DIGITAL TWIN-DRIVEN STRUCTURAL HEALTH MONITORING: EMERGING PARADIGMS, SIMULATION STRATEGIES AND PREDICTIVE INTELLIGENCE

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ABSTRACT

The resilience and sustainability of modern infrastructure depend not only on detecting damage after it occurs but also on anticipating failure before it materializes. Traditional Structural Health Monitoring (SHM) systems are effective for condition assessment but remain limited in their ability to provide predictive insights required for proactive asset management. Digital Twin (DT) technology has emerged as a transformative solution, creating dynamic, intelligent replicas of physical structures through the combination of real-time sensor data, high-fidelity simulations and advanced analytics. This study presents a comprehensive review of the evolving field of DT-driven SHM with simulation methodologies and predictive intelligence. Drawing on a thorough synthesis of recent research, the study shows how DT frameworks enhance diagnostic precision, support real-time response evaluation and enable forecasting of structural deterioration under varying operational and environmental conditions. Recent advances show the increasing importance of simulation-driven twins for modelling structural behaviour, data-driven algorithms for anomaly detection, and hybrid architectures that integrate physics-based models with machine learning to strengthen predictive capacity. Despite all these developments, significant challenges exist. Issues of data interoperability, model fidelity, and scalability across large and complex infrastructure networks hamper widespread adoption. Addressing these limitations will require the establishment of standardized frameworks and adaptive DT systems that will incorporate artificial intelligence, distributed sensing and cloud-edge computing. The review concludes that by shifting SHM from a reactive to a predictive paradigm, DT technology has the potential to extend service life, optimize maintenance cycles and reduce lifecycle costs while contributing to safer and more sustainable infrastructure systems.

Keywords: *Digital Twin, Structural Health Monitoring, Simulation, Predictive Intelligence, Smart Infrastructure*

1. INTRODUCTION

In this current modern world, infrastructure systems are working as the backbone of the society. Civil infrastructure, including buildings, roads, tunnels, bridges, and other properties, contributes significantly to social well-being and economic growth in developed and developing countries (Rodrigue, 2020). In many developed countries, civil infrastructure contributes 6% to 12% of the GDP (Soga & Schooling, 2016). However, the deterioration and aging of these structures cause significant hindrance to economic sustainability and safety. To assess the condition and performance of structures, a continuous and periodic monitoring is conducted using networks of sensors to detect damage and to collect data, known as Structural Health Monitoring (SHM) (Farrar & Worden, 2012; Sony et al., 2019). It has been the cornerstone effort to help engineers to evaluate the structural integrity and plan intervening measures (X. W. Ye et al., 2014). Traditional SHM is only effective for condition assessment and in a reactive mode. The limitation of responding only to deterioration instead of anticipating it, is highly problematic for infrastructure, as these networks face operational demands and climate changing environmental hazards (Tokognon et al., 2017; Dong & Frangopol, 2015).

As the global infrastructure industry is going through a paradigm shift, the emergence of Digital Twin (DT) technology represents a virtual replica of the physical world capturing its characteristics and behavior, and evolving through real time data exchange (Batty, 2018; Grieves & Vickers, 2017; Tao et al., 2019). In civil infrastructure, DT provides dynamic computational modeling, substituting the previous static finite element with a high fidelity simulations by incorporating sensor data, and advanced analytics to provide a comprehensive simulation of predictive future performance, potential damage, and optimized strategies for maintenance (Bado et al., 2022; Jiang et al., 2021; You et al., 2022). The evolution of the new field "Digital Twin-driven SHM" leverages a few key technologies: pattern recognition and anomaly detection using data driven machine learning (ML) algorithms (Mao et al., 2021; Zhao et al., 2020), high fidelity physics-based simulations for modeling fundamental structural behavior (Angjeliu et al., 2020; Ritto & Rochinha, 2021), and physics-based models with ML to produce adaptive predictive models (Cross et al., 2022; Zhang et al., 2020). Figure 1 shows framework of DT implementation in SHM. Several studies conducted by researchers demonstrated the versatility of DT-driven SHM across diverse infrastructure types. The development of a 3D digital twin model for prestressed concrete bridges was pioneered by Shim et al. (2019), combining inspection data with Building Information Modeling (BIM) to enable systematic maintenance planning. Kaewunruen et al. (2021) used DT technology to assess vulnerability and conduct risk-based maintenance of bridge infrastructures under critical climate conditions. For long-span structures, Lin et al. (2021) constructed a sophisticated DT-based framework to examine the collapse fragility of cable-stayed bridges under seismic loading, incorporating high-fidelity FE models with real-time sensor feedback. Furthermore, the proliferation in the adoption of DT in structural engineering for complex computation and real-time analytics has become possible because of the advancements in cloud and edge computing, and IoT sensors, which provide vast real time monitoring data (Pan & Zhang, 2021; C. Ye et al., 2019). Despite these auspicious developments, DT-driven SHM faces obstacles with model validation, computational efficacy, and interoperability of large infrastructure data networks (Lu et al., 2019; Opoku et al., 2021). To address these gaps, a proper consensus is necessary among researchers and practitioners on how DT can support design and construction of buildings and civil smart infrastructure.

Therefore, this review paper explores the current state of DT-driven SHM, particularly focusing on simulation techniques and predictive intelligence. The purpose of this study is to provide a comprehensive knowledge of how DT technology is converting infrastructure monitoring into a predictive paradigm capable of extending service life and improving the resilience of civil smart infrastructure systems.

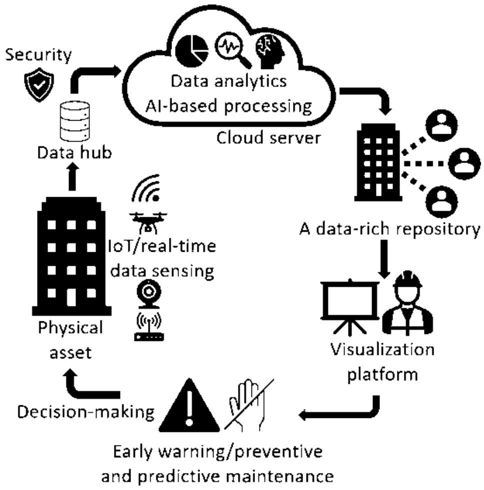

Figure 1: Framework of DT implementation in SHM (Sakr & Sadhu, 2024)

2. METHODOLOGY

The methodology that is adopted in this review provides a concise yet systematic approach. A structured process was followed to ensure that the selected studies were rigorously identified, screened, and synthesized to extract core themes related to Digital Twin-driven Structural Health Monitoring. A brief description of the individual stages is provided below, and a summarized representation in Table 1.
Stage 1 – Data Acquisition:
Collection of structural and environmental data using sensing systems and IoT-enabled devices.
Stage 2 – Data Processing and Management:
Preprocessing, filtering, and storage of sensor data to ensure reliability and usability for analysis.
Stage 3 – Model Development and Updating:
Integration of physics-based and data-driven models, with continuous updating based on observed data.
Stage 4 – Analysis and Decision Support:
Damage detection, performance prediction, and maintenance support using the updated digital twin.

Table 1: Structured methodology for the review process

Stage	Purpose	Actions Taken	Outcome
Literature Search	Identify relevant DT–SHM publications	Searched Scopus, Web of Science, IEEE Xplore, ScienceDirect using targeted keywords	Initial dataset of studies
Screening & Eligibility	Ensure quality and relevance	Applied inclusion criteria, removed duplicates and non-technical content	Refined selection of key papers
Classification	Group literature into meaningful categories	Organized studies into DT foundations, simulations, hybrid architectures	Structured thematic categories
Thematic Analysis	Extract core insights	Compared computational approaches, sensing technologies, UQ strategies	Identified patterns, gaps, and methods

Stage	Purpose	Actions Taken	Outcome
Synthesis	Integrate findings	Mapped insights into a coherent technical narrative	Final review structure ready for discussion

3. CONCEPTUAL FOUNDATIONS OF DIGITAL TWIN IN SHM

Structural Health Monitoring (SHM) refers to the continuous or periodic observation of civil infrastructure using sensing, data acquisition, and analytical techniques to assess structural condition, detect damage, and support maintenance decisions using vibration-based monitoring, strain- and displacement-based measurements, vision-based inspection, and data-driven damage detection approaches.A Digital Twin (DT) is a virtual representation of a physical asset that is dynamically linked with its real-world counterpart through data exchange. Unlike static numerical models, digital twins maintain bidirectional communication between physical and virtual domains, enabling real-time or near-real-time assessment, simulation, and prediction.While traditional SHM systems primarily provide reactive diagnostics, digital twin–enabled SHM facilitates model updating, damage prognosis, and decision support across the asset life cycle. The origin of DT was from aerospace engineering and product manufacturing life cycle management, which was first initiated by Grieves & Vickers (2017), later evolved in structural engineering. Its precise conceptual framework enhanced it's transformative potential and made it distinguishable from simpler modeling approaches. Digital Shadow is an unidirectional link where data flows only from the physical object to the digital model, which does not allow for real time control or predictive simulation (Sepasgozar, 2021). Whereas, digital twin is a virtual, dynamic replica of physical structures that holds bidirectional synchronization throughout its life cycle by continuous data exchange, enabling predictive analysis (Wang et al., 2025). Kritzinger et al. (2018) proposed a classification framework that differentiates three levels: a digital model with manual data exchange, a digital shadow featuring one-way automated data flow from physical to virtual space, and a true digital twin characterized by bidirectional automated data exchange. The framework of DT for SHM integrates several interconnected layers. The physical twin is ebedded with a dense network of sensors, utilizing Internet of Things (IoT) devices for data acquisition (Armijo & Zamora-Sánchez, 2024; Mishra et al., 2022). The physical-digital interaction is realized through a Cyber-Physical System (CPS) loop by processing incoming sensor streams, and generating predictive insights (Mengesha, 2025). The connectivity layer applies wireless communication protocols for uninterrupted data transmission between physical and digital counterparts (Hu et al., 2024). This raw data is then processed and integrated into sophisticated computational models by digital twin (Wimmer & Braml, 2024).

A Digital Twin consists of three main components in a general architecture design:

1. The physical world: DT will need to be developed in this existing physical twin, where there are some important components, such as IoT (sensors), data processing, and AI datasets.
2. The virtual world: For this already developed DT, major components are required using AI and ML for the DT model.
3. Connectivity: This creates bridge between the physical world and the virtual world, with some need of sub-components such as internet, satellite, Bluetooth, etc.

Digital twin–based SHM frameworks mostly rely on an integrated software ecosystem which supports physics-based modeling, system coordination, and data analytics. Finite element modeling environemnts enable simulation of structural behavior and model updating, while data analytics and machine learning platforms process sensor data for anomaly detection and predictive assessment. Visualization and integration tools, often linked with BIM and cloud-based systems, support real-time synchronization, data management, and decision support. In Table 2, the types of devices required for data collection are mentioned catagorically.

Table 2: IoT-based sensing devices for SHM in civil infrastructure

Infrastructure Type	Sensor Category	Typical Devices	Measured Parameters	Primary Function in SHM
Buildings	Strain sensors	Foil gauges, FBG sensors	Strain, deformation	Damage localization, serviceability assessment
Buildings	Vibration Sensors	Accelerometers	Natural frequencies, mode shapes	Modal-based damage detection
Bridges	Vibration Sensors	MEMS accelerometers	Dynamic response	Structural integrity monitoring
Bridges	Displacement sensors	LVDTs, GNSS	Deflection, movement	Load response evaluation
Roadways	Vision-based sensors	Cameras, LiDAR	Cracks, surface distress	Pavement condition monitoring
General	Environmental sensors	Temperature, humidity sensors	Environmental effects	Data correction and normalization

The components of DT are visualized in Figure 2. Systematic reviews indicate that effective implementation of digital twins in civil structural health monitoring cohesive integration of architectural components, guaranteeing data interoperability, model precision, real-time adaptability to changing structural conditions, and strong cyber-physical connectivity (Mengesha, 2025; Tran et al., 2024)

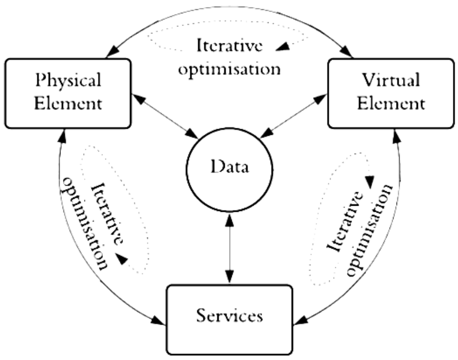

Figure 2: Component of DT (Sun et al., 2025)

4. SIMULATION-DRIVEN AND PHYSICS-BASED DIGITAL TWINS

The ability to effectively demonstrate how smart infrastructures behave under different loads and environmental circumstances is at the basis of effective DT-driven SHM. Physics-based models lay the groundwork for understanding the intricate mechanics that drive structural response, degradation, and failure mechanisms (Li & Brennan, 2024). The major computational technique for high-fidelity structural modelling is still the finite element method, which enables precise description of geometry, material properties, boundary conditions, and interactions between many physics. However, real-time DT applications, which need quick model evaluation for ongoing monitoring and decision-making, have significant challenges due to the computational demands of full-scale FEM simulations (Zhou et al., 2022). Reduced order modelling techniques have become crucial for enabling computationally efficient DTs to get around this restriction. These techniques preserve important behavioural characteristics while reducing the dimensionality of high-fidelity models (He et al., 2024; Kapteyn et al., 2020). In the following sections, there are some thematic case studies and technical research articles on the application of physical-based digital twins in building structures, transportation infrastructures, and other civil engineering elements and assets. Below information are summarized in Table 3.

4.1 Physics-based Approaches in Bridges and Tunnels

The capabilities of a DT for bridge evaluation of a multi-girder steel stringer test bridge were explored by Ye et al., (2020). Both manually and automatically, the FE models were updated and calibrated using the experimental data. A DT framework was presented by Lin et al., (2021) for the evaluation of a long-span cable-stayed bridge's fragility. The bridge's collapse fragility curves were computed using FEM models using incremental dynamic analysis (IDA). The study emphasized how crucial nonlinear FEM update is for increased accuracy in DT applications. A DT for bridge maintenance was created by Wenner et al., (2021). IoT technology sent the data to the system via Wi-Fi connections, and BIM made it possible to visualize integrated real-time features in addition to structural classification. In the end, the users created a human-machine interface for the DT platform's navigation and visualization.

4.2 Physics-based Approaches Involving Buildings

A small-scale three-story structure was used to show a DT's construction by Wagg et al., (2020). To determine the model parameters of a model that behaved nonlinearly, they used system identification. Following training, the users used standard deviation to forecast areas without bumper contact. As a result, the DT could identify the existence of uncertainty. Gardner et al. (2020) investigated how a DT may use data-based and physics-based models to target predictive maintenance. The primary goals of the project were to improve model parameter estimation, add more physics-based modelling to the DT, and add or update a data-based component to simulate unknown physics. The physics-based model was used with a GP regressor to investigate harsh linearity behaviour and enhance predictive maintenance. A methodology for applying DTs for structural engineering was developed by Chiachío et al. (2022). The authors' goal was to use a connecting system to update the virtual asset depending on the measured physical interactions. Smart devices, network connections, and an integration platform comprised the DT. User visualization was done on the front end, and data storage, analytics, and Internet of Things applications were done on the back end.

Table 3: Summary of DT-based SHM studies involving bridges, tunnels, and buildings

Authors	Data collection types	Data analysis types
Ye et al., (2020).	Inspections, wind/radar/fiber-optic sensors	Manual and optimization functions
Lin et al., (2021)	Accelerometers, displacement sensors, transducers	SSI, linear/non-linear model updating, IDA
Wagg et al., (2020)	Piezoelectric accelerometers	Self-adaptive differential evolution algorithm, Bayesian calibration, Gaussian process
Gardner et al. (2020)	Acceleration responses	Gaussian process regression, active learning
Chiachío et al. (2022)	Ultrasonic sensor	High-level Petri Net, probabilistic Bayesian model updating
Wenner et al., (2021)	Inspection data, sensor-based monitoring	Criticality analysis, condition rating by structural analysis, data-based anomaly detection

5. HYBRID DIGITAL TWIN ARCHITECTURES

Hybrid digital twins (DTs) seamlessly integrate physics-based simulation with data-driven learning to minimize model-form error while maintaining interpretability and robust extrapolation. In Table 4, the applications of hybrid DT in architectures are summarized.

Table 4: Hybrid DT building blocks

Block	Purpose	Typical methods	Outputs	Workflow spot
Model updating	Align physics with reality	OMA; sensitivity/Bayesian FE update; RAOs	Calibrated params; reliability idx	Physical to Virtual (post-sensing)
DAM / discrepancy	Learn physics–data residual	GP/regularized ML; AE/CNN/RNN; physics priors	Bias-corrected preds; damage prob.	Virtual core (parallel to physics)
UQ & reporting	Quantify confidence	Bayesian/ensembles; PIs; credibility plots	PIs on stress/life; risk thresholds	Wraps physics + DAM outputs
ROMs & edge	Near–real-time sim/forecast	POD/Krylov/neural ROMs; edge features	Low-latency responses; alerts	Between features ↔ dashboards
Decision layer	Turn insights into actions	Rules/optimization/POMDP	Routes, schedules, set-points	Virtual→Physical feedback

A common approach is the grey-box loop: a calibrated finite element (FE) or reduced-order model enforces the core mechanics and boundary conditions, while a data-driven layer continuously learns the model discrepancy (residual) from streaming sensor data and corrects predictions in near-real time. (Wagg et al., 2020). Formally, observations can be represented as,

$$z(x) = \eta(x, \theta) + \delta(x) + e \quad (1)$$

Where η is the physics model, δ is a learned discrepancy, and e is measurement noise, enabling bias-aware calibration and reliable forecasting even under nonstationary conditions (Wagg et al., 2020). For integrity management, this hybrid approach is further strengthened by explicit uncertainty quantification (UQ), ensuring that maintenance decisions are supported by well-defined confidence bounds (Li & Brennan, 2024).

The data component in modern structural health monitoring (SHM) is heterogeneous, employing a portfolio of modalities such as strain, acceleration, temperature, and distributed optical fiber sensing (DOFS), each with distinct spatial and temporal resolutions and noise characteristics. DOFS provides extremely fine spatial resolution, down to approximately 0.63 mm, and long-range coverage with minimal intrusiveness. This capability is particularly effective for mapping strain fields that inform model updating or serve as targets for discrepancy learning (Bado & Casas, 2021). Hybrid DTs leverage these dense data fields: the physics-based model supplies compatibility or regularization, while DOFS captures localized behaviours, such as those at joints, cracks, or bond slip, which may be missed by pure FE models. However, practical challenges with DOFS include strain transfer through coatings or adhesives and long-term bonding stability, which must be incorporated into the data-driven layer's uncertainty model (Bado & Casas, 2021). In summary, hybrid DTs for civil assets integrate (i) sensing,

(ii) FE or reduced-order model (ROM) response prediction, (iii) data-augmented modelling for unmodeled effects, and (iv) UQ with decision-oriented outputs (Wagg et al., 2020; Li & Brennan, 2024).

6. APPLICATIONS ACROSS CIVIL INFRASTRUCTURE DOMAINS

Hybrid DTs have matured from single-demo prototypes into domain-specific workflows. In marine and bridges, virtual monitoring frameworks infer short-term environmental loads (e.g., sea state) from measured motions or hindcast data; FE-derived stress response amplitude operators (RAOs) translate these into spectral fatigue estimates for inspection planning and life extension (Li & Brennan, 2024). SHM task sensor modality and applications outcomes are in Table 5 and Table 6 respectively.

Table 5: Sensor modality to SHM task

Modality	Best use	Resolution / range	Key caveats
DOFS (Rayleigh/DAS)	Dense strain; hot-spots; FE update	sub-mm–cm; 10–1000+ m	Bonding/strain transfer; temp; big data
DOFS (Brillouin)	Long-range quasi-static trends	0.1–1 m; 1–10+ km	Lower spatial/temporal; temp comp
Accelerometers	OMA; modal shifts; serviceability	µg–g; Hz–kHz; global	Env/operational confounds
Disp./vision/LiDAR/GNSS	Deflection; geometry; model update	µm–mm (laser/LVDT); cm (GNSS)	LOS/lighting/occlusion; registration

Table 6: Civil domain applications & outcomes

Domain	Loads	Physics core	Discrepancy target	KPIs
Highway bridge	Traffic/WIM; wind; temp	3D FE + OMA updating	Temp/ops effects; bearings/joints	Latency; reliability; false alarms
Railway bridge	Train dynamics; seasons	FE + state-space/DBN	Residual dynamics vs. trains/temps	Opt. maintenance; cost–risk reduction
Tall building	Stochastic wind; occupancy	Modal FE; serviceability	Stiffness/damping drift	Drift exceedance; comfort; alarms
Pipeline	Pressure; soil movement	Beam/pipe FE + SSI	Local strain hot-spots; ground	Fatigue usage; remaining life; leak risk

Many deployments close the physical to virtual loop (sensing to model updating), while fewer explicitly enact virtual to physical feedback (twin-guided inspection routing/control) a near-term opportunity (Li & Brennan, 2024).For buildings and bridges in structural dynamics, data-augmented modeling (DAM) corrects FE predictions where joints, friction, or hysteresis dominate, improving modal properties and response prediction under operational variability. Wagg et al. (2020) identify DAM as a defining building block for a simulation digital twin used in asset management; Wagg et al. (2020) extend this to capability levels and V&V/UQ expectations.

Sensor-rich structural cases increasingly leverage DOFS: deployments span laboratory beams, in-service bridges and buildings, tunnels, pipelines, geotechnical systems, and wind structures; their long-gauge/long-range coverage plus sub-millimeter spatial resolution give hybrid DTs dense strain fields for damage localization, model updating, and prognosis (Bado & Casas, 2021). In practice: (i) DOFS feeds hybrid twins with spatially rich measurements; (ii) the physics model enforces compatibility and physical plausibility; and (iii) UQ communicates confidence in hot-spot predictions (Bado & Casas, 2021; Li & Brennan, 2024). Decision-oriented civil DT frameworks formalize the twin as a probabilistic/dynamic decision system continuous assimilation, diagnostics, and policy optimization for maintenance demonstrated on beams and railway bridges (Torzoni et al., 2024).

7. CHALLENGES AND LIMITATIONS

Model-form uncertainty and joints/contact: even high-fidelity models struggle with joint nonlinearities and aging; without explicit discrepancy modeling, calibration can be biased (Wagg et al., 2020). Verification/validation and UQ: for inspection deferrals or load restrictions, DTs must report predictive confidence (intervals on fatigue damage/reliability). Clear, repeatable V&V pipelines (e.g., OMA + FE updating) and standardized UQ reporting remain unevenly adopted (Wagg et al., 2020). In Table 7, the problems and solutions are mentioned.

Table 7: Challenges & mitigations for hybrid DTs

Challenge	Symptom	Mitigation	Validation to report
Model-form uncertainty	Biased calibration	DAM w/ physics features; substructure tests	Pre/post error; joint params CIs
V&V / UQ gaps	Low trust at decisions	Bayesian/ensemble UQ; PIs; V&V plan	90% PIs; OMA+FE update report
Real-time limits	Dashboard/control latency	ROMs; edge feature extraction	Latency budget; ROM RMSE
Data quality & drift	Dropouts; thermal bias	Redundancy; drift alarms; temp comp; DOFS QA	QA/QC checklist; residual plots
No feedback loop	No field action change	Decision layer (rules/opt/POMDP)	Policy vs. baseline cost–risk

Sensing realism and data QA: long-term reliability requires redundancy, drift detection, and standardized data schemas, especially important when merging DOFS with conventional sensors in hybrid twins (Li & Brennan, 2024; Bado & Casas, 2021). DOFS-specific concerns include strain-transfer through coatings/adhesives and durability of bonding; these should be reflected in the twin's error models (Bado & Casas, 2021).

8. FUTURE DIRECTIONS AND RESEARCH AGENDA

Looking ahead, advancing Digital Twin–enabled SHM will require coordinated progress across several technical and methodological fronts. The following priorities outline the key areas where focused research and standardization can meaningfully strengthen future DT deployment in civil infrastructure:

1. Develop decision-ready uncertainty measures, such as 90% prediction intervals for fatigue or reliability, consistently aligned with verification and validation (V&V) artifacts (Wagg et al., 2020).

2. Enhance residual learning by embedding mechanics-aware features, environmental context, and physics-based constraints to improve model fidelity (Wagg et al., 2020).
3. Translate Digital Twin outputs directly into inspection routing, maintenance scheduling, and control strategies to move toward true Learning-Twin behavior (Li & Brennan, 2024).
4. Establish robust rules for redundancy, drift management, and unified data schemas that integrate DOFS with conventional SHM sensors, ensuring long-term dependability of hybrid DT systems (Bado & Casas, 2021; Li & Brennan, 2024).
5. Combine diagnostics, forecasting, and maintenance optimization within dynamic decision models, supported by benchmarks on open bridge, tower, and offshore datasets (Torzoni et al., 2024).
6. Target quantifiable improvements such as ≥30% RMSE reduction for stress/strain hotspots after discrepancy learning and ≥20% reduction in unscheduled inspections through DT-guided maintenance planning.

9. CONCLUSION

A viable approach to fully functional SHM in civil infrastructure is through Hybrid Digital Twins, in which data continuously corrects physics-based models and explicit uncertainty quantification supports them. Buildings, bridges, and offshore structures provide evidence of significant advancements in condition assessment, forecasting, and maintenance scheduling. However, establishing standardized UQ procedures, fortifying the virtual–physical feedback loop, guaranteeing strict quality assurance for a variety of sensor portfolios (including DOFS), and incorporating decision-theoretic frameworks to link diagnostics with maintenance actions are still necessary to achieve reliable large-scale deployment (Wagg et al., 2020; Bado & Casas, 2021; Li & Brennan, 2024; Torzoni et al., 2024).

DECLARATION OF USE OF AI

The authors used artificial intelligence (AI) tools in a limited capacity for language editing, clarity, and structural refinement only. AI tools were not used for data generation, analysis, or to influence the study's methodology or conclusions. All scientific content and interpretations remain the responsibility of the authors.

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