenance Frameworks and Operational Benefits

The ultimate objective of integrating DT and AI is the realization of Predictive Maintenance (PdM). Unlike reactive maintenance, which occurs after failure, or preventive maintenance, which follows fixed schedules, Tab 2, PdM uses real-time monitoring and advanced analytics to forecast failures before they occur (Borgers et al., 2024).

5.1. Fault Detection and Response Efficiency

AI-driven systems have demonstrated remarkable efficiency in fault detection. In urban infrastructure projects, Deep Learning models achieved a fault detection accuracy with an F1-score of 92.5%, reducing the average detection time from 15 days to just 3 days. This proactive approach has led to a 30% reduction in maintenance costs and a 40% decrease in infrastructure downtime (Paolini et al., 2026).

5.2. Remaining Useful Life (RUL) Prediction

Predictive maintenance frameworks also include the prediction of Remaining Useful Life (RUL). By incorporating IoT data capture and machine learning for anomaly detection, hybrid AI-DT models have achieved predictive accuracies of up to 95% in identifying the RUL of critical infrastructure components. This allows asset managers to prioritize repairs based on actual condition indices and risk-informed decision-making rather than arbitrary schedules (Mahmud et al., 2025).

Table 2. Operational Metrics Comparison for Maintenance Strategies

Metric	Traditional/Reactive Maintenance	AI-Driven Predictive Maintenance
Anomaly-to-Action Time	~14 Days	< 4 Hours
Prediction Accuracy	55-65%	88-93%
Fault Detection F1-Score	N/A	92.5%
Unplanned Downtime	High Baseline	78% Reduction
Annual ROI	2-3x	8-12x

The convergence of these technologies leads to an autonomous maintenance loop where IoT sensors report "what is happening," the digital twin simulates "what will happen," and the maintenance system executes "what needs to happen" (Mohammed, 2026).

6. Computational Efficiency and Real-Time Performance

The high dimensionality and complexity of structural models often pose a challenge for real-time digital twin applications. Traditional high-fidelity models can take days to deliver results on high-performance computing (HPC) clusters. To overcome this, researchers employ Reduced-Order Modeling (ROM) and surrogate modeling techniques (Chen et al., 2025).

6.1. Reduced-Order Modeling (ROM)

ROMs are simplifications of complex models that capture dominant effects while significantly reducing the computational burden. For instance, a full fluid simulation of a heat exchanger might take over two hours, while a ROM can provide a solution in as little as one second. Techniques such as Proper Orthogonal Decomposition (POD) and modal space mapping are used to reduce a Full-Order Model (FOM) to a ROM, serving as a critical physics-driven component of digital twin models (Martin, 2025).

6.2. Edge Computing and Federated Learning

To enhance real-time performance, edge inference modules are deployed to process data locally before transmission to the cloud. Additionally, federated learning and privacy-preserving collaboration allow multiple structures or agencies to share model improvements without exposing sensitive data, improving model generalization across diverse infrastructure types (Zhan et al., 2025).

7. Lifecycle Cost (LCC) Estimation and Decision-Making

The integration of Life-Cycle Costing (LCC) with BIM and AI is essential for sustainable and data-driven management of built assets. Traditional LCC often suffers from fragmented approaches and lack of standardized data. By embedding cost data directly into BIM objects or linking external databases via APIs, stakeholders can conduct more accurate and early-stage cost evaluations (Avogaro et al., 2025).

7.1. Software Tools and Economic Impact

NIST developed BridgeLCC software specifically to help engineers assess the cost-effectiveness of alternative construction materials using a life-cycle costing methodology. The inclusion of "user costs" such as driver delay costs and accident costs during repairs provides a more comprehensive view of an asset's economic impact. AI-enhanced LCC estimation can further incorporate uncertainty and risk assessments through Monte Carlo simulations (Mock, 2020).

7.2. Environmental and Social Dimensions

Digital twins also support environmental sustainability by optimizing resource allocation and extending asset service life. For example, doubling the lifespan of a bridge through smart monitoring drastically reduces emissions and material consumption associated with replacement construction (Franciosi et al., 2024).

8. Case Studies and Practical Implementations

The efficacy of AI-driven Digital Twins is demonstrated through real-world applications across various infrastructure sectors (Samuel et al., 2023).

8.1. Bridges: The Öresund Bridge Lifespan Extension

The Öresund Bridge Consortium has installed over 5,500 sensors to monitor vibrations, temperature, and movement. By updating scientific models with this data, researchers have developed a framework that could extend the bridge's lifespan from 100 to 200 years. This service life extension is achieved through specific modeling of chemical ingress and reinforcement corrosion (Leander et al., 2019).

8.2. Dams: Three Gorges Dam and Yangtze River Basin

China has leveraged digital twin technology for the Three Gorges Dam and the Yangtze River basin to enhance flood management. This twin integrates data from hydrological stations and infrastructure sensors to create a live model of the river system, allowing for predictive flood simulations and real-time management of water flow. In 2024, the digital twin issued early warnings that enabled proactive evacuation and flood diversion, saving lives and reducing damage (Peng, 2025).

8.3. Tunnels and Urban Systems: Subway and Healthcare

Digital twins have been applied to subway station construction using the arch-cover method, where IoT sensors monitor structural integrity in confined spaces. In the healthcare sector, Manchester University NHS Foundation Trust implemented a digital twin of six hospitals to manage estates, safety (including asbestos and RAAC management), and energy analysis (Machado et al., 2025).

9. Challenges and Future Research Directions

Despite the advantages of Digital Twins, several barriers impede their widespread adoption (Opoku et al., 2023).

9.1. Technological and Financial Barriers

High implementation costs remain a primary challenge, driven by the need for sophisticated sensors and high-performance computing. Interoperability gaps between different BIM, GIS, and structural monitoring platforms result in data fragmentation and inefficiency (Savalskii, 2025).

9.2. Cybersecurity and Data Governance

As digital twins rely on real-time monitoring of critical infrastructure, they are vulnerable to cybersecurity threats. Standardized protocols for secure data exchange and ethical data governance are essential to protect physical systems from potential cyber-physical attacks (Wang, 2019).

9.3. Future Outlook

The future of digital twins is linked to advancements in AI-native 6G networks, which will provide the "hybrid computing fabric" required to distribute intelligence across device, edge, and cloud. Continued research into physics-informed machine learning and standardized data formats (such as further refinements to the IFC schema) will be necessary to bridge the gap between theoretical developments and practical implementation (Jung, 2019).

10. Systematic Review of Life-Cycle Phases in Infrastructure

A comprehensive systematic literature review involving 89 relevant research papers indicates that the application of Digital Twin technology is not uniform across an asset's life cycle, Tab 3. The review examined the frequency of DT applications, identifying specific purposes and the most commonly applied technologies for bridges and tunnels (Kaveh & Alhajj, 2025).

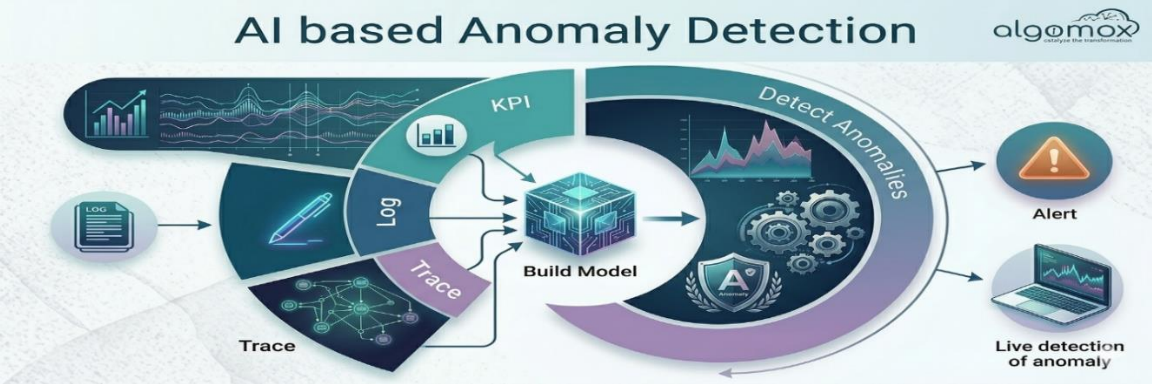
Table 3. Summary of Digital Twin Application Domains by Life-Cycle Phase

Life-Cycle Phase	Bridge Applications	Tunnel Applications	Key DT Technologies
Design	Load rating, simulation	Geotechnical complexity	BIM, FEM, BrIM
Construction	Logistics, progress tracking	Settlement monitoring	IoT, 4D BIM, UAVs
Operation & Maintenance	SHM, Fatigue, Corrosion	Ventilation, Fire safety	DT-IoT, AI, ML
Special Cases	Seismic, flood resilience	Emergency evacuation	AR, Digital Shadows

11. Machine Learning Algorithms for Anomaly Detection

As Ilustrated in Fig 2, In the context of structural health monitoring, the selection of the AI model is critical to the accuracy of fault detection (Liu et al., 2023).

Figure:2 Architecture of an AI-based Anomaly Detection System



11.1. Supervised Learning

Supervised learning algorithms, such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), are trained on labeled datasets to identify damage like cracks and stiffness loss. However, these models require extensive high-quality data, which can be costly to collect (Zabadi et al., 2025).

11.2. Unsupervised and Hybrid Approaches

Unsupervised learning offers an alternative for anomaly detection when labeled data is unavailable, identifying deviations from normal operating patterns. Hybrid approaches that integrate supervised, unsupervised, and physics-informed learning are increasingly prioritized to enhance accuracy (Zabadi et al., 2025).

11.3. Transformers for Sequential Data

Time Series Analysis Transformers have emerged as a powerful approach for modern time-series analysis in Structural Health Monitoring (SHM). By leveraging self-attention mechanisms, these models are able to capture both short- and long-range temporal dependencies within multivariate sensor data, making them particularly well suited for forecasting structural behavior and identifying degradation patterns. To address the sequential nature of SHM data, Transformer-based architectures incorporate causal masking to preserve temporal order and local attention mechanisms to focus on the most relevant neighboring observations during structured prediction tasks (Zhan et al., 2025).

For a sequence consisting of Ltime steps, the attention mechanism is formulated by projecting the input matrix Xinto query, key, and value representations:

$$Q = XW_Q, K = XW_K, V = XW_V$$

The scaled dot-product attention is then computed as:

$$A = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)$$

where W_Q, W_K, and $W_V$are learnable projection matrices, and $d_k$denotes the dimensionality of the key vectors. The resulting attention matrix Aquantifies the relevance of each time step to every other time step in the sequence. This mechanism enables the digital twin to selectively focus on historical events within the sensor data that exhibit strong correlations with ongoing degradation trends, thereby enhancing the accuracy and interpretability of predictive maintenance and structural prognosis models (Xie et al., 2023).

12. Autonomous Maintenance and Robotic Systems

The integration of Digital Twins with autonomous robotic systems represents the pinnacle of predictive maintenance maturity. In this framework, the digital twin serves as the prediction engine, while robotic systems provide the physical agency (Opoku et al., 2023).

12.1. The Autonomous Maintenance Stack

The autonomous maintenance stack includes three main pillars: the Digital Twin for physics simulation and RUL calculation, the IoT sensor network for real-time awareness, and the robotic systems for physical execution, Taab 4. These are orchestrated by a Computerized Maintenance Management System (CMMS) that auto-generates work orders (Kilic et al., 2025).

Table 4. Robotic Systems and Their Maintenance Functions

Robotic System Type	Application in Infrastructure	Maintenance Function
Inspection Drones	Bridges, high-rise buildings	Visual inspection, thermal imaging
Crawling Robots	Tunnels, pipelines	Leakage detection, thickness measurement
Autonomous Lubricators	Dams, industrial machinery	Routine maintenance, wear reduction
3D Scanning AMRs	Construction sites, warehouses	Progress tracking, as-built verification

13. The Role of 6G Connectivity in Future Infrastructure

As the telecommunications sector moves beyond 5G, 6G is being designed to merge the physical and virtual worlds through AI-native architectures (Raissi et al., 2019).

13.1. AI-Native Networks and Geo-Spatial Twins

6G technology will provide higher sustained uplink capacity and predictable low latency, which are determinants of AI performance for context-aware agentic intelligence. Geo-spatial and network digital twins in 6G will allow operators to optimize site placement and beamforming strategies through high-fidelity ray-tracing simulations (Samuel et al., 2023).

13.2. "Zero-Touch" and Self-Healing Systems

The vision of 6G involves a "zero-touch" paradigm where networks manage themselves across radio, core, and cloud domains. This connectivity enables real-time data exchange for intelligent manufacturing and autonomous mobility (Mousavi et al., 2024).

14. Economic Evaluation through Life-Cycle Costing (LCC)

The economic feasibility of predictive maintenance is assessed through Life-Cycle Cost Analysis (LCCA). This process evaluates the total economic worth of a project by analyzing initial costs and discounted future costs (Avogaro et al., 2025).

14.1. User and Environmental Costs

LCCA methodologies have expanded to include environmental impacts and estimated environmental costs. Tools like BridgeLCC 2.0 allow for the estimation of "user costs," which can significantly affect the overall lifecycle cost effectiveness of a design (Paolini et al., 2026).

Table 5. AI-DT Improvements in Life-Cycle Cost Categories

Cost Category	Components in Infrastructure LCC	AI-DT Improvement
Agency Costs	Initial construction, repairs, maintenance	Optimized scheduling, 30% cost reduction
User Costs	Driver delay, fuel consumption, accidents	40% reduction in unplanned closures
Environmental Costs	Carbon emissions, material waste	Lifespan extension (e.g., 100 to 200 years)
Social Costs	Disruption to essential services	Enhanced resilience, faster recovery

15. Conclusion

The integration of Digital Twin technology with AI-based structural performance modeling has emerged as a transformative solution for predictive maintenance and intelligent management of civil infrastructure systems. This review demonstrates that Digital Twins provide a dynamic and continuously updated virtual representation of physical assets, enabling real-time monitoring, simulation, and predictive decision-making throughout the infrastructure lifecycle. The incorporation of IoT sensors, cloud-edge communication systems, semantic synchronization frameworks, and advanced computational models significantly improves the accuracy and responsiveness of structural health monitoring systems. Advanced AI techniques including deep learning, LSTM networks, Graph Neural Networks, Transformers, and Physics-Informed Neural Networks have shown exceptional capability in fault detection, Remaining Useful Life prediction, anomaly recognition, and performance optimization under uncertain operational conditions. Furthermore, reduced-order modeling, federated learning, and edge computing enhance computational efficiency and support real-time infrastructure management. Case studies involving bridges, tunnels, dams, and urban systems confirm that AI-driven Digital Twins can substantially reduce maintenance costs, minimize downtime, extend infrastructure lifespan, and improve resilience against environmental and operational hazards. However, several challenges continue to limit widespread implementation, including high deployment costs, interoperability issues among BIM-GIS-IoT platforms, cybersecurity risks, and the absence of standardized data governance frameworks. Future research should focus on scalable and cost-effective deployment strategies, secure AI-native 6G communication systems, improved semantic interoperability standards, and hybrid physics-informed AI models capable of providing transparent and physically consistent predictions. Overall, Digital Twin-enabled predictive maintenance offers a highly promising pathway toward sustainable, autonomous, and data-driven infrastructure management for future smart cities and resilient engineering systems.

References

Ajayi, O. O., Kurien, A., Djouani, K., & Dieng, L. (2025). Artificial Intelligence for infrastructure resilience: Transportation systems as a strategic case for policy and practice. *Sustainability*, *17*(17), 8992. https://doi.org/10.3390/su17178992

Kaveh, H., & Alhajj, R. (2025). Advancing civil infrastructure with digital twins: A review of applications and challenges. *Journal of Civil Engineering and Management*, *31*(8), 828–842. https://doi.org/10.3846/jcem.2025.24921

Liu, C., Zhang, P., & Xu, X. (2023). Literature review of digital twin technologies for civil infrastructure. *Journal of Infrastructure Intelligence and Resilience*, *2*(3), 100050. https://doi.org/10.1016/j.iintel.2023.100050

Uddin, R., & Koo, I. (2024). Real-time remote patient monitoring: a review of biosensors integrated with multi-hop IoT systems via cloud connectivity. *Applied Sciences*, *14*(5), 1876.

Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2022). Towards a semantic Construction 4.0: Integrating BIM and digital twin for advanced building life-cycle management. *Automation in Construction*.

Deng, M., Menassa, C. C., & Kamat, V. R. (2021). From BIM to digital twins: A systematic review of the evolution of digital representation in the AEC-FM industry. *Journal of Information Technology in Construction (ITcon)*, *26*, 58–83.

Lovell, J., Chatsuwan, K., & Hakimi, M. (2026). From BIM to Digital Twins in Public Healthcare Facility Management: Bridging the Gap Between Technological Potential and Operational Reality. *Frontiers in the Built Environment*, *12*. https://doi.org/10.3389/fbuil.2026.1828585

Mousavi, S. H., Sepasgozar, S. M., & Zhang, W. (2024). Evolutionary progression from static information models toward dynamic, data-driven representations. *Applied Sciences*, *14*(3), 112.

Sepasgozar, S. M. E., Ghansah, F. A., & Mousavi, S. H. (2023). The Role of BIM in Integrating Digital Twin in Building Construction: A Literature Review. *Sustainability*, *15*(13), 10462. https://doi.org/10.3389/fbuil.2026.1828585

Xie, X., Lu, Q., Parlikad, A. K., & Schooling, J. M. (2023). Digital twin-enabled fault detection and maintenance planning in building services. *Energy and Buildings*, *291*.

Yousef Zabadi, H. R., Zemedkun, F. F. A., Hosamo, H., & Kraniotis, D. D. (2026). Integration of digital twins and machine learning for predictive maintenance using APAR method rules in non-residential buildings. *Frontiers in the Built Environment*, *12*. https://doi.org/10.3389/fbuil.2025.1734945

Zabadi, H. R. Y., Zemedkun, F. F. A., & Hosamo, H. (2025). Digital Twins and BIM Toward the Smart Management of Post Occupancy Public Buildings. *Preprints.org*. https://doi.org/10.20944/preprints202503.0123.v1

Kone, A., & Mahesh, G. (2025). An ontology-driven bi-directional workflow for integrating project management data into the IFC standard. *Journal of Information Technology in Construction (ITcon)*, *30*, 1768–1785. https://doi.org/10.36680/j.itcon.2025.073

Merino, J., García-Bermúdez, P., Martínez-Rojas, M., & Poveda-Villalón, M. (2022). A data-lake architecture for the digital twin of a building based on IFC and Brick. *Automation in Construction*, *142*.

Pan, Y., & Zhang, L. (2021). A BIM-data mining integrated self-adaptive predictive model for building energy consumption. *Automation in Construction*, *123*.

Sakr, M., & Sadhu, A. (2023). Integration of BIM and IoT for structural health monitoring: A digital twin approach. *Frontiers in Energy Research*, *11*. https://doi.org/10.3389/fenrg.2023.1334192

Biau, G., Bleakley, B., & Cadre, B. (2024). On the convergence of PINNs. *Journal of Machine Learning Research*, *25*(1), 2125–2138. https://perso.lpsm.paris/~biau/BIAU/dbb.pdf

Borgers, S., Ghorab, M. E., & Baitsch, M. (2024). Exploring the potential of physics-informed neural networks for the structural analysis of 2D frame structures. *CivilEng*, 6(4), 84–102. https://doi.org/10.3390/civileng6040084

Kilic, B., Guler, M., & Yilmaz, O. (2025). Physics-informed neural networks for the structural analysis and monitoring of railway bridges: A systematic review. *Mathematics*, *13*(10), 1571–1590. https://doi.org/10.3390/math13101571

Nuugulu, S. M., Akuka, M., & Farea, S. (2025). A physics informed neural network (PINN) framework for fractional order modeling of Alzheimer's disease. *Scientific Reports*, *15*(2), 450–468. https://pmc.ncbi.nlm.nih.gov/articles/PMC12957160/

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, *378*, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

Paolini, D., Dini, P., Elhanashi, A., & Saponara, S. (2026). Advanced Fault Detection and Diagnosis Exploiting Machine Learning and Artificial Intelligence for Engineering Applications. *Electronics*, *15*(2), 476.

Mahmud, A. R., Hriti, R. I., Hasan, M. M., Uddin, M. N., & Roy, A. R. (2025). AI-Augmented Digital Twin Architecture for Predictive Maintenance in Smart Urban Infrastructure: A Cross-Domain Engineering Framework. *European Journal of Applied Science, Engineering and Technology*, *3*(5), 45-58.

Mohammed, B. (2026). The sentient infrastructure paradigm: a review of novel sensors, digital twins, and AI for civil structural health monitoring. *Sensor Review*, 1-19.

Chen, H., Chen, J., Li, Z., Liu, Y., & Wang, J. (2025). Digital twin modeling Enabling structure full field data reconstruction by Variable fidelity data fusion. *Mechanical Systems and Signal Processing*, *230*, 112619.

Martin, H. M. (2025). From Simulation to Application: Advancements in Numerical Modeling of Energy Systems. *Energy Conversions*.

Zhan, S., Huang, L., Luo, G., Zheng, S., Gao, Z., & Chao, H. C. (2025). A review on federated learning architectures for privacy-preserving AI: Lightweight and secure cloud–edge–end collaboration. *Electronics*, *14*(13), 2512.

Avogaro, D., Cassandro, J., Dall'Anese, E., Dori, C., Farina, A., & Laurini, E. (2025). Mapping Cost Intersection Through LCC, BIM, and AI: A Systematic Literature Review for Future Opportunities. *Buildings*, *15*(18), 3345.

Mock, A. (2020). *Development of a life-cycle cost analysis tool for improved maintenance and management of bridges* (Master's thesis, Iowa State University).

Franciosi, M., Kasser, M., & Viviani, M. (2024). Digital twins in bridge engineering for streamlined maintenance and enhanced sustainability. *Automation in Construction*, *168*, 105834.

Samuel, P., Saini, A., Poongodi, T., & Nancy, P. (2023). Artificial intelligence–driven digital twins in Industry 4.0. In *Digital Twin for Smart Manufacturing* (pp. 59-88). Academic Press.

Leander, J., Karoumi, R., Rohner, C., Höglund, J., Wirström, N., Rosengren, P., & Kool, P. (2019). *Smart condition assessment, surveillance and management of critical bridges*. KTH Royal Institute of Technology.

Peng, J. (2025). Digital twin technology and its application in water governance: China's practices and achievements. *International Journal of Water Resources Development*, *41*(5-6), 974-989.

Machado, L. B., Santos, R. R., Ruiz, D. V., Bittencourt, T. N., & Futai, M. M. (2025). Advancements of Digital Twin Technology for Bridges and Tunnels: A Systematic Literature Review. *Journal of Infrastructure Systems*, *31*(4), 03125002.

Opoku, D. G. J., Perera, S., Osei-Kyei, R., Rashidi, M., Bamdad, K., & Famakinwa, T. (2023, January). Barriers to the adoption of digital twin in the construction industry: a literature review. In *Informatics* (Vol. 10, No. 1, p. 14). MDPI.

Savalskii, D. (2025). *Integrating Building Information Modeling (BIM) and Geographic Information Systems (GIS) for Enhanced Management and Efficiency of Urban Infrastructure in Smart Cities* (Doctoral dissertation, Hochschule für Technik Stuttgart).

Wang, H., Pan, Y., & Luo, X. (2019). Integration of BIM and GIS in sustainable built environment: A review and bibliometric analysis. *Automation in construction*, *103*, 41-52.

Jung, B. C. (2024). Toward artificial intelligence-native 6G services [Mobile Radio]. *IEEE Vehicular Technology Magazine*, *19*(4), 9-14.