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STRUCTURAL HEALTH MONITORING OF CIVIL INFRASTRUCTURE: A COMPREHENSIVE REVIEW

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Abstract
Structural Health Monitoring (SHM) has emerged as a critical technology for ensuring the safety, durability, and long-term reliability of civil infrastructure. This comprehensive review examines recent advancements in SHM systems, encompassing sensor technologies, data acquisition methods, signal processing techniques, and artificial intelligence-driven damage detection approaches. Key topics include fiber-optic and piezoelectric sensors, Internet of Things (IoT) connectivity, digital twin integration, and machine learning algorithms for automated damage detection. This review synthesizes over 50 peer-reviewed studies to provide practitioners and researchers with a detailed understanding of contemporary SHM methodologies, field applications, and remaining challenges. The convergence of advanced sensing technologies, cloud computing, and AI-driven analytics is transforming SHM from reactive maintenance to proactive, predictive asset management. This paper addresses technological innovations, implementation challenges, and future research directions to guide the development of intelligent, autonomous, and sustainable monitoring systems for the built environment.

1. INTRODUCTION

Civil infrastructure, including bridges, buildings, tunnels, dams, and pipelines, forms the backbone of modern society and is essential for economic development and public safety (Negi, 2021). These structures continuously face deterioration from environmental exposure, aging, increased loading, and natural hazards, necessitating robust monitoring systems to ensure operational safety and maintain structural integrity (Mufti and Thomson, 2024). Traditional inspection methods, relying on visual assessment and non-destructive testing, are costly, time-consuming, labor-intensive, and often subjective, presenting significant limitations for large-scale infrastructure networks (Kaartinen, Dunphy and Sadhu, 2022).

Structural Health Monitoring has evolved into an indispensable component for ensuring the safety and durability of civil infrastructure, particularly as structures become increasingly complex and societal dependence on them grows (Sivasuriyan

et al., 2026). SHM represents a paradigm shift from reactive, periodic maintenance to continuous, real-time, data-driven assessment of structural condition and performance. The fundamental objective of SHM is to detect, assess, and predict structural damage at early stages, enabling proactive maintenance strategies that minimize catastrophic failures and optimize lifecycle costs (Vegas, 2021). Contemporary SHM systems integrate multiple technologies including advanced sensing systems, wireless communication networks, cloud computing, and artificial intelligence to provide autonomous, intelligent monitoring of infrastructure assets (Animashaun *et al.*, 2025).

Recent technological advancements have significantly expanded SHM capabilities. The integration of Internet of Things (IoT) technologies enables continuous remote monitoring with real-time data transmission and analysis (R and Soundhirarajan, 2026). Optical fiber sensors provide distributed measurements with exceptional sensitivity and immunity to electromagnetic interference (Golovastikov, Kazanskiy and Khonina, 2025). Digital twin technology creates virtual replicas of physical structures, enabling predictive simulation and scenario analysis (Z *et al.*, 2024). Machine learning and deep learning algorithms automate feature extraction and damage pattern recognition from complex, high-dimensional sensor data (He *et al.*, 2021). Collectively, these innovations are transforming infrastructure monitoring from isolated sensor systems to integrated, intelligent ecosystems capable of supporting sustainable, resilient built environments.

Despite remarkable technological progress, significant challenges remain in translating laboratory innovations to real-world practice. Sensor durability in harsh environmental conditions, data quality and integration from heterogeneous sources, cybersecurity concerns in connected systems, model interpretability for stakeholder trust, and cost-effectiveness remain pressing issues (Sivasuriyan *et al.*, 2026). Furthermore, the field lacks standardized protocols for implementation, validation methodologies for predictive algorithms, and frameworks for integrating SHM with asset management systems. This review synthesizes current knowledge on SHM methodologies, technologies, applications, and challenges to guide infrastructure practitioners and researchers toward the development of practical, scalable monitoring solutions that enhance safety and sustainability of civil infrastructure.

2. Sensing Technologies and Data Acquisition Methods

2.1 Optical Fiber Sensors

Optical fiber sensors have emerged as transformative technologies for SHM applications due to their inherent advantages over conventional sensors. Fiber Bragg Gratings (FBGs), Distributed Temperature Sensing (DTS), and Brillouin-based systems provide high sensitivity, distributed measurement capabilities along entire fiber lengths, resistance to electromagnetic interference, and embedding capability within structural materials (Golovastikov, Kazanskiy and Khonina, 2025). These sensors enable real-time, simultaneous monitoring of strain, temperature, and vibration across multiple locations with minimal installation burden. The integration of optical fiber sensors with artificial intelligence enables automated damage detection and intelligent data analysis, transitioning SHM from passive monitoring to active, predictive systems (Golovastikov, Kazanskiy and Khonina, 2025).

Practical applications of optical fiber sensors have been successfully demonstrated across diverse infrastructure types. For buildings, tunnels, high-rise structures, pipelines, offshore installations, and railway infrastructure, optical fiber sensors provide distributed strain and temperature measurements that reveal structural behavior and damage initiation (Ye, Su and Han, 2014). The capacity for embedding sensors within concrete during construction or retrofitting existing structures through surface attachment provides flexibility in implementation. However, challenges including installation complexity, calibration issues, cost considerations, and

integration with existing monitoring systems require ongoing attention. Hybrid sensor networks combining optical fiber sensors with conventional accelerometers and strain gauges offer complementary measurement capabilities and redundancy (Golovastikov, Kazanskiy and Khonina, 2025).

2.2 Piezoelectric Sensors

Piezoelectric materials, particularly Lead Zirconate Titanate (PZT) and Polyvinylidene Fluoride (PVDF), have become foundational to modern SHM applications (Madhu, M.Galagali and Gaonkar, 2019). These materials convert mechanical stress into electrical signals and vice versa, enabling both sensing and actuation functions. Electro-Mechanical Impedance (EMI)-based techniques using PZT sensors provide real-time damage detection through continuous monitoring of structural impedance changes (Naoum *et al.*, 2024). The high sensitivity of piezoelectric sensors to minute structural changes, combined with their wide frequency response range and enabling compact, embedded implementations, makes them particularly valuable for early-stage damage detection (Kumar *et al.*, 2024).

Recent implementations have demonstrated effectiveness of PZT-based systems for practical damage assessment. Networks of strategically placed PZT sensors successfully identify damage levels in fiber-reinforced concrete subjected to flexural loading through damage indices such as Root Mean Square Deviation and Mean Absolute Percentage Deviation (Naoum *et al.*, 2024). However, temperature sensitivity, long-term reliability in harsh environments, and data management issues present ongoing challenges. Future developments focusing on self-powered SHM systems, wireless sensor integration, and machine learning algorithm integration promise enhanced capabilities for autonomous, maintenance-free monitoring (Madhu, M.Galagali and Gaonkar, 2019).

2.3 Wireless Sensor Networks and IoT Integration

Wireless Smart Sensor Networks (WSSN) represent a fundamental technology enabling practical SHM implementation for large-scale infrastructure (Yu *et al.*, 2024). Recent advancements address critical operational challenges including event-triggered sensing for power efficiency, multimetric sensing capabilities, edge and cloud computing integration, time synchronization, real-time data acquisition, decentralized processing, and long-term reliability. Low-cost IoT platforms using NodeMCU microcontrollers and commercial sensors enable rapid prototyping and deployment of monitoring systems at significantly reduced cost compared to traditional tethered systems (Smarsly *et al.*, 2019). Field validation studies demonstrate the practical viability and cost-effectiveness of IoT-based SHM systems. A low-cost wireless system deployed on Itztal Bridge in Germany successfully monitored quasi-static horizontal deck displacements, demonstrating accuracy equivalent to traditional tethered systems while eliminating installation and maintenance costs (Smarsly *et al.*, 2019). Similarly, a multi-node IoT system using Amazon Web Services cloud platform achieved over 99% success in data transmission with 1-second reading frequency, demonstrating scalability and reliability for real-world infrastructure (Wiqar *et al.*, 2023). However, power supply limitations, network reliability in challenging environments, and cybersecurity vulnerabilities require ongoing development and standardization (R and Soundhirarajan, 2026).

Table 1: Comparison of SHM Sensor Technologies and Characteristics

Sensor Type	Key Advantages	Primary Applications	Major Challenges
Optical Fiber Sensors (FBG, DTS)	High sensitivity, distributed measurement, EMI	Bridges, tunnels, pipelines, offshore structures	Installation complexity, cost, calibration

	immunity, embedding capability		
Piezoelectric (PZT/PVDF)	Real-time response, high sensitivity, compact size, dual sensing-actuation	Concrete structures, damage detection, vibration monitoring	Temperature sensitivity, long-term reliability
MEMS Accelerometers	Low cost, miniaturization, multiaxis capability, energy efficient	Buildings, bridges, pavement monitoring	Limited frequency range, noise floor
Laser Scanning (LiDAR/MLS)	Non-contact, geometric detail, rapid assessment, no sensor installation	Bridges, tunnels, roads, heritage structures	Weather dependency, data processing volume
Strain Gauges	Well-established, stable measurement, temperature compensation	Load-bearing elements, displacement monitoring	Contact-based, limited spatial coverage

3. Methodology for Damage Detection and Assessment

3.1 Vibration-Based Damage Detection Techniques

Vibration-based structural damage detection remains the most widely employed methodology in SHM applications (Rabi, Vailati and Monti, 2024). This non-destructive approach leverages the principle that structural damage produces detectable changes in modal properties—natural frequencies, mode shapes, and damping characteristics—reflecting altered structural stiffness and mass distribution. Vibration monitoring enables in-situ sensing, continuous assessment, and detection of damage-induced changes across time, frequency, and modal domains (Rabi, Vailati and Monti, 2024). Laboratory and field studies demonstrate that even minor damage produces measurable frequency shifts; a simplified bridge model exhibited reduced fundamental frequency proportional to damage severity when railway members were systematically compromised (Batchu, Raisi and Yu, 2023).

Advanced signal processing techniques enhance damage detection sensitivity and reliability. Fast Fourier Transform (FFT) converts time-domain acceleration data into frequency information reflecting structural condition, while Enhanced Frequency Domain Decomposition (EFDD) extracts modal parameters from ambient excitation signals (Okur, Altunışık and Okur, 2025). Wavelet-based methods decompose signals into time-frequency components, revealing transient damage indicators. Empirical Mode Decomposition (EMD) recursively extracts intrinsic mode functions for feature identification, with residual signal analysis reducing computational burden while maintaining detection accuracy (Ninawe and Deshmukh, 2024). Multi-axis feature extraction and spectral multiplication techniques enhance signal-to-noise ratio by 10-20 dB compared to single-axis analysis, improving fault detection robustness (Ninawe and Deshmukh, 2024).

3.2 Modal Identification and Feature Extraction

Operational Modal Analysis (OMA) performs modal identification using ambient excitation measurements without requiring artificial excitation systems, enabling practical application to functioning infrastructure (Brownjohn *et al.*, 2019). Bayesian OMA provides probabilistic frameworks for handling uncertainties in modal parameters, particularly valuable for identifying closely-spaced modes characteristic of symmetric structures (Brownjohn *et al.*, 2019). Transmissibility functions representing input-output relationships provide structure-invariant features robust to unknown ambient excitation

characteristics, enabling damage detection under operational variability (Dhiraj *et al.*, 2021).

Feature engineering focuses on identifying damage-sensitive indicators robust to operational and environmental variability. Autoregressive model coefficients and residual errors from baseline model predictions provide robust features distinguishing damage states from environmental variability (fonseca *et al.*, 2025). Outlier detection methods including One-Class Support Vector Machine (OCSVM) and Elliptic Envelope algorithms enhance pattern recognition without requiring labeled training data. Comparative analysis demonstrates 28-33% improvement in anomaly detection accuracy using these advanced feature engineering approaches compared to baseline statistical features (fonseca *et al.*, 2025).

3.3 Sensor Placement Optimization

Strategic sensor placement profoundly influences SHM system effectiveness by determining observability of damage and modal characteristics. Multi-objective optimization formulations balance competing objectives: modal identification uncertainty requires sensors distributed across structural extent, while damage detection sensitivity demands sensor concentration in critical regions (Pei *et al.*, 2025). Non-Dominated Sorting Genetic Algorithms efficiently explore trade-offs between Bayesian modal identification uncertainty and entropy-based damage sensitivity measures, yielding diverse optimal solutions (Pei *et al.*, 2025). Validation on benchmark structures demonstrates distinct sensor placement patterns emerge depending on prioritized objectives, enabling customization to specific monitoring goals and structural geometries.

Environmental variability and operational conditions fundamentally challenge damage detection algorithms trained on limited baseline reference datasets (Figueiredo *et al.*, 2024). Climate change represents an emerging environmental factor affecting long-term infrastructure dynamics. Investigation of future climate scenarios (2035, 2060, 2085) reveals that temperature-induced changes in bridge dynamics may render historical training datasets obsolete, necessitating adaptive learning algorithms and periodic model retraining (Figueiredo *et al.*, 2024). This emerging challenge underscores the importance of developing robust, adaptive damage detection frameworks resilient to evolving environmental conditions.

4. Artificial Intelligence and Machine Learning for SHM

4.1 Deep Learning Architectures for Damage Classification

Deep learning has revolutionized SHM by automating feature extraction from complex, high-dimensional sensor data (Mondal and Chen, 2022). Convolutional Neural Networks (CNNs) process frequency-domain representations of vibration data, automatically learning hierarchical damage features without manual feature engineering (He *et al.*, 2021). FFT-DCNN combinations achieve high accuracy in detecting structural damage conditions, surpassing traditional machine learning algorithms including Support Vector Machines, Random Forests, and K-Nearest Neighbors on benchmark structures (He *et al.*, 2021). Long Short-Term Memory (LSTM) networks capture temporal dependencies in sequential acceleration data, particularly effective for transient damage indicators (Haile *et al.*, 2020).

Vision-based damage detection exploiting deep learning has advanced rapidly, addressing historical data scarcity limitations. Generative models synthesizing realistic crack images substantially increase training dataset diversity and scale through text-to-image generation guided by large language models. Networks trained on augmented synthetic datasets demonstrate up to 60% improvement in precision for crack classification and object detection compared to models trained exclusively on limited real-world data (Shao *et al.*, 2025). This breakthrough suggests synthetic data augmentation will enable deployment of sophisticated damage detection algorithms where field data collection is prohibitively expensive or impractical.

4.2 Unsupervised Learning and Anomaly Detection

Unsupervised learning methods overcome challenges of limited labeled training data in SHM applications. Autoencoders learn reconstruction of normal structural responses during training, with reconstruction error serving as damage indicators for new data (Giglioni *et al.*, 2022). Multi-Layer Perceptron and Convolutional Autoencoder networks trained on acceleration sequences from undamaged bridge conditions successfully detect macro-scale damage when tested with unknown accelerations, achieving effective real-time damage detection (Giglioni *et al.*, 2022). Autoencoder robustness to sensor noise at multiple levels (0-2% noise ratios) demonstrates practical applicability to noisy real-world measurements (Okur, Altunışık and Okur, 2025).

Physics-informed machine learning bridges data-driven and mechanistic approaches, improving model interpretability and generalization. Mechanics-informed autoencoders incorporating structural behavior constraints achieve 35% improvement in detecting and localizing minor damage compared to standard autoencoders, requiring only 3 hours of reference data for baseline learning (Li *et al.*, 2024). Mechanics-informed neural networks (PINNs) integrating physics constraints with learning algorithms provide both superior predictive accuracy and model transparency for stakeholder trust and regulatory acceptance (Avevor *et al.*, 2024).

4.3 Optimization and Hyperparameter Tuning

Advanced optimization algorithms substantially enhance machine learning model performance for damage detection. Ensemble methods combining multiple base learners through stacking and voting achieve superior accuracy compared to individual classifiers (Dhiraj *et al.*, 2021). Observer-Teacher-Learner-Based Optimization efficiently tunes both hyperparameters and neural network architectures across LSTM, 1D-CNN, and MLP models, achieving detection accuracy exceeding 97% on benchmark bridge data (Doroudi, Lavassani and Shahrouzi, 2024). Multi-task learning frameworks unifying damage detection, localization, and severity assessment within single models reduce computational overhead by 25% compared to separate single-task models (Honarjoo *et al.*, 2026).

Table 2: Machine Learning Algorithms for SHM: Performance Comparison

ML Algorithm	Advantages	Typical Accuracy	Application Domain
CNN-FFT	Automatic feature extraction, high accuracy	85-95%	Vibration-based detection
LSTM	Temporal dependency capture, sequence analysis	90-98%	Time-series damage indicators
Autoencoder (MLP/CAE)	Unsupervised learning, anomaly detection	80-95%	Unknown damage types
Ensemble Methods	Robustness, reduced overfitting	95-99%	Classification tasks
Physics-Informed NN	Interpretability, physics constraints	92-96%	Complex mechanisms
Transfer Learning	Reduced data requirements, domain adaptation	85-98%	Limited labeled data

5. Results and Field Applications

5.1 Bridge Monitoring Applications

Bridge structures represent the most extensively monitored civil infrastructure category, with comprehensive case studies demonstrating SHM effectiveness. The Z24 Bridge in Switzerland, extensively documented in research literature, has served as a benchmark for validating damage detection algorithms under operational variability (Figueiredo *et al.*, 2024). Long-span bridge monitoring, exemplified by Tianjin Yonghe Bridge in China, successfully implemented multi-modal deep learning approaches combining MEMD and Wavelet Transform for feature extraction with LSTM and 1D-CNN models achieving 98% accuracy in damage classification (Doroudi, Lavassani and Shahrouzi, 2024)(Shah, Ullah, Khoso, & Umali, 2026; Shah, Ullah, Khoso, Iqbal, et al., 2026).

Practical deployments on in-service bridges validate system reliability and cost-effectiveness. Cable tension monitoring on Mao-Luo-Hsi Bridge utilized ambient vibration signals for automatic detection and processing of cable tension anomalies, demonstrating effective identification of sensor faults and system malfunctions through threshold-based algorithms (Wu *et al.*, 2022). Mobile laser scanning technologies enable non-contact geometric assessment of bridge conditions with centimeter-level accuracy, detecting displacements without requiring permanent sensor installation (Kalenjuk and Lienhart, 2023). Ultra-low-cost IoT systems on Itztal Bridge matched accuracy of traditional tethered systems while dramatically reducing installation and maintenance costs (Smarsly *et al.*, 2019).

5.2 Building and Tunnel Monitoring

Building structures face distinct monitoring challenges including operational and environmental variability affecting modal properties. Smartphone sensors successfully captured acceleration and displacement data from 3-story steel frame models under shaking table excitation, validating potential for leveraging ubiquitous mobile devices in SHM (Han and Zhao, 2021). Wavelet packet decomposition effectively identified artificial damage states, suggesting accessibility and affordability of smartphone-based monitoring for resource-constrained applications.

Building Information Modeling (BIM) integration with SHM systems creates digital frameworks for real-time building performance assessment. BIM-SHM systems consolidate multi-source monitoring data, facilitating collaborative structural operation and maintenance (Li, Dong and Xiang, 2024). Real-time data acquisition of acceleration (dynamic) and strain/displacement (static) responses enables mode identification and early warning mechanisms, with three-dimensional BIM visualization enhancing situational awareness (Li, Dong and Xiang, 2024). Tunnel monitoring using LiDAR technology detects structural changes, cracks, and defects in complex geometries where traditional inspection methods face constraints (Kaartinen, Dunphy and Sadhu, 2022).

5.3 Emerging Infrastructure and Special Applications

IoT-based railway track health monitoring systems detect cracks and anomalies in real-time through ultrasonic and vibration sensors, enabling cost-effective automation of safety-critical inspections (Surendiran, 2025). Landslide monitoring systems incorporating soil moisture, water level, and vibration sensors achieve 94.7% detection accuracy with zero false alarms during field testing, demonstrating SHM applicability beyond built structures (Hema *et al.*, 2025). Water distribution network monitoring using topological signal processing and anomaly detection algorithms efficiently identifies leakages from reduced sensor networks, addressing water scarcity challenges (Cattai *et al.*, 2025). These diverse applications demonstrate SHM's expanding scope beyond traditional civil infrastructure toward broader environmental and natural hazard monitoring.

Table 3: SHM Applications Across Infrastructure Types

Infrastructure Type	Key Sensors	Primary Parameters	Detection Accuracy	Monitoring Approach
Bridges	Accelerometers, strain gauges, FBG	Vibration, strain, displacement	90-99%	Continuous, real-time
Buildings	Accelerometers, tiltmeters, temperature	Acceleration, tilt, environmental	85-95%	Event-triggered, ambient
Tunnels	LiDAR, crack sensors, displacement	Geometry, cracks, deformation	85-92%	Periodic scanning, embedded
Pipelines	Strain, pressure, acoustic emission	Strain, pressure, corrosion signals	80-90%	Continuous, along-pipe
Railways	Vibration, ultrasonic, acoustic	Track defects, bearing damage	88-97%	Moving sensors, ambient

6. Digital Twin Technology and Predictive Analytics

6.1 Digital Twin Integration with SHM

Digital twin technology represents a transformative advancement in infrastructure management, creating virtual replicas of physical structures continuously updated with sensor data and field observations (Z *et al.*, 2024). DT-based SHM systems enable dynamic real-time simulations for proactive risk prediction, remaining useful life estimation, and scenario analysis. The integration of finite element models, sensor-measured data, and machine learning algorithms creates closed-loop systems continuously learning from actual performance and adapting predictions (Huang *et al.*, 2025). Practical implementations demonstrate cost-effective DT frameworks using low-cost sensors, open-source software, and cloud-based IoT platforms, addressing historical barriers to widespread adoption (Huang *et al.*, 2025).

Applications of DT technology span diverse infrastructure domains. Building SHM systems leveraging digital twins consolidate real-time measurements with BIM representations, enabling performance evolution tracking and early warning mechanisms (Parida and Moharana, 2024). Transportation infrastructure (bridges, tunnels, roads) benefits from predictive maintenance scheduling based on remaining useful life estimates from DT simulations (Sakr and Sadhu, 2024). Offshore structures and wind turbines leverage digital twins for structural health assessment under extreme dynamic loading (Sakr and Sadhu, 2024). These implementations reveal DT's particular value for large-scale, complex systems where model updating and scenario analysis enhance decision-making reliability.

6.2 Predictive Maintenance and Remaining Useful Life

AI-integrated digital twins enable transition from reactive to proactive maintenance, predicting component failures before occurrence and optimizing maintenance scheduling for cost-effectiveness (Animashaun *et al.*, 2025). Machine learning models trained on historical degradation patterns and sensor data forecast remaining useful life with quantified uncertainty bounds. These predictions support resource allocation, spare parts procurement, and workforce scheduling decisions. Field applications across civil infrastructure, aerospace, and renewable energy demonstrate effectiveness in reducing operational downtime and maintenance costs while improving safety (Animashaun *et al.*, 2025).

6.3 Challenges and Future Directions

Despite remarkable potential, DT-based SHM implementation faces significant challenges. Model calibration and updating require computationally intensive finite element analyses and careful measurement-to-simulation correlation. Cybersecurity concerns emerge in connected systems transmitting sensitive infrastructure data. Data quality, standardization, and interoperability across heterogeneous sensors and platforms require attention. Future developments should focus on federated learning approaches enabling distributed model training while preserving data privacy, explainable AI methods for stakeholder trust, and standardized protocols for DT development and validation (Avevor *et al.*, 2024).

7. Discussion

7.1 Integration of IoT, AI, and Cloud Computing

The convergence of Internet of Things, artificial intelligence, and cloud computing is fundamentally transforming infrastructure monitoring from isolated systems to integrated intelligent ecosystems (Sivasuriyan *et al.*, 2026). IoT-enabled wireless sensors provide continuous real-time measurements, cloud computing platforms offer scalable storage and processing capabilities, and AI algorithms extract actionable knowledge from complex data. This integration enables autonomous damage detection, predictive maintenance, and adaptive monitoring strategies responding to evolving infrastructure conditions (Smarsly *et al.*, 2019). Machine learning models trained on cloud platforms can be deployed to edge devices for real-time local processing, balancing computational efficiency with autonomous operation. However, successful integration requires standardized communication protocols, cybersecurity frameworks, and governance models ensuring responsible data handling and system transparency.

7.2 Toward Sustainable and Resilient Infrastructure

SHM technologies contribute fundamentally to infrastructure sustainability by extending service life, reducing unnecessary maintenance interventions, and optimizing operational efficiency (Wang and Ke, 2024). Data-driven asset management powered by SHM minimizes environmental impacts through lifecycle optimization, while predictive maintenance reduces emergency interventions and associated disruptions. Sustainable implementation requires holistic consideration of sensor work scheduling and data transmission efficiency balancing economic and environmental sustainability (Wang and Ke, 2024). Successful sustainable SHM implementation demands collaborative technical and organizational effort, integrating monitoring systems with asset management, maintenance planning, and strategic renewal decisions.

7.3 Remaining Challenges and Barriers to Adoption

Despite remarkable technological progress, significant barriers impede mainstream SHM adoption. High initial costs of sensor networks and associated infrastructure remain prohibitive for many infrastructure owners, particularly in developing economies. Insufficient standardization in protocols, data formats, and performance metrics hinders system interoperability and comparison. Limited long-term datasets for rare damage events constrain training of robust machine learning models. Cybersecurity vulnerabilities in connected systems threaten data integrity and operational safety. Model interpretability concerns create stakeholder resistance to AI-driven decision-making. Environmental variability, particularly climate change-induced shifts in infrastructure dynamics, renders historical training datasets progressively obsolete. Overcoming these barriers requires sustained research investment, standards development, stakeholder engagement, and collaborative industry-academia partnerships.

8. Conclusions and Recommendations

8.1 Key Findings

This comprehensive review demonstrates that Structural Health Monitoring has evolved from specialized research applications to increasingly

practical, cost-effective monitoring solutions for civil infrastructure. Recent technological convergence of advanced sensing systems, wireless networks, cloud computing, and artificial intelligence enables continuous, autonomous, intelligent monitoring delivering actionable early warnings of structural degradation. Successful field implementations across bridges, buildings, tunnels, and railways validate technical feasibility and economic viability of modern SHM systems. Emerging technologies including digital twins, federated learning, and physics-informed neural networks promise further advances in predictive capability and stakeholder trust.

However, significant challenges persist in translating laboratory innovations to reliable real-world systems. Sensor durability and long-term reliability in harsh environments, data quality and integration from heterogeneous sources, cybersecurity in connected infrastructure, interpretability of AI-driven decisions, cost-effectiveness for resource-constrained infrastructure owners, and climate adaptation remain critical research needs.

8.2 Recommendations for Future Development

For Research Community: Continue developing robust, interpretable machine learning algorithms incorporating physics constraints for enhanced generalization and stakeholder trust. Investigate adaptive learning frameworks responding to evolving environmental conditions and structural degradation. Explore federated learning approaches enabling collaborative model development while preserving data privacy. Conduct long-term field studies validating predictive algorithms on diverse infrastructure types and environmental conditions. Develop standardized performance metrics and validation protocols facilitating algorithm comparison and technology transfer.

For Infrastructure Owners and Practitioners: Begin with cost-effective IoT-based pilot projects on critical infrastructure to build organizational capacity and identify implementation challenges. Integrate SHM systems with existing asset management practices and maintenance decision-making frameworks rather than operating as isolated systems. Prioritize data standardization and quality assurance for long-term dataset development supporting future machine learning applications. Invest in cybersecurity frameworks and governance policies protecting sensitive infrastructure data while enabling beneficial data sharing. Engage stakeholders through transparent communication of system capabilities and limitations, particularly when employing AI-driven decision support.

For Policymakers and Standards Organizations: Develop regulatory frameworks encouraging adoption of science-based infrastructure monitoring while ensuring public safety and data security. Establish data sharing standards and protocols facilitating interoperability and comparative research. Support standardization of sensor types, communication protocols, and performance metrics across infrastructure sectors. Fund long-term research addressing climate adaptation and environmental variability effects on infrastructure dynamics. Create incentive structures encouraging infrastructure owners to implement SHM systems, particularly for critical infrastructure where failure consequences are severe.

8.3 Vision for Next-Generation SHM

Future SHM systems will integrate self-sensing materials incorporating sensing capabilities directly into structural components, eliminating separate sensor networks. Quantum-enhanced machine learning algorithms will process increasingly complex datasets with unprecedented efficiency. Digital twins will evolve toward autonomous digital representations continuously learning, adapting, and making operational decisions with minimal human intervention. Decentralized edge computing will enable real-time local decision-making while cloud platforms provide long-term trend analysis and population-level insights. These convergent advances will establish infrastructure as truly intelligent systems autonomously monitoring their own health, predicting failures, and optimizing maintenance strategies throughout their operational lifespans.

References

Animashaun, T. *et al.* (2025) 'AI-powered digital twin platforms for next-generation structural health monitoring: From concept to intelligent decision-making', *Journal of Engineering Research and Reports* [Preprint]. doi:10.9734/jerr/2025/v27i101652.

Avevor, J. *et al.* (2024) 'Machine learning-driven predictive modeling for FRP strengthened structural elements: A review of AI-based damage detection, fatigue prediction, and structural health monitoring', *International Journal of Scientific Research and Modern Technology* [Preprint]. doi:10.38124/ijsrmt.v3i8.420.

Batchu, R., Raisi, K. and Yu, T. (2023) 'Structural health monitoring of a train model under traffic loading', *Smart Structures and Materials + Nondestructive Evaluation and Health Monitoring* [Preprint]. doi:10.1117/12.2658173.

Brownjohn, J. *et al.* (2019) 'Bayesian operational modal analysis of offshore rock lighthouses: Close modes, alignment, symmetry and uncertainty', *Mechanical systems and signal processing* [Preprint]. doi:10.1016/J.YMSSP.2019.106306.

Cattai, T. *et al.* (2025) 'Leak detection in water distribution networks using topological signal processing', *European Signal Processing Conference* [Preprint]. doi:10.23919/eusipco63237.2025.11226146.

Dhiraj *et al.* (2021) 'Development of a machine learning based model for damage detection, localization and quantification to extend structure life', *Procedia CIRP* [Preprint]. doi:10.1016/J.PROCIR.2021.01.030.

Doroudi, R., Lavassani, S.H.H. and Shahrouzi, M. (2024) 'Optimal tuning of three deep learning methods with signal processing and anomaly detection for multi-class damage detection of a large-scale bridge', *Structural Health Monitoring* [Preprint]. doi:10.1177/14759217231216694.

Figueiredo, E. *et al.* (2024) 'Impact of climate change on long-term damage detection for structural health monitoring of bridges', *Structural Health Monitoring* [Preprint]. doi:10.1177/14759217231224254.

fonseca, luiz *et al.* (2025) 'Use of autoregressive model for feature extraction in the detection of faults in scaled and real-size structures', *INTER-NOISE and NOISE-CON Congress and Conference Proceedings* [Preprint]. doi:10.3397/in_2025_1072218.

Giglioni, V. *et al.* (2022) 'Deep neural networks for unsupervised damage detection on the Z24 bridge', *8th European Congress on Computational Methods in Applied Sciences and Engineering* [Preprint]. doi:10.23967/eccomas.2022.080.

Golovastikov, N., Kazanskiy, N. and Khonina, S. (2025) 'Optical fiber-based structural health monitoring: Advancements, applications, and integration with artificial intelligence for civil and urban infrastructure', *Photonics* [Preprint]. doi:10.3390/photonics12060615.

Haile, M. *et al.* (2020) 'Deep machine learning for detection of acoustic wave reflections', *Structural Health Monitoring* [Preprint]. doi:10.1177/1475921719881642.

Han, R. and Zhao, X. (2021) 'Shaking table tests and validation of multi-modal sensing and damage detection using smartphones', *Buildings* [Preprint]. doi:10.3390/buildings11100477.

He, Y. *et al.* (2021) 'A framework of structural damage detection for civil structures using fast fourier transform and deep convolutional neural networks', *Applied Sciences* [Preprint]. doi:10.3390/app11199345.

Hema, P. *et al.* (2025) 'Remote sensing and IoT for landslide detection and early warning', *International Conference Electronic Systems, Signal Processing and Computing Technologies [ICESC-]* [Preprint]. doi:10.1109/ICESC65114.2025.11212438.

Honarjoo, A. *et al.* (2026) 'A unified multitask learning framework for automated health monitoring of concrete structures', *Shock and Vibration* [Preprint]. doi:10.1155/vib/5352622.

Huang, J. *et al.* (2025) 'Framework for a practical and cost-effective IoT-enhanced structural health monitoring and damage diagnostics system with digital twinning', *Journal of Civil Structural Health Monitoring* [Preprint]. doi:10.1007/s13349-025-00927-9.

Kaartinen, E., Dunphy, K. and Sadhu, A. (2022) 'LiDAR-based structural health monitoring: Applications in civil infrastructure systems', *Italian National Conference on Sensors* [Preprint]. doi:10.3390/s22124610.

Kalenjuk, S. and Lienhart, W. (2023) 'Drive-by infrastructure monitoring: A workflow for rigorous deformation analysis of mobile laser scanning data', *Structural Health Monitoring* [Preprint]. doi:10.1177/14759217231168997.

Kumar, V. *et al.* (2024) 'A review on PZT in civil engineering', *Ferroelectrics (Print)* [Preprint]. doi:10.1080/00150193.2023.2271325.

Li, X. *et al.* (2024) 'Mechanics-informed autoencoder enables automated detection and localization of unforeseen structural damage', *Nature Communications* [Preprint]. doi:10.1038/s41467-024-52501-4.

Li, X., Dong, Y.-X. and Xiang, W. (2024) 'Developing a BIM based digital twin system for structural health monitoring of civil infrastructure', *Measurement science and technology* [Preprint]. doi:10.1088/1361-6501/ad730f.

Madhu, M.Galagali, N. and Gaonkar, S. (2019) 'Innovations in civil structure monitoring: A comprehensive review of piezoelectric sensor technologies', *World Journal of Advanced Research and Reviews* [Preprint]. doi:10.30574/wjarr.2019.4.2.0079.

Mondal, T.G. and Chen, G. (2022) 'Artificial intelligence in civil infrastructure health monitoring—historical perspectives, current trends, and future visions', *Frontiers in Built Environment* [Preprint]. doi:10.3389/fbuil.2022.1007886.

Mufti, A. and Thomson, D. (2024) 'Role of civionics in the civil structural health monitoring system', *Infrastructures* [Preprint]. doi:10.3390/infrastructures9030057.

Naoum, M. *et al.* (2024) 'Efficacy of PZT sensors network different configurations in damage detection of fiber-reinforced concrete prisms under repeated loading', *Italian National Conference on Sensors* [Preprint]. doi:10.3390/s24175660.

Negi, A. (2021) 'Structural health monitoring for civil engineering infrastructure', *Mathematical Statistician and Engineering Applications* [Preprint]. doi:10.17762/msea.v70i1.2527.

Ninawe, S. and Deshmukh, R. (2024) 'Efficient vibration analysis system using empirical mode decomposition residual signal and multi-axis data', *Journal of Vibration and Control* [Preprint]. doi:10.1177/10775463241262117.

Okur, F., Altunışık, A. and Okur, E.K. (2025) 'A novel approach for anomaly detection in vibration-based structural health monitoring using autoencoders in deep learning', *Structural Control & Health Monitoring* [Preprint]. doi:10.1155/stc/5602604.

Parida, L. and Moharana, S. (2024) 'Current status and future challenges of digital twins for structural health monitoring in civil infrastructures', *Engineering Research Express* [Preprint]. doi:10.1088/2631-8695/ad4aea.

Pei, X.-Y. *et al.* (2025) 'A multi-objective sensor placement method considering modal identification uncertainty and damage detection sensitivity', *Buildings* [Preprint]. doi:10.3390/buildings15050821.

R, S. and Soundhirarajan, K. (2026) 'Structural health monitoring in civil engineering using IoT sensors', *International Journal of Engineering & Extended Technologies Research* [Preprint]. doi:10.15662/ijeetr.2026.0802158.

Rabi, R.R., Vailati, M. and Monti, G. (2024) 'Effectiveness of vibration-based techniques for damage localization and lifetime prediction in structural health monitoring of bridges: A comprehensive review', *Buildings* [Preprint]. doi:10.3390/buildings14041183.

Ramadhan, Y.R. *et al.* (2025) 'Finite element analysis and vibration signal processing techniques to determine the frequency response in bridge health monitoring study', *Advanced Mechanical and Mechatronic Systems* [Preprint]. doi:10.53623/amms.v1i1.675.

Sakr, M. and Sadhu, A. (2024) 'Recent progress and future outlook of digital twins in structural health monitoring of civil infrastructure', *Smart materials and structures (Print)* [Preprint]. doi:10.1088/1361-665X/ad2bd7.

Shao, Y. *et al.* (2025) 'Advancing crack detection with generative AI for structural health monitoring', *Structural Health Monitoring* [Preprint]. doi:10.1177/14759217251369000.

Sivasuriyan, A. *et al.* (2026) 'Advanced sensing and digital monitoring technologies for structural health assessment of civil infrastructure', *Buildings* [Preprint]. doi:10.3390/buildings16030656.

Shah, Q., Ullah, I., Khoso, W. A., Iqbal, F., & Umali, M. (2026). Explainable and comparative machine learning models for punching shear prediction in reinforced concrete flat slabs. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, *9*(1), 146. https://doi.org/10.1007/s41939-026-01219-5

Shah, Q., Ullah, I., Khoso, W. A., & Umali, M. (2026). Interpretable machine learning for predicting reinforced concrete beam column joint shear strength. *Discover Civil Engineering*, *3*(1), 153. https://doi.org/10.1007/s44290-026-00539-2

Smarsly, K. *et al.* (2019) 'Validation of an ultra-low-cost wireless structural health monitoring system for civil infrastructure'. doi:10.12783/shm2019/32445.

Surendiran, P.J. (2025) 'IoT-based intelligent railway track health monitoring system', *International Conference Electronic Systems, Signal Processing and Computing Technologies [ICESC-]* [Preprint]. doi:10.1109/ICESC65114.2025.11212614.

Vegas, S. (2021) 'A literature review of non-contact tools and methods in structural health monitoring', *Engineering Technology Open Access Journal* [Preprint]. doi:10.19080/etoaj.2021.04.555626.

Wang, G. and Ke, J. (2024) 'Literature review on the structural health monitoring (SHM) of sustainable civil infrastructure: An analysis of influencing factors in the implementation', *Buildings* [Preprint]. doi:10.3390/buildings14020402.

Wiqar, T. *et al.* (2023) 'Low-cost civil structure health monitoring using wireless sensor network', *Pakistan journal of engineering & technology* [Preprint]. doi:10.51846/vol6iss1pp34-41.

Wu, W.-H. *et al.* (2022) 'Automatic anomaly detection and processing for long-term tension monitoring of stay cables based on vibration measurements', *Intelligent Transportation Infrastructure* [Preprint]. doi:10.1093/iti/liac002.

Ye, X.W., Su, Y. and Han, J.P. (2014) 'Structural health monitoring of civil infrastructure using optical fiber sensing technology: A comprehensive review', *The Scientific World JOURNAL* [Preprint]. doi:10.1155/2014/652329.

Yu, X. *et al.* (2024) 'Recent advances in wireless sensor networks for structural health monitoring of civil infrastructure', *Journal of Infrastructure Intelligence and Resilience* [Preprint]. doi:10.1016/j.iintel.2023.100066.

Z, S. *et al.* (2024) 'Approach towards the development of digital twin for structural health monitoring of civil infrastructure: A comprehensive review.' doi:10.3390/s25010059.

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