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Advances, Applications, and Future Directions of Structural Health Monitoring in Civil Infrastructure: A Comprehensive Review

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A B S T R A C T

Structural Health Monitoring (SHM) has emerged as a core discipline in modern civil engineering, providing a systematic means to safeguard the safety, durability, and long-term functionality of infrastructure. This review synthesizes current advancements in SHM for civil infrastructure, beginning with its foundational concepts and classification schemes, and progressing through key sensing technologies and their applications across the built environment. From bridges, tunnels, and high-rise buildings to culturally significant heritage structures, SHM has proven effective in detecting early-stage damage, optimizing maintenance schedules, and supporting rapid response following natural disasters or other disruptive events. Despite these capabilities, widespread adoption remains constrained by persistent challenges. These include sensor calibration drift over extended service periods, environmental and operational variability that obscures damage signals, the overwhelming volume of monitoring data requiring timely interpretation, and the absence of universal data and system standards. In response, the research community is advancing solutions such as real-time digital twins, machine learning–driven analytics, autonomous and self-powered sensing devices, and seamless integration with Building Information Modelling (BIM) platforms. Looking ahead, the continued evolution of SHM lies in enhancing interoperability, automating data interpretation, and ensuring the reliability of monitoring systems over the entire service life of assets. Achieving these objectives will position SHM as not merely a diagnostic tool, but as an essential component of predictive maintenance, smart asset management, and resilience planning within an increasingly complex and dynamic built environment. This review highlights three dominant trends across recent SHM research: the rapid shift toward data-driven diagnostics, the emergence of digital twin–integrated monitoring frameworks, and the increasing adoption of fibre-optic and wireless sensing technologies in large-scale deployments. Collectively, these trends point to a sector moving steadily toward autonomous, real-time, and lifecycle-oriented structural management.

1. INTRODUCTION

The ageing of existing infrastructure, coupled with the increasing complexity of modern civil engineering systems, has heightened global concerns regarding structural safety, durability, and lifecycle performance. Within this context, Structural Health Monitoring (SHM) has evolved as a proactive, data-driven strategy that enables engineers to assess structural behaviour in real time or at predetermined intervals. By integrating advanced sensing devices, high-speed data acquisition systems, and intelligent interpretation algorithms, SHM facilitates the early detection of micro-cracks, material degradation, abnormal vibrations, and other subtle anomalies. Identifying such issues at an early stage not only helps prevent catastrophic failures but also extends the operational lifespan of critical infrastructure.

Early SHM practices were limited in scope, relying primarily on periodic visual inspections and simple mechanical measurement tools. However, rapid advancements in sensing materials, microelectronics, wireless communication, and automated diagnostics have transformed the field. Contemporary SHM systems now incorporate wireless sensor networks, robust edge computing, and machine learning algorithms capable of generating early warnings before damage escalates [1]. This technological evolution aligns with broader civil engineering objectives, including enhanced infrastructure resilience, condition-based maintenance, and predictive asset management. Notably, recent research has expanded SHM applications to structures incorporating advanced composite materials, such as fibre-reinforced polymers (FRPs), which are increasingly used in sustainable retrofits and new construction [2].

Despite significant progress, the widespread adoption of SHM remains hindered by several challenges. High installation and maintenance costs, sensor performance degradation under harsh environmental conditions, and the computational demands of processing large datasets continue to limit deployment. Effective SHM also requires close collaboration between structural engineers, data scientists, and operational managers—coordination that is not always easily achieved [2]. Technical gaps persist in areas such as long-term sensor calibration, environmental noise compensation, and seamless integration with digital engineering platforms. For example, targeted SHM solutions for bridges must account for complex dynamic loads and environmental variability, which can significantly influence data accuracy [3].

Over the past two years, several comprehensive investigations have expanded the understanding of SHM deployment challenges in complex environments, particularly those related to environmental modelling, autonomous sensing, and long-term signal interpretation [4-6]. These studies collectively illustrate a decisive movement toward hybrid, AI-supported monitoring strategies.

This review synthesises recent advancements in SHM technologies, sensing methodologies, and practical applications across civil infrastructure. It critically evaluates the current state of the art, identifying both achievements and persistent limitations, and outlines strategic research directions for more accurate, automated, and sustainable monitoring solutions. By consolidating findings from the past decade, this paper provides a comprehensive perspective on the potential of SHM to transform the management, safety, and resilience of infrastructure in the decades ahead. The novelty of this review lies in its integrated assessment of SHM across sensing technologies, monitoring architectures, and application domains while synthesising recent emerging concepts such as AI-enabled diagnostics, digital twins, and self-powered sensing systems. Unlike previous reviews, this work consolidates trends reported between 2020 and 2025 and proposes a forward-looking research agenda for next-generation SHM systems.

As this work is designed as a comprehensive review article, it does not include numerical modelling, experimental testing, or thermal comfort simulations. Therefore, indices such as PMV/PPD, simulation algorithms, or model validation are outside the scope of this manuscript.

2. PRINCIPLES AND OBJECTIVES OF STRUCTURAL HEALTH MONITORING

Structural Health Monitoring (SHM) provides a systematic and continuous framework for evaluating the condition of engineering structures throughout their operational life. Its primary goal is to detect damage at the earliest possible stage—well before it progresses into a state that could compromise safety or functionality. In practical terms, SHM involves the deployment of strategically positioned sensors to collect data either continuously or at scheduled intervals. This information is subsequently processed to detect signs of structural distress, such as abnormal strain distributions, stiffness loss due to fatigue, or the initiation of cracks [7]. By enabling timely interventions, SHM facilitates proactive maintenance, prolongs service life, and reduces the likelihood of unexpected failures and costly operational disruptions. A schematic representation of this five-level process is shown in Fig. 1 to illustrate how SHM progresses from detecting anomalies to predicting structural performance.

Damage identification in SHM typically follows a well-recognised five-level functional hierarchy:

1. Detection – recognising the potential presence of structural anomalies.
2. Localisation – determining the precise location of the anomaly.
3. Classification – identifying the type of damage (e.g., crack, corrosion, delamination).
4. Quantification – assessing the severity or extent of the damage.
5. Prognosis – estimating the remaining useful life of the structure.

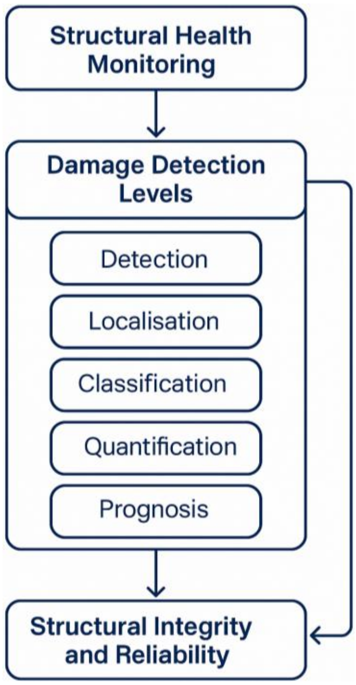

Fig. 1 Illustrates the functional hierarchy of SHM and its role in safeguarding structural integrity and reliability.

This hierarchical framework not only structures the diagnostic process but also sets the operational scope for SHM methodologies [8]. Each stage introduces distinct challenges, ranging from the precision and durability of sensors to the computational demands of real-time processing and interpretation.

An effective SHM system generally consists of four core components:

- Sensing units that measure key physical parameters such as strain, displacement, temperature, vibration, and acoustic emissions.
- Data acquisition hardware responsible for digitising, storing, and sometimes pre-processing sensor outputs.
- Communication infrastructure that ensures reliable transmission of data between field nodes and processing centres.
- Decision-making algorithms capable of interpreting incoming data and generating actionable insights.

Among these, sensors play a pivotal role in determining overall system performance. Selecting appropriate sensors involves balancing multiple factors—measurement accuracy, resilience under harsh environmental conditions, ease of integration with existing systems, and cost-effectiveness [9]. Recent technological advances have introduced wireless, self-powered, and multi-parameter sensing devices capable of monitoring multiple structural and environmental variables simultaneously. These innovations help reduce installation complexity and lower maintenance requirements, making SHM more practical for large-scale deployment.

Over time, SHM has evolved from a diagnostic aid into a strategic asset management tool**.** By enabling the shift from traditional time-based maintenance to a condition-based maintenance approach, SHM reduces unnecessary interventions, optimises resource allocation, and enhances operational safety [7,9]. In many engineering sectors, it has transitioned from being a supplementary feature to becoming an essential component for ensuring the long-term durability and resilience of critical infrastructure [10].

Importantly, the principles underpinning SHM are not confined to the monitoring of existing assets. They also influence the design philosophy of new infrastructure, ensuring that structures are conceived with embedded monitoring capabilities from the outset. This alignment with broader goals in asset lifecycle optimisation and digital transformation reflects the growing recognition of SHM as a fundamental practice for maintaining structural integrity, operational reliability, and sustainability in an increasingly complex built environment.

3. CLASSIFICATION OF STRUCTURAL HEALTH MONITORING SYSTEMS

Structural Health Monitoring (SHM) systems can be categorised based on their sensing methodology, data transmission approach, processing architecture, and monitoring scale. This classification is essential when selecting an SHM configuration for a specific infrastructure type, as each category presents unique trade-offs in cost, accuracy, deployment complexity, and long-term reliability under operational conditions.

3.1 Passive and Active Sensing Approaches

A primary distinction in SHM lies between passive and active sensing strategies:

- Passive systems record the structure's natural response to in-service loading without introducing an external excitation. Examples include strain gauges and accelerometers measuring deformation or vibrations under ambient conditions. These systems are generally easy to install, require minimal power, and are well-suited for long-term continuous monitoring. However, their sensitivity to small-scale or internal defects is limited, especially when such defects do not significantly alter the global structural response. Recent comparative evaluations of passive and active sensing in civil infrastructure further emphasise that hybrid configurations often outperform single-mode systems, particularly under variable operational conditions [11].
- Active systems, in contrast, deliberately introduce controlled excitations—such as ultrasonic pulses, radar waves, or electromagnetic signals—and analyse the structural response. This enables the detection of subsurface cracks, delamination, or other internal defects that may not be visible externally [12]. Although active methods offer higher diagnostic precision, they require additional hardware, more complex installation, and greater power consumption, making them best suited for critical components where accuracy outweighs logistical constraints.

3.2 Wired and Wireless Data Transmission

Data transmission architecture is another important classification criterion:

- Wired systems transmit data via physical cables directly from sensors to a central processing unit. They provide high data fidelity and robust communication, making them ideal for permanent installations in accessible environments. However, their installation can be labour-intensive, costly, and inflexible in terms of reconfiguration.
- Wireless systems transfer data via radio communication, enabling rapid deployment and scalability. Many modern wireless SHM networks use smart sensor nodes that combine sensing, processing, and communication capabilities, often powered by batteries or energy-harvesting technologies [3]. While well-suited for remote or large-scale structures such as bridges and tunnels, they face challenges related to battery life, environmental interference, and transmission stability. New-generation wireless systems increasingly employ energy-harvesting techniques and edge AI modules for onboard filtering and fault detection [5].

3.3 Centralised and Decentralised Processing Models

SHM systems can also be distinguished by their data processing strategy:

- Centralised processing sends all collected data to a single hub for analysis. This approach simplifies management, software updates, and algorithm deployment, but can create communication bottlenecks, increase transmission loads, and introduce a single point of failure.

- Decentralised processing distributes computation across multiple nodes, allowing each sensor or group of sensors to pre-process data locally. This reduces communication demands, enhances fault tolerance, and is particularly suited to wireless sensor networks. Advanced decentralised approaches, such as stochastic subspace identification, can estimate structural properties without requiring a complete centralised dataset [13].

3.4 Global and Local Monitoring Scales

The spatial coverage of monitoring further differentiates SHM systems:

- Global monitoring evaluates the overall dynamic behaviour of a structure, detecting changes in modal parameters or vibration patterns that may indicate large-scale deterioration. While effective for general assessments, it may overlook fine-scale or localised damage.
- Local monitoring targets specific components or zones, using high-resolution sensors to detect small-scale damage such as cracks, corrosion pits, or material delamination. Although highly precise, these systems are expensive to scale across large structures. In practice, hybrid configurations combining global and local monitoring are often the most effective for complex infrastructure [3]. Table 1 provides a consolidated view of how SHM systems are typically classified, highlighting the operational principles, strengths, and constraints of each category.

Table 1. Classification of Structural Health Monitoring (SHM) Systems.

Classification	Category	Description	Advantages	Limitations	Typical Use
Sensing Approach	Passive	Measures natural structural response (e.g., strain gauges, accelerometers)	Low power, simple setup	Less sensitive to internal flaws	Long-term stress or vibration monitoring
	Active	Injects a known signal and observes response (e.g., ultrasonic, radar)	High sensitivity, internal defect detection	Requires more power and hardware	Material-level flaw detection
Data Transmission	Wired	Physical cables connect sensors to central unit	High data fidelity, robust communication	Complex installation, inflexible	Permanent monitoring in accessible sites
	Wireless	Sensor nodes transmit data wirelessly	Flexible deployment, easy scaling	Power limitations, signal interference	Bridges, tunnels, remote structures
Processing Model	Centralised	All data sent to one analysis hub	Easier management, simpler updates	Single point of failure, higher communication load	Smaller or simpler SHM systems
	Decentralised	Processing distributed across nodes	Scalable, fault-tolerant, reduces data transfer	More complex architecture	Large wireless sensor networks
Monitoring Scale	Global	Monitors entire structural behaviour (e.g., modal analysis)	Detects large-scale changes	May miss small defects	Large bridges, tall buildings
	Local	Monitors specific zones (e.g., crack detection)	High-resolution, pinpoint damage detection	Costly for large structures	Critical joints, foundations

4. Monitoring Techniques and Technologies

The effectiveness of Structural Health Monitoring (SHM) fundamentally depends on how data is acquired and interpreted. Sensing and measurement techniques form the core of this process, with the choice of method influenced by the type of structure, expected damage mechanisms, environmental conditions, and the required level of diagnostic detail. Selecting the optimal technique is therefore a balance between practicality, precision, and cost-effectiveness.

4.1 Non-Destructive Testing (NDT) and Conventional Methods

Non-Destructive Testing remains one of the most established pillars of SHM. Techniques such as ultrasonic inspection, radiographic imaging, magnetic particle testing, and eddy current analysis are widely used to detect both surface and subsurface flaws without impairing the structural integrity. While originally designed for manual, point-by-point inspections, recent advances in automation have improved repeatability and reduced reliance on operator expertise [14].

These methods excel in detailed, localised inspections—such as weld assessments or critical joint evaluations—but are less suited for continuous, large-scale monitoring unless integrated with automated scanning systems. Automation of NDT workflows using robotic scanning systems has shown significant progress, particularly for large bridge bearings and tunnel interfaces [6].

4.2 Vibration-Based Monitoring

Vibration-based methods are among the most widely adopted SHM techniques for large civil structures, particularly bridges, towers, and high-rise buildings, where full-scale inspections are impractical. Structural damage alters the stiffness–mass distribution, thereby changing the system's natural frequencies, mode shapes, and damping ratios [15].

One primary diagnostic indicator is the natural frequency:

$$\mathrm{f_n} = \frac{1}{2\pi}\sqrt{\frac{\mathrm{k}}{\mathrm{m}}} \tag{1}$$

where f_n is the natural frequency (Hz), k is the structural stiffness (N/m), and m is the mass (kg). Monitoring frequency shifts can help localise and quantify structural degradation.

To assess mode shape consistency over time, the Modal Assurance Criterion (MAC) is widely used:

$$\mathrm{MAC}(\phi_i, \phi_i) = \frac{|\phi_i^T \phi_j|^2}{(\phi_i^T \phi_i)(\phi_j^T \phi_j)} \tag{2}$$

where, ϕ_i and ϕ_i are mode shape vectors from two different states. Significant MAC reduction often signals structural change.

Finite Element (FE)-based SHM methods frequently employ strain energy change as a damage index:

$$DI_i = \frac{SE_i^0 - SE_i^d}{SE_i^0} \tag{3}$$

where $SE_i{}^0$ and $SE_i{}^d$ represent the strain energy of element i in the healthy and damaged states, respectively. Larger values of DI_i imply higher likelihood of localised damage.

In practice, applying controlled excitation to large infrastructure is challenging. Operational Modal Analysis (OMA) addresses this by extracting modal parameters from ambient excitation (e.g., wind, traffic). The frequency-domain relationship is:

$$S_{yy}(\omega) = H(j\omega) \cdot S_{ee}(\omega) \cdot H^H(j\omega) \tag{4}$$

where $S_{yy}(\omega)$ is the output Power Spectral Density (PSD) matrix, $S_{ee}(\omega)$ is the input PSD (often modelled as broadband noise), and $H(j\omega)$ the frequency response function. OMA techniques such as Frequency Domain Decomposition (FDD) and Stochastic Subspace Identification (SSI) are widely used to identify natural frequencies and mode shapes without requiring known input forces.

While powerful for global monitoring, vibration-based methods may miss small or localised defects unless combined with higher-resolution techniques.

4.3 Acoustic Emission and Ultrasonic Techniques

Acoustic Emission (AE) monitoring captures transient stress waves generated by events such as crack initiation, fibre breakage, or corrosion damage. It is particularly effective for real-time detection of active damage in composite materials [16].

Ultrasonic testing sends high-frequency sound waves through a material and analyses changes in wave propagation to detect voids, cracks, or other discontinuities. While ultrasonics offer excellent sensitivity, they require good coupling surfaces and can be difficult to apply in noisy environments or on irregular geometries. Combining AE and ultrasonics often yields more reliable diagnostics.

4.4 Fibre Optic Sensors (FOS)

Fibre optic sensors—particularly Fibre Bragg Grating (FBG) systems—are increasingly used for SHM due to their immunity to electromagnetic interference, ability to operate over long distances, and capability to measure multiple parameters such as strain, temperature, and vibration. They can be embedded in composite materials or mounted on the surface of structures for long-term monitoring of bridges, tunnels, and offshore platforms [14,16].

Their precision and stability make them ideal for critical applications, though the high cost of interrogation units and specialised installation requirements remain adoption barriers.

4.5 Wireless Sensor Networks (WSNs) and Smart Nodes

Wireless sensor networks allow large-area monitoring without extensive cabling. Modern WSNs use smart nodes that integrate sensing, local signal processing, and data filtering, thereby reducing power consumption and communication loads [15]. Several recent field deployments demonstrate that wireless nodes integrated with onboard anomaly detection significantly reduce communication load without loss of diagnostic precision [4].

While WSNs offer flexibility and scalability, their performance hinges on effective power management. Battery replacement or recharging can be challenging in remote or hazardous areas, and maintaining signal reliability in harsh environments requires robust communication protocols.

4.6 UAV-Based Monitoring and Remote Sensing

Unmanned Aerial Vehicles (UAVs) equipped with optical, thermal, LiDAR, or acoustic sensors are transforming SHM by enabling rapid, contactless inspections of hard-to-reach areas such as bridge decks, tall towers, and dam faces [17]. UAVs can safely gather high-resolution data that is easily integrated into digital twin models for advanced analysis.

Limitations include sensitivity to weather conditions, regulatory restrictions, and the need for skilled operators. However, advances in autonomy and sensor payloads are expected to make UAV-based SHM a mainstream tool in the near future. Table 2 offers a consolidated overview of the principal SHM techniques, outlining how each method operates and where it is most effectively applied.

Table 2. Summary of Structural Health Monitoring Techniques and Technologies.

Technique	Key Principle	Advantages	Limitations	Typical Applications
Non-Destructive Testing (NDT)	Inspects without causing damage (e.g., ultrasound, X-ray)	Detailed internal flaw detection	Manual use, limited scalability	Pipelines, welds, foundation elements
Vibration-Based Monitoring	Analyses changes in natural frequency or damping	Good for global assessment of dynamic structures	Sensitive to environment; damage must affect dynamic behaviour	Bridges, towers, high-rise buildings
Acoustic Emission Monitoring	Captures stress waves from internal crack growth	Real-time detection; sensitive to active damage	Noisy environments reduce effectiveness	Composite materials, pressure vessels
Ultrasonic Techniques	Sends sound waves to detect reflection/refraction patterns	High precision for internal flaws	Requires coupling, hard to apply on irregular surfaces	Critical components in steel or concrete
Fibre Optic Sensors	Measures strain/temperature through light signal changes	Long-range, high precision, EMI immune	Expensive equipment; needs trained personnel	Bridges, tunnels, offshore platforms
Wireless Sensor Networks (WSNs)	Distributed data collection using smart nodes	Flexible, scalable, supports real-time monitoring	Power supply limits, reliability in harsh conditions	Large-scale deployments, remote monitoring
UAV-Based Monitoring	Captures aerial or hard-to-access visual/thermal/LiDAR data	Rapid, contactless, safe for operators	Weather-sensitive, requires operator skill and regulatory compliance	Bridge decks, towers, dams, rooftops

5. APPLICATIONS IN CIVIL INFRASTRUCTURE

Over the last decade, Structural Health Monitoring (SHM) has evolved from a specialised research topic into a core practice across diverse sectors of civil infrastructure. This growth reflects not only advances in sensing technologies and data analytics, but also a shift in how asset managers, operators, and policymakers perceive its value. Accurate, real-time structural data can extend service life, optimise maintenance budgets, and, most importantly, prevent catastrophic failures. While the theoretical principles of SHM have been understood for decades, only in recent years has its large-scale integration begun to match its full technical potential.

The following sections illustrate how SHM is applied in different infrastructure domains, highlighting both established practices and emerging innovations.

5.1 Bridges

As vital links in transportation networks, bridges face constant dynamic loads from traffic, wind, and temperature variations. Ensuring their safety and serviceability has made them one of the most extensively monitored structural types. Traditionally, bridge SHM has relied on strain gauges, displacement transducers, and accelerometers. Today, modern systems increasingly combine wireless sensor networks, fibre optic sensors, and AI-based analytics to detect early signs of deterioration [18].

A notable advancement is Indirect SHM (iSHM), where sensors mounted on passing vehicles—especially connected and autonomous vehicles—record the bridge's vibration and deflection during transit. These data are transmitted to a central processing unit, where algorithms analyse them for signs of structural change. Several European research initiatives are now trialling iSHM as a cost-effective, scalable alternative to dense, fixed sensor arrays [19], potentially transforming long-span bridge monitoring practices.

5.2 Buildings and High-Rise Structures

In high-rise and complex buildings, SHM serves multiple purposes—from tracking wind-induced sway and thermal expansion to monitoring occupancy-driven load variations. In seismically active regions, continuous monitoring provides not only immediate post-event safety verification but also long-term performance tracking.
With the rise of IoT-enabled smart buildings, engineers can now access live structural data remotely, enabling diagnostics without physical site visits [20]. An increasingly common practice is to extend SHM beyond the construction phase, comparing measured structural responses against design predictions. This performance-based approach not only supports targeted maintenance but also offers valuable feedback for improving future design strategies.

5.3 Tunnels, Dams, and Transportation Networks

Monitoring tunnels and dams presents unique challenges: difficult access, harsh environmental conditions, and the need for sensors that can function reliably for decades. In these cases, autonomous IoT-based sensor nodes are increasingly deployed to minimise human intervention.

For tunnels, 3D laser scanning and point cloud modelling are now standard tools for tracking gradual deformations, enabling engineers to predict and address problems before they escalate. For dams, SHM systems monitor critical parameters such as uplift pressures, seepage rates, and thermal stress gradients—factors that are directly linked to structural safety [21].

Across broader transportation networks, SHM data are often integrated into digital twin models alongside traffic and environmental datasets. These digital twins provide real-time visualisations and scenario simulations, supporting proactive maintenance and contingency planning [22].

5.4 Historical and Cultural Heritage Sites

In heritage preservation, SHM must protect both the structural safety and the aesthetic integrity of historic landmarks. This often means using low-profile, wireless sensors that can be discreetly embedded within architectural features. These systems track long-term degradation trends such as settlement, slow crack growth, or vibration-induced wear without altering the site's appearance.

SHM also plays a key role in post-disaster heritage recovery. Following earthquakes or floods, pre-installed monitoring systems can provide instant structural assessments, enabling rapid, informed conservation decisions [23]. However, acceptance among heritage custodians can be a challenge, making non-invasive, reversible monitoring solutions essential.

5.5 Post-Disaster Rapid Response and Resilience Planning

In the aftermath of natural disasters—such as earthquakes, hurricanes, or floods—rapid structural assessment is critical to safeguarding lives and optimising resource allocation. Recent advances in UAV-based aerial inspections and mobile ground sensor units have significantly reduced the time required to evaluate damaged infrastructure. These systems can quickly identify which structures are safe for occupancy and which require immediate closure or repair.
A growing trend is the integration of SHM into centralised urban resilience platforms, where live structural data feed into real-time decision dashboards used by emergency management agencies [18]. Over time, this integration could evolve into city-wide structural health networks, enabling predictive resilience planning rather than purely reactive response strategies. Fig. 2 provides a visual summary of the main infrastructure domains where SHM is applied and the operational objectives it serves.

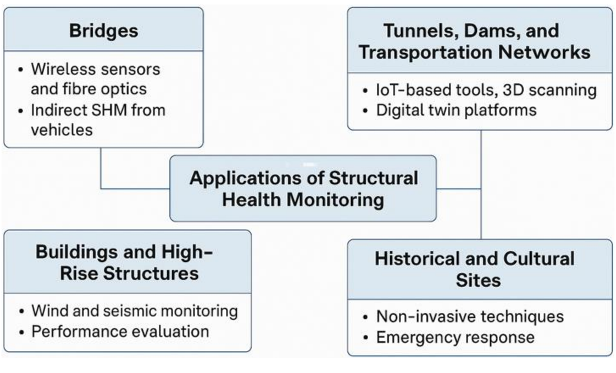

Fig. 2 Applications of Structural Health Monitoring across infrastructure types and use cases.

6. CHALLENGES AND LIMITATIONS

Despite significant progress in sensing technologies, data analytics, and system integration, the practical deployment of Structural Health Monitoring (SHM) in real infrastructure still faces persistent barriers. These challenges—both technical and operational—affect adoption rates, increase maintenance costs, and can undermine confidence in long-term monitoring programmes. The following subsections discuss the most critical issues, their root causes, and emerging solutions.

6.1 Sensor Calibration and Long-Term Reliability

The reliability of any SHM system ultimately depends on its sensors. In controlled laboratory conditions, sensors can operate accurately for many years; however, real-world installations—such as on bridges, offshore platforms, or exposed skyscrapers—are subjected to mechanical fatigue, extreme temperatures, moisture ingress, and even biological fouling. These factors can cause gradual signal drift or sudden failure [24].

Recalibration presents logistical and financial challenges. For example, recalibrating accelerometers mounted on a suspension bridge may require lane closures, specialised lifting equipment, and trained access teams. These operational disruptions often lead to postponed recalibrations, which increases the risk of inaccurate readings and can erode trust in the monitoring system.

6.2 Environmental and Operational Variability

SHM and Non-Destructive Testing (NDT) systems are inherently sensitive to environmental and operational fluctuations. Temperature swings, humidity changes, wind loading, and varying traffic patterns can all affect sensor outputs in ways that mimic or obscure actual damage.

For instance, thermal expansion in steel bridges can cause seasonal spikes in strain measurements. Without proper environmental compensation, such variations could be mistaken for fatigue cracking [25]. Advanced filtering algorithms can help separate genuine structural changes from environmental “noise,” but they require site-specific calibration, and their effectiveness may drop under extreme or atypical conditions.

6.3 Data Overload and Interpretation Complexity

Ironically, one of SHM's greatest technical strengths—its ability to collect massive amounts of data—can also become a major obstacle. Dense sensor networks may produce gigabytes of raw data daily. While this theoretically enables early detection of micro-level damage, in practice, processing bottlenecks, limited analytical capacity, and a shortage of skilled interpreters often result in underutilised datasets [26].

The absence of universal standards for data format, labelling, and storage further complicates integration across platforms. Even in technically compatible systems, critical warning signs may be lost in the noise unless advanced filtering, anomaly detection, and prioritisation tools are in place. Without them, significant issues might go unnoticed until they escalate into costly repairs or safety incidents.

6.4 Human Factors and Decision-Making Constraints

Although SHM technology is increasingly automated, human judgement remains central to many maintenance decisions. Engineers' responses to system alerts can vary widely—some place complete trust in automated outputs, while others rely heavily on personal experience. This subjectivity can result in inconsistent decision-making, especially when the algorithms' underlying logic is not well understood by end users.

In the offshore sector, structured decision-making frameworks that combine sensor outputs with expert interpretation have shown promising results [27]. However, such frameworks are still rare in civil infrastructure. Bridging this gap between technical capability and operational practice is essential if SHM is to evolve into a truly autonomous decision-support system.

6.5 Uncertainty and Risk Quantification

All SHM systems operate under uncertainty. Structural models are simplifications of reality, and no sensor is completely free from measurement error. Additional uncertainty arises from material variability, unpredictable damage progression, and incomplete baseline data—especially in heritage structures or very old infrastructure [28].

Without robust probabilistic risk models—such as Bayesian inference or Monte Carlo simulations—engineers may respond to uncertainty either with excessive caution, leading to unnecessary interventions, or with inaction, potentially missing early warning signs. Integrating quantified uncertainty into decision thresholds remains one of SHM's most important research frontiers. Table 3 summarises the major challenges associated with modern SHM systems, outlining their root causes, practical consequences, and the research efforts aimed at addressing them.

Table 3. Summary of Structural Health Monitoring Challenges.

Challenge	Primary Source	Typical Impact	Research Maturity	Representative Literature	Emerging Research Responses
Sensor Reliability & Calibration	Sensor degradation, environmental wear	Long-term drift, false readings, costly maintenance	Moderate	[24]	Redundant sensor arrays; self-diagnosing/self-calibrating nodes
Environmental & Operational Variability	Temperature, humidity, load variability	False alarms or missed damage due to signal noise	Moderate–High	[25]	AI-based noise filtering; environment-aware compensation models
Data Overload & Lack of Interpretation	Dense sensor networks, lack of analytics	Delayed or ignored alerts, poor decision-making	Moderate	[26]	Edge computing; intelligent dashboards; auto-prioritisation
Human Factors in Decision-Making	Interpretation inconsistency, trust gap	Overreliance on automation or neglect of warnings	Low	[27]	Human-in-the-loop models; Explainable AI (XAI)
Uncertainty & Risk Quantification	Material variability, lack of baselines	Inaction or over-maintenance due to unclear thresholds	Low	[28]	Probabilistic models (Bayesian, Monte Carlo); risk-based SHM frameworks

7. FUTURE DIRECTIONS

Structural Health Monitoring (SHM) is evolving beyond passive condition assessment toward proactive, adaptive, and fully integrated decision-support systems. The next generation of SHM will need to manage complex, interconnected infrastructure networks, respond dynamically to environmental and operational changes, and guide strategic interventions over the full asset lifecycle. As urban environments become increasingly digitalised and data-rich, several research and development trends stand out as pivotal for advancing SHM capabilities.

7.1 Digital Twins and Integrated Monitoring Environments

The integration of SHM with digital twin technology—high-fidelity, real-time virtual replicas of physical assets—represents one of the most transformative advances in the field. Unlike traditional monitoring platforms that simply store historical data, digital twins continuously update their models with live sensor inputs, enabling real-time simulation of structural performance under both current and projected scenarios [29].

This two-way feedback loop allows model predictions to guide targeted inspections and maintenance, while inspection results refine the predictive accuracy of the model. In connected urban infrastructure networks, such integration could evolve toward city- or region-wide asset management platforms, enabling decision-makers to allocate resources based on prioritised risk and performance forecasts rather than isolated asset assessments.

7.2 Artificial Intelligence and Autonomous Monitoring

The scale of SHM datasets often exceeds what can be manually analysed in operationally relevant timeframes. Artificial Intelligence (AI), particularly machine learning (ML) approaches, is increasingly applied to detect subtle patterns indicative of early-stage damage, fatigue, or other anomalies [30].

Modern AI models are becoming adept at distinguishing environmental variations from genuine structural changes, reducing false alarms and improving system reliability. As these algorithms mature, the vision of fully autonomous SHM systems—capable of continuous monitoring, anomaly detection, prioritisation, and even maintenance scheduling without human intervention—becomes more achievable. Such systems could fundamentally reshape inspection regimes, shifting from periodic checks to truly condition-based, real-time strategies.

7.3 Self-Powered and Self-Healing Sensors

Sensor reliability and maintenance remain limiting factors for long-term SHM deployment, particularly in remote or hard-to-access environments. Emerging self-powered sensors, which harvest energy from ambient vibrations, solar radiation, or thermal gradients, offer a pathway toward maintenance-free monitoring solutions.

Complementing this are self-healing sensor materials, capable of restoring partial or full functionality after minor physical damage [31]. Although still in early research stages, these technologies could significantly reduce operational downtime, extend sensor lifespans, and enable monitoring in locations where manual intervention is impractical.

7.4 Standardisation and Interoperability with BIM

A persistent barrier to large-scale SHM adoption is the lack of unified data standards. Without consistent protocols, integrating SHM into broader asset management ecosystems—particularly Building Information Modelling (BIM) platforms—remains challenging.

When effectively linked, BIM can visualise sensor networks in 3D, integrate inspection and maintenance histories, and simulate repair scenarios. This makes it an invaluable tool for lifecycle planning and smart city infrastructure management [32]. Moving toward open data protocols and interoperable frameworks will require coordinated efforts between civil engineers, IT specialists, and urban planners.

7.5 Sustainability and Systems Thinking

SHM is increasingly viewed not only as an engineering tool but as a strategic enabler of sustainability. By extending service life, reducing unnecessary repairs, and optimising resource allocation, SHM can lower the environmental impact of infrastructure management.

When combined with lifecycle cost analysis and environmental performance modelling, SHM supports a systems-thinking approach—aligning asset management with broader sustainability and resilience objectives [33]. Embedding SHM into such frameworks could influence both policy and design practices, positioning it as a cornerstone of sustainable infrastructure planning. As SHM continues to evolve, several research paths are emerging that aim not only to overcome existing limitations but also to redefine how structural systems are monitored, interpreted, and managed. Table 4 highlights these strategic directions, outlining their core capabilities, expected system-level impact, current technological readiness, and the barriers that remain.

Table 4. Strategic Research Directions in SHM: Capabilities, Impact, and Readiness.

Research Direction	Core Capability	Systemic Impact	Readiness	Current Limitation
Digital Twins	Real-time simulation, predictive analytics	Dynamic asset management, forecasting	Medium–High	High data/model alignment cost
AI & Autonomous Monitoring	Pattern recognition, damage detection, noise filtering	Reduced human workload, early alerts	Medium	Model interpretability, domain generalisation
Self-Powered / Self-Healing Sensors	Durable, maintenance-free sensing	Extended coverage, long-term viability	Low–Medium	Scalability, environmental reliability
BIM Integration & Data Standards	System interoperability, unified modelling	Efficient retrofits, smart city integration	Medium	Lack of standardisation, high initial setup complexity
Sustainability & Systems Thinking	Lifecycle optimisation, resource-aware planning	Reduced environmental impact, extended lifespan	Low–Medium	Integration into planning frameworks still early stage

Taken together, these advancements point to a consistent set of insights regarding the strengths and limitations of current SHM strategies. Table 5 summarises these themes in a concise form, showing what each approach offers and where its primary constraints remain.

Table 5. Summary of Key Insights from Structural Health Monitoring Strategies.

Strategy	Key Findings	Limitations
Vibration-based SHM	Effective for global structural changes	Low sensitivity to local damage
Fibre-optic SHM	High precision and durability	High installation cost
Wireless Monitoring	Scalable and flexible	Power management issues
AI-based SHM	Robust interpretation of complex data	Black-box concerns
Digital Twins	Real-time prediction	High computational cost

8. CONCLUSION

Structural Health Monitoring (SHM) has evolved from a specialised research area into a fundamental component of modern civil engineering practice, providing a systematic framework for evaluating, safeguarding, and optimising the performance of infrastructure over its entire service life. This review has charted the field's progression—from its theoretical foundations and classification frameworks to the diverse sensing technologies and real-world applications now employed in bridges, tunnels, high-rise buildings, transportation networks, and heritage structures.

Despite these advances, several challenges continue to limit the consistent and large-scale implementation of SHM. Persistent issues include sensor degradation and calibration demands, environmental and operational variability, overwhelming data volumes, and the difficulty of quantifying uncertainty with sufficient reliability. In many cases, converting raw monitoring data into actionable insights still depends heavily on human judgment, underscoring the need for more autonomous, adaptive, and context-aware analytical systems.

The future of SHM lies in deeper integration with emerging digital technologies. The convergence of Artificial Intelligence, digital twins, self-powered and self-healing sensors, and interoperable

Building Information Modelling (BIM) platforms has the potential to shift asset management from reactive inspection regimes to predictive, real-time maintenance strategies. Such an evolution would not only improve diagnostic precision and reduce operational costs but also embed SHM as a core enabler of sustainable, resilient, and intelligent infrastructure.

Realising this vision will require progress toward universal data standards, cross-platform interoperability, and stronger interdisciplinary collaboration between engineers, data scientists, policy-makers, and urban planners. Achieving these goals will position SHM as more than a diagnostic tool—it will become a strategic driver of 21st-century infrastructure stewardship, capable of delivering continuous performance optimisation, extending service life, and ensuring safety in an increasingly complex and interconnected built environment.

Data Accessibility Statement

No new datasets were generated or analysed during the current study. All data supporting the findings of this review are derived from previously published sources, which are appropriately cited throughout the manuscript.

Author Contributions

James Riffat conceptualised the structure of the review, conducted the literature research, performed the analysis, and wrote the manuscript. All sections were reviewed and revised by the Seyed Reza Samaei and Bilsay Pastakkaya to ensure consistency, accuracy, and coherence. The authors approved the final version of the manuscript.

Declaration of Competing Interests

The author declares no competing financial or personal interests.

REFERENCES

[1] M. Ramesh, M. Tamil Selvan, and A. Saravanakumar, “Evolution and recent advancements of composite materials in structural applications,” in *Applications of Composite Materials in Engineering*. Elsevier, 2025, pp. 97–117, doi: 10.1016/B978-0-443-13989-5.00004-8.

[2] G. Wang and J. Ke, “Literature review on the structural health monitoring (SHM) of sustainable civil infrastructure: An analysis of influencing factors in the implementation,” *Buildings*, vol. 14, p. 402, 2024, doi: 10.3390/buildings14020402.

[3] O. S. Sonbul and M. Rashid, “Algorithms and techniques for the structural health monitoring of bridges: Systematic literature review,” *Sensors*, vol. 23, p. 4230, 2023, doi: 10.3390/s23094230.

[4] J. Riffat, H. Ahadpour Doudran, and S. R. Samaei, “AI-enhanced damage detection in jack-up rig legs using an improved modal strain energy index: A numerical, experimental, and digital twin-based approach,” *Green Technology and Innovation*, 2025, doi: 10.36922/GTI025340014.

[5] J. Riffat, H. Ahadpour Doudran, and S. R. Samaei, “AI-driven digital twin for uncertainty-aware structural health monitoring of offshore wind turbines considering biofouling effects and reliability prediction,” *Green Technology and Innovation*, vol. 1, no. 2, p. 025330013, 2025, doi: 10.36922/GTI025330013.

[6] S. R. Samaei and J. Riffat, “Intelligent structural health monitoring of jack-up platform legs using high-density sensor networks, real-time digital twins, and machine learning-based damage detection,” *Future Cities and Environment*, vol. 11, 2025, doi: 10.70917/fce-2025-031.

[7] C. Boller, “Structural Health Monitoring—An Introduction and Definitions,” in *Encyclopedia of Structural Health Monitoring*, C. Boller, F. Chang, and Y. Fujino, Eds. Wiley, 2008, doi: 10.1002/9780470061626.shm204.

[8] D. A. Tibaduiza Burgos, R. C. Gomez Vargas, C. Pedraza, D. Agis, and F. Pozo, “Damage identification in structural health monitoring: A brief review from its implementation to the use of data-driven applications,” *Sensors*, vol. 20, p. 733, 2020, doi: 10.3390/s20030733.

[9] A. Mardanshahi, A. Sreekumar, X. Yang, S. K. Barman, and D. Chronopoulos, “Sensing techniques for structural health monitoring: A state-of-the-art review on performance criteria and new-generation technologies,” *Sensors*, vol. 25, p. 1424, 2025, doi: 10.3390/s25051424.

[10] Y. Chamaine, *Integrating Structural Health Monitoring for Safeguarding Infrastructure Resilience and Durability*, 2023, doi: 10.13140/RG.2.2.34068.68489.

[11] S. R. Samaei, M. Ghodsi Hassanabad, M. Asadian Ghahfarrokhi, and M. J. Ketabdari, “Numerical and experimental investigation of damage in environmentally sensitive civil structures using modal strain energy (case study: LPG wharf),” *Int. J. Environ. Sci. Technol.*, vol. 18, no. 6, pp. 1939–1952, 2021, doi: 10.1007/s13762-021-03321-2.

[12] R. Perera, A. Pérez, M. García-Diéguez, and J. Zapico-Valle, "Active wireless system for structural health monitoring applications," *Sensors*, vol. 17, p. 2880, 2017, doi: 10.3390/s17122880.

[13] S. Cho, J.-W. Park, and S.-H. Sim, "Decentralized system identification using stochastic subspace identification for wireless sensor networks," *Sensors*, vol. 15, pp. 8131–8145, 2015, doi: 10.3390/s150408131.

[14] S. Hassani and U. Dackermann, "A systematic review of advanced sensor technologies for non-destructive testing and structural health monitoring," *Sensors*, vol. 23, p. 2204, 2023, doi: 10.3390/s23042204.

[15] F. Kosova, Ö. Altay, and H. Ö. Ünver, "Structural health monitoring in aviation: A comprehensive review and future directions for machine learning," *Nondestructive Testing and Evaluation*, vol. 40, pp. 1–60, 2025, doi: 10.1080/10589759.2024.2350575.

[16] R. O. Ogunleye, S. Rusnáková, J. Javořík, M. Žaludek, and B. Kotlánová, "Advanced sensors and sensing systems for structural health monitoring in aerospace composites," *Advanced Engineering Materials*, vol. 26, p. 2401745, 2024, doi: 10.1002/adem.202401745.

[17] T. M. Fayyad, S. Taylor, K. Feng, and F. K. P. Hui, "A scientometric analysis of drone-based structural health monitoring and new technologies," *Advances in Structural Engineering*, vol. 28, pp. 122–144, 2025, doi: 10.1177/13694332241255734.

[18] Z. Deng, M. Huang, N. Wan, and J. Zhang, "The current development of structural health monitoring for bridges: A review," *Buildings*, vol. 13, p. 1360, 2023, doi: 10.3390/buildings13061360.

[19] European Commission Joint Research Centre, *Indirect Structural Health Monitoring (iSHM) of Transport Infrastructure in the Digital Age: MITICA workshop report*. LU: Publications Office, 2023.

[20] M. Mishra, P. B. Lourenço, and G. V. Ramana, "Structural health monitoring of civil engineering structures by using the internet of things: A review," *Journal of Building Engineering*, vol. 48, p. 103954, 2022, doi: 10.1016/j.jobe.2021.103954.

[21] Y. Zhang, G. Nie, and D. Wang, "Structural health monitoring based on three-dimensional point cloud technology: A systematic review," *Results in Engineering*, vol. 27, p. 106552, 2025, doi: 10.1016/j.rineng.2025.106552.

[22] V. Plevris and G. Papazafeiropoulos, "AI in structural health monitoring for infrastructure maintenance and safety," *Infrastructures*, vol. 9, p. 225, 2024, doi: 10.3390/infrastructures9120225.

[23] M. Rossi and D. Bournas, "Structural health monitoring and management of cultural heritage structures: A state-of-the-art review," *Applied Sciences*, vol. 13, p. 6450, 2023, doi: 10.3390/app13116450.

[24] Y. Yang, T. Chen, W. Lin, M. Jing, and W. Xu, "Research progress on calibration of bridge structural health monitoring sensing system," *Advanced Bridge Engineering*, vol. 5, p. 32, 2024, doi: 10.1186/s43251-024-00143-3.

[25] A. Keshmiry, S. Hassani, M. Mousavi, and U. Dackermann, "Effects of environmental and operational conditions on structural health monitoring and non-destructive testing: A systematic review," *Buildings*, vol. 13, p. 918, 2023, doi: 10.3390/buildings13040918.

[26] H. Pezeshki, H. Adeli, D. Pavlou, and S. C. Siriwardane, "State of the art in structural health monitoring of offshore and marine structures," *Proc. ICE – Maritime Engineering*, vol. 176, pp. 89–108, 2023, doi: 10.1680/jmaen.2022.027.

[27] J. Bardiani, C. Mazzolatti, A. Manes, and C. Sbarufatti, "A hybrid approach to enhance decision-making in marine structures: Combining sensor data with human perception," *Results in Engineering*, vol. 27, p. 105670, 2025, doi: 10.1016/j.rineng.2025.105670.

[28] F. Lorenzoni, F. Casarin, M. Caldon, K. Islami, and C. Modena, "Uncertainty quantification in structural health monitoring: Applications on cultural heritage buildings," *Mechanical Systems and Signal Processing*, vol. 66–67, pp. 268–281, 2016, doi: 10.1016/j.ymssp.2015.04.032.

[29] E. García-Macías, I. A. Hernández-González, and F. Ubertini, "Incorporating digital twins and artificial intelligence for next-generation SHM software," in *IOMAC 2024*, Springer, 2024, pp. 435–447, doi: 10.1007/978-3-031-61421-7_43.

[30] H. Hasani, F. Freddi, and R. Piazza, "AI-driven automated and integrated structural health monitoring under environmental and operational variations," *Automation in Construction*, vol. 176, p. 106222, 2025, doi: 10.1016/j.autcon.2025.106222.

[31] D. Jiao, S. Gu, L. Cheng, S. Li, and C. Liu, "Flexible, self-healing and portable supramolecular visualization smart sensors for monitoring and quantifying structural damage," *Materials Horizons*, vol. 12, pp. 190–204, 2025, doi: 10.1039/D4MH01233J.

[32] C. Gragnaniello, G. Mariniello, T. Pastore, and D. Asprone, "BIM-based design and setup of structural health monitoring systems," *Automation in Construction*, vol. 158, p. 105245, 2024, doi: 10.1016/j.autcon.2023.105245.

[33] J. Juarez-Quispe et al., "Advancing sustainable infrastructure management: Insights from system dynamics," *Buildings*, vol. 15, p. 210, 2025, doi: 10.3390/buildings15020210.