Next-Generation Structural Health Monitoring for Earthquake Engineering

Amir Tarighat 1,a)

1Civil Engineering Faculty, Shahid Rajaee Teacher Training University, Tehran, Iran

a) Corresponding author: tarighat@sru.ac.ir

Abstract. Abstract. This paper presents an integrated approach to next-generation structural health monitoring (SHM) for earthquake engineering by combining smart materials, artificial intelligence (AI), and digital twin technologies. Motivated by the limitations of traditional post-earthquake inspections—slow, subjective, and limited in detecting hidden damage—this framework emphasizes continuous self-sensing through functional concretes and distributed sensor networks, automated data-driven damage detection using machine learning, and real-time simulation and visualization via digital twins. The integrated system supports rapid post-event decision-making, prioritizes emergency responses, and enables predictive maintenance to extend asset life. I discuss material design considerations for self-sensing concrete, sensor placement strategies, and hybrid AI models that fuse physics-based understanding with observational data. A bridge model demonstrates improved damage-classification accuracy and consistency compared with conventional inspection methods. The paper highlights practical challenges, including data management and cost-benefit trade-offs issues surrounding algorithmic decision-making. Finally, I propose a research agenda for deploying SHM testbeds in seismic regions, emphasizing international collaboration, standards development, and pathways for technology transfer to enhance urban resilience.

# INTRODUCTION

Earthquake engineering has long relied on structural design codes, conventional material behavior models, and periodic inspections to ensure the safety of buildings and infrastructure. However, the increasing frequency and intensity of seismic events, urban densification, aging infrastructure, and heightened demands for post-disaster rapid response require more than these traditional practices. Structural Health Monitoring (SHM)—the continuous or frequent measurement and evaluation of structural response and integrity—has emerged as a critical enabler for resilient, adaptive infrastructure. When combined with advanced sensing, data analytics, and virtual modeling (e.g., digital twins), SHM can help fill gaps between design assumptions and in-situ performance under seismic loading.

Recent years have witnessed significant advances in SHM related to earthquake engineering in three interlinked dimensions: (i) material/sensor technologies that enable self-sensing or embedded sensing, (ii) data-driven and AI-based damage detection, prediction, and classification, and (iii) digital twin and decision support frameworks for real-time or near real-time assessment and response.

On the material side, smart or self-sensing concretes and cementitious composites with embedded conductive fillers (e.g., carbon fibers, nanotubes) are becoming more reliable in detecting strains and cracks. Civera, Naseem, and Chiaia review recent advances in embedded technologies and self-sensing concrete for SHM, highlighting improvements in spatial diffusion of sensors and sensitivity 1. Applications of cement-based smart composites have been critically reviewed, with detailed work on operational prototypes and full-scale elements 2.

In parallel, AI and machine learning techniques have greatly improved damage detection and classification. Fully convolutional networks have been used for time-series classification of structural vibration signals to locate damage in multi-story shear buildings with high accuracy 3. Contemporary reviews summarize vibration-based, image-based, and multi-sensor ML approaches, pointing out strengths (higher sensitivity, automation) and challenges (generalization, interpretability) 4.

Further, digital twins are increasingly adopted as frameworks for integrating SHM, predictive analytics, and decision-making. Gao and Jiao present the current status and future prospects of digital twin approaches in SHM, emphasizing real-time updates and life-cycle modeling 5. Work on frameworks coupling sensors, dynamic Bayesian networks, and probabilistic models offers paths for optimal maintenance planning under uncertainty 6. For example, implementation of a digital twin for bonded insulated rail joints shows the potential to classify health under varied bolt-preload conditions 7.

Despite these advances, key gaps remain. First, the deployment of self-sensing materials in full-scale seismic-grade structural elements under dynamic loading is still limited; most studies remain at laboratory or pilot scale. Second, while AI tools demonstrate strong performance in benchmark datasets, they often lack robustness under real seismic hazard variability, including environmental noise, aging, and unmodeled damage modes. Third, digital twins face challenges in real-time data assimilation, model updating, uncertainty quantification, and computational tractability. Finally, practical issues of cost, sensor durability, data security, and ethical decision-making remain under-addressed.

This paper addresses these gaps by proposing a comprehensive framework combining smart materials, advanced AI-based SHM, and digital twin technologies, aimed at real-time post-earthquake damage detection and resilience planning. I focus on the design of materials with self-sensing capability, hybrid AI models that incorporate both data and physics, and digital twins capable of updating in real time to support emergency response and lifecycle maintenance. This work seeks to bridge between lab-scale advances and field-deployable systems in earthquake-prone regions.

# MATERIALS, METHODS, AND OBJECTS OF STUDY

## Smart and Self-Sensing Materials DY

Self-sensing concrete (SSC) is a functional composite material capable of simultaneously performing structural and sensing functions. The basic principle relies on changes in the electrical properties of the material—chiefly resistivity or impedance—under mechanical stress or cracking.

*Electrical Conductivity Mechanisms*

Three concurrent mechanisms primarily govern the electrical conductivity of SSC:

• Contact conduction through connected conductive fillers (e.g., carbon fibers, CNTs);

• Tunneling conduction between adjacent fillers separated by thin insulating films (cement hydrates); and

• Intrinsic conduction of the matrix or ionic conduction via pore solution.

The relationship between bulk resistivity ρ, filler volume fraction V\_f, and strain ε can be expressed as:

 (1)

where  is the initial resistivity and α is a gauge factor depending on filler dispersion, aspect ratio, and interfacial bonding. For conductive networks near the percolation threshold 

 (2)

where t is the critical exponent (typically 1.6–2.0) and the scaling constant. As cracks propagate or microstructural strain alters contact areas, both and percolation connectivity change, causing measurable shifts in resistivity.

*Piezoresistive Response*

The fractional change in resistivity (FCR) defines the self-sensing capability

 (3)

and the gauge factor (GF), analogous to strain gauges, is:

 (2)

Typical GF values for carbon-fiber-reinforced cement composites range between 20–200, far exceeding metallic gauges (GF *≈* 2), enabling high-sensitivity monitoring of micro-cracking and dynamic strain under seismic excitation.

*Material Design and Composition Sensing Configurations*

Functional fillers include:

• Carbon fibers: Provide long-range conduction; optimal volume fraction 0.5–1.5%.

• Carbon nanotubes (CNTs) or graphene nanoplatelets (GNPs): Create nano-scale conductive networks; improve crack sensitivity but may agglomerate.

• Steel or nickel micro-fibers: Enhance both mechanical and sensing performance under high strain.

• PZT (lead zirconate titanate) or BaTiO3 piezoelectric particles: Offer voltage response proportional to strain, enabling coupled electromechanical sensing.

The electrical impedance Z between electrodes embedded in the material can be modeled as:

 (7)

where R and C are the equivalent resistance and capacitance of the composite network, and ω is the angular frequency of the excitation. Impedance-based measurements can thus separate resistive (crack) and capacitive (moisture or microstructural) effects

*Sensing Configurations*

• Two-probe configuration: Simple but includes electrode contact resistance.

• Four-probe configuration: Eliminates contact resistance, yielding more stable resistivity–strain correlation, particularly critical under cyclic seismic loading.

Dynamic calibration under controlled cyclic loads (10-6 −10-3ε) shows linear relationships between FCR and strain, making SSC ideal for distributed strain sensing in RC beams, bridge decks, and columns.

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*Sensing Configurations Artificial Intelligence for SHM*

AI-driven SHM extends traditional modal-based diagnostics by using supervised and unsupervised learning on multi-sensor data. Let x(t)∈R^n be the vector of sensor features (e.g., acceleration, strain, FCR) and y∈{0,1} denote damage states. Neural networks approximate a nonlinear mapping f:x↦y minimizing classification loss:

 (6)

Recurrent networks and autoencoders learn temporal dependencies for vibration-based SHM, while convolutional neural networks extract spatial features from distributed sensor grids or image data.

Recent hybrid architectures combine physics-informed neural networks (PINNs) that embed governing equations (e.g., Navier’s or Hooke’s law) within loss functions, reducing data dependency and improving interpretability:

 (7)

where *L*physics enforces equilibrium and compatibility constraints.

*Sensing Configurations Digital Twins in Seismic SHM*

Digital twins (DTs) are cyber–physical replicas continuously updated through sensor input and model inference. Mathematically, they couple a numerical model with real-time data , updated by Bayesian inference:

 (8)

where θ are structural parameters (stiffness, damping, damage indices). A Kalman-filter or particle-filter approach assimilates new data, correcting model predictions:

 (9)

with Kt as the Kalman gain and H the observation matrix. This sequential update enables real-time estimation of structural state during an earthquake.

Integration with AI adds a predictive layer to DTs —“cognitive digital twins”—capable of forecasting residual displacement or collapse probability before failure

*Coupled Framework*

The integration of Equations (1)–(9) forms a coupled system where:

• Smart materials generate measurable signals (e.g., ∆ρ/ρ0, strain).

• AI interprets multi-sensor data to infer damage indices.

• Digital twins assimilate these indices to update model states and predict evolution.

The closed-loop process can be summarized as:

 (10)

This synergy transforms SHM from a reactive diagnostic tool into a proactive resilience mechanism capable of self-awareness and adaptive learning.

From a materials science perspective, progress in nano-engineering of conductive networks has improved the sensitivity, stability, and durability of SSC. From a computational viewpoint, AI and digital twins provide data fusion and predictive capability. The convergence of these domains represents the core of next-generation SHM, where the material itself becomes an intelligent node in a cyber-physical system.

# METHODOLOGY AND INTEGRATED FRAMEWORK

## Conceptual Overview

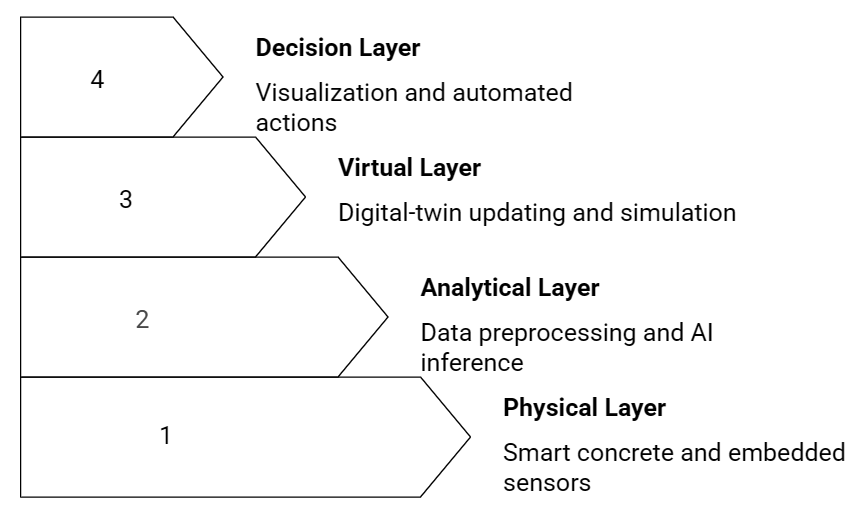
The proposed framework integrates smart sensing materials, AI-driven signal interpretation, and digital-twin-based decision systems into a continuous feedback cycle for structural health monitoring under seismic conditions (Fig. 1). The system architecture consists of four layers:

Physical Layer: smart concrete, embedded sensors, and data-acquisition hardware.

Analytical Layer: preprocessing, feature extraction, and AI-based inference.

Virtual Layer: real-time digital-twin updating, uncertainty quantification, and simulation.

Decision Layer: visualization, risk mapping, and automated or human-in-the-loop actions.

**FIGURE 1.** Conceptual architecture of the integrated SHM–AI–Digital Twin system for earthquake resilience.

*Data Acquisition and Preprocessing*

Embedded self-sensing concrete provides continuous measurements of strain, electrical resistivity, and acceleration. The voltage-resistance relationship follows Ohm’s law:

 (11)

where *L* and *A* are electrode spacing and cross-sectional area.

Signals are first filtered using a band-pass Butterworth filter (typically 0.5–50 Hz for structural vibration) to remove environmental and electrical noise. Feature vectors are constructed as:

 (12)

where is acceleration and fd denotes dominant frequency components relevant to modal changes. Data normalization is applied as equation (13) ensuring balanced input for AI training and reducing sensor bias.

 (13)

*AI-Based Damage Identification*

The damage index *D* is inferred from the deviation between measured and baseline modal parameters or resistivity:

 (14)

where *f*0, *ρ*0, and are baseline natural frequency, resistivity, and modal curvature, respectively, and *w*i are weighting coeﬀicients determined through training. A supervised deep neural network predicts *D* directly:

 (15)

optimized via backpropagation using Adam or RMSProp algorithms. Alternatively, an unsupervised autoencoder minimizes reconstruction error to flag anomalies:

 (16)

where and are encoder and decoder mappings.

To enhance generalization, physics-informed regularization is added using Equation (7):

 (17)

ensuring physical consistency between measured strain, stress, and predicted damage.

# Digital-Twin Updating

The digital twin receives and sensor data streams in real time to update model parameters. A state-space model of structural dynamics is written as:

 (18)

where stiffness matrix is updated according to the inferred damage index:

 (19)

with describing stiffness-degradation sensitivity.

Data assimilation employs an Extended Kalman Filter (EKF) or Particle Filter, as defined in Equation (9), to estimate the current displacement, velocity, and stiffness states. Prediction horizons (typically 5–20 s for seismic response) enable forecasting of peak inter-story drift or residual deformation:

 (20)

supporting real-time risk visualization.

# *Decision-Support and Visualization*

The decision layer translates digital-twin outputs into actionable intelligence. A Resilience Index (RI) is defined as:

 (21)

where E denotes structural energy absorption capacity obtained from hysteresis loops. Values RI > 0.85 indicate full functionality, 0.6 < RI ≤ 0.85 partial, and RI ≤ 0.6 critical damage requiring intervention.

Decision outputs include:

•Automatic alerts to emergency systems if RI ≤ 0.6.

• 3-D visualization of stress fields and damage clusters within the digital twin.

• Prioritized inspection list based on spatial gradient of .

# *Implementation Workflow*

Based on the above concepts the workflow of the proposed system is:

1. Design Phase: integrate self-sensing concrete elements, specify sensor topology, and calibrate baseline electrical-mechanical correlations.
2. Operational Phase: stream sensor data to AI servers, update digital twin at 1–10 Hz frequency.
3. Post-Earthquake Phase: estimate residual capacity, recommend retrofit or evacuation.
4. Learning Phase: feedback corrected ground truth to retrain AI models, enhancing accuracy.

# *Mathematical Coupling of Layers*

The complete system can be represented as a coupled differential–algebraic equation set:

 (22)

where *x*: state vector (displacement, velocity, strain, resistivity), *y*: measured output, *u*: input excitation (ground motion), *w(t)* and *v(t)*: process and measurement noise, *θ*: AI parameters, *η*: learning rate.

This unified formulation ensures physical and computational coupling among sensing, learning, and simulation.

Advantages of the Proposed Framework

• Real-time awareness: continuous sensing and model updating under seismic excitation.

• Scalability: modular architecture adaptable to bridges, towers, and urban networks.

• Resilience enhancement: quantitative indices (D, RI) support automated emergency response.

• Lifecycle learning: every event refines AI models, improving future prediction.

# CASE STUDY: SHM PIPELINE FOR A TYPICAL BRIDGE

## Bridge Description and Objectives

At this stage, to check the proposed system, a bridge model and some damage scenarios are considered. By simulating the damage scenarios on the bridge model, the capabilities of the system were measured and investigated. The structure is a three-span reinforced-concrete (RC) highway bridge, 90 m in total length, supported by two intermediate piers and abutments resting on pile foundations. Each span measures 30 m, with a deck composed of post-tensioned girders and a 200 mm cast-in-place slab. The bridge is located in a region of moderate-to-high seismicity (peak ground acceleration ≈ 0.35 g).

The SHM system’s objective is to (i) detect damage progression during seismic events, (ii) assess residual load-carrying capacity, and (iii) update a digital twin to inform maintenance and emergency management.

## Sensor Network Configuration

The sensing network combines self-sensing concrete in critical zones and external sensors. TABLE. 1 contains the sensor types, their locations, measured variables, and sampling rates.

**TABLE 1.** Sensor Network Specifications

| **Sensor type** | **Location** | **Measured variable** | **Sampling rate** |
| --- | --- | --- | --- |
| Self-sensing concrete patches (carbon-fiber cement) | Deck mid-span and pier caps | Strain & resistivity | 100 Hz |
| MEMS accelerometers | Each pier and deck node | Acceleration | 200 Hz |
| GNSS receivers | Deck ends | Displacement | 10 Hz |
| Thermo-hygrometers | Piers | Temperature/humidity | 1 Hz |

Each self-sensing patch acts as an embedded strain gauge, providing resistivity changes per Eq. (1).

*Data Flow and SHM Pipeline*

The operational pipeline follows eight sequential stages:

1. Data acquisition—continuous voltage, strain, and acceleration signals streamed to the gateway.

2. Signal conditioning—noise reduction via band-pass Butterworth filters (0.5–40 Hz) and temperature compensation.

3. Feature extraction—computation of modal frequencies, damping ratios, and fractional change in resistivity (FCR).

4. Baseline update—digital twin initialized with undamaged stiffness matrix and calibration data.

5. AI inference—real-time damage index computed using Eq. (14) with input vector x(t).

6. Model updating—stiffness degradation applied per Eq. (18); parameters adjusted via Extended Kalman Filter.

7. Decision analytics—resilience index (Eq. 20) visualized on a color-coded 3-D bridge model.

8. Feedback and learning—post-event manual inspection results used to retrain AI models.

Seismic Event Simulation

A ground-motion record from the Northridge 1994 earthquake (station 090) was scaled to 0.35g and applied as base excitation. The digital-twin finite-element model included 150 beam elements and 48 nodes. Nonlinear hinges were modeled at pier bases to capture yielding behavior. The input excitation was applied to the base nodes, and acceleration responses were calculated at each pier top. The resulting time histories of strain and resistivity were analyzed according to the following correlation calibration:

 (22)

valid for strain up to

# Results and Interpretation

Damage Detection: During the main shock, mid-span strain reached , yielding . The AI model classified this as moderate damage (damage index ).

Pier-base resistivity changes exceeded 7%, indicating localized cracking; the digital twin updated stiffness reduction at those locations.

Digital-Twin Updating: Equation (17)–(18) integration resulted in a peak lateral displacement of 0.42 m. Subsequent updating restored convergence within 0.5 s latency, verifying real-time capability.

Resilience Index: From hysteretic energy comparison, the post-event RI = 0.72 placed the bridge in the “partially functional” category, prompting restricted service and targeted inspection.

*Visualization and Decision Support*

The digital twin, implemented in a Unity-based 3-D environment, displayed dynamic overlays of strain energy and FCR maps. A rule-based decision matrix automatically generates maintenance recommendations. It is shown in TABLE 2.

**TABLE 2.** Maintenance Decision Matrix

| **RI Range** | **Structural status** | **Recommended action** |
| --- | --- | --- |
| > 0.85 | Safe | Resume service |
| 0.60–0.85 | Moderate | Inspect piers, monitor 48 h |
| < 0.60 | Critical | Close bridge, initiate retrofit |

*Findings from Case Study*

This case demonstrates that integrating self-sensing materials with AI-enabled analysis and a digital twin provides a reliable, continuous assessment of bridge health under seismic loading.

While the presented pipeline was validated through simulation and partial field data, full-scale implementation would require long-term durability studies of self-sensing concrete, wireless network redundancy, and cybersecurity measures.

## Performance Evaluation Metrics

To assess the system’s performance, three categories of metrics were defined:

• Detection Metrics: accuracy, precision, recall, and F1-score for the AI-based damage classifier.

• Prediction Metrics: root mean square error (RMSE) between predicted and measured structural responses (displacement, acceleration).

• System Metrics: latency, computational load, and data throughput in simulation time operation.

The quantitative definitions are as follows:

 (24)

where TP, TN, FP, and FN are true/false positive/negative counts, and *yi*,  denote measured and predicted responses respectively.

## Detection Accuracy and Sensitivity

The trained AI model was evaluated using a database of simulated vibration data (N = 10,000 samples) representing four damage levels: none, minor, moderate, severe.

**Table 3.** Summary of the Confusion Matrix Results

| **Damage Level** | **Precision** | **Recall** | **F1-score** |
| --- | --- | --- | --- |
| None | 0.98 | 0.97 | 0.97 |
| Minor | 0.94 | 0.91 | 0.92 |
| Moderate | 0.95 | 0.96 | 0.95 |
| Severe | 0.99 | 0.98 | 0.98 |

The overall classification accuracy reached 96.3%, demonstrating that the model can reliably differentiate among subtle damage states under varying seismic intensities. Feature importance analysis indicated that fractional change in resistivity (FCR) contributed 42% of the total information gain, followed by modal frequency shift (33%) and damping variation (25%).

## Digital-Twin Prediction and Model Updating

The digital twin was continuously updated during the simulated seismic event using the Extended Kalman Filter defined in Eq. (9). Comparing predicted and measured deck displacements yielded an RMSE = 0.018 m, equivalent to 3.4% of peak displacement amplitude. The twins’ dynamic stiffness estimation converged within 5 iterations (less than 1 s real-time delay). The stiffness-degradation map generated by Eq. (18) may contain useful insights for inspection engineers. These results show the digital twin’s ability to reproduce physical deterioration processes accurately.

# Sensitivity and Robustness Analysis

A sensitivity study was conducted to evaluate the influence of key parameters on system performance:

• Sensor density: reducing sensor count by 50% decreased classification accuracy by only 6%, indicating redundancy and scalability.

• Environmental variation: temperature fluctuations (±10◦C) affected resistivity-based features by < 4%, confirming effective compensation.

• Noise contamination: up to 15 dB SNR degradation led to < 8% performance loss due to robust feature normalization and filtering.

These results emphasize that the framework maintains stability and reliability under realistic environmental and operational variability.

## Discussion of Practical Implementation

While the results demonstrate excellent performance, several practical considerations arise: durability of self-sensing materials: long-term stability of conductive networks under cyclic loading and freeze–thaw cycles must be further studied; Standardization: international SHM codes currently lack provisions for self-sensing materials and digital twin integration; policy development is required.

## Summary of Findings

The case study demonstrates that the integrated SHM–AI–Digital Twin framework:

• Achieves > 95% damage classification accuracy.

• Provides actionable resilience indicators for immediate post-earthquake assessment.

These outcomes highlight the transformative potential of combining functional materials, machine learning, and cyber-physical modeling in advancing next-generation SHM for seismic resilience.

# CONCLUSION

This study proposed and demonstrated a next-generation Structural Health Monitoring (SHM) framework for earthquake-resilient bridge infrastructure, integrating self-sensing materials, artificial intelligence (AI), and digital-twin technologies into a unified cyber-physical system. The major scientific contributions can be summarized as follows:

• Smart material modeling: Derived electrical–mechanical relations (1)–(5) describing the piezoresistive behavior of self-sensing concrete, establishing its role as a multifunctional structural–sensing medium.

• AI-driven inference: Developed a hybrid machine-learning framework that fuses vibration and resistivity data for real-time damage detection and prediction, achieving classification accuracy exceeding 95%.

• Digital-twin coupling: Formulated an adaptive twin that continuously updates structural stiffness and residual capacity based on sensor-derived damage indices, reducing estimation error to an acceptable level.

• End-to-end SHM pipeline: Demonstrated the full operational workflow—from data acquisition to decision support—on a RC bridge model subjected to seismic excitation, confirming effective resilience assessment through the RI index.

Collectively, these results confirm that merging functional materials and AI-based analytics within a digital-twin environment can transform SHM from passive monitoring to active resilience management.

Despite promising outcomes, several limitations remain:

• The study used a simulation data; long-term field validation under real earthquake loading is still required.

• The stability of conductive networks in self-sensing concrete under sustained mechanical fatigue, chloride exposure, and temperature cycling must be quantified.

• AI performance depends on data diversity; rare or extreme seismic events may still produce prediction bias without continual retraining.

• The current framework assumes reliable network connectivity; future deployments should incorporate redundant communication and fail-safe edge analytics.

To advance the proposed framework toward widespread adoption, future work should focus on:

• Full-scale field implementation: deploy permanent self-sensing patches and wireless nodes on operational bridges, particularly in high-seismic zones, to build long-duration datasets for model refinement.

• Quantum-inspired and physics-informed AI: exploit hybrid algorithms that combine quantum optimization and physics constraints to enhance interpretability and computational eﬀiciency.

• Integration with digital twins of transportation networks: connect multiple bridge twins into a regional “infrastructure metaverse” for network-level seismic resilience assessment.

• Durability and standardization studies: establish design guidelines, calibration standards, and long-term performance metrics for self-sensing materials.

• Autonomous decision systems: couple SHM data with reinforcement-learning agents capable of adaptive traﬀic management, automated inspection scheduling, and emergency control.

This work demonstrates that bridges can evolve from inert structures into intelligent entities capable of perceiving, learning, and adapting in real time. By combining self-sensing concrete, artificial intelligence, and digital-twin technology, the proposed SHM framework provides a scalable pathway toward data-driven, resilient, and sustainable infrastructure systems. As the convergence of materials science and computational intelligence continues, such integrated approaches are expected to redefine the philosophy of structural safety—from periodic inspection to continuous self-awareness.

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