

1 *Type of the Paper is Review*

2 **Integration of Structural Health Monitoring with Sustainability** 3 **Indicators: A Systematic Review Bridging Resilience and** 4 **Green Construction Goals**

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12 **Abstract**

13 The increasing demand for resilient and environmentally responsible infrastructure has
14 driven a shift from conventional structural safety assessment toward integrated, perfor-
15 mance-driven sustainability management. Structural Health Monitoring (SHM), tradi-
16 tionally used for damage detection and condition assessment, is increasingly recognized
17 as a key enabler of sustainable infrastructure by providing continuous, data-driven in-
18 sights across the asset life cycle. This systematic review synthesizes peer-reviewed litera-
19 ture published between 2000 and 2025 using a PRISMA-based methodology to examine
20 how SHM can be integrated with sustainability indicators to bridge resilience objectives
21 and green construction goals. The review traces the evolution of SHM technologies, sensor
22 systems, and data analytics, highlighting their growing role in performance assessment,
23 predictive maintenance, and post-event resilience evaluation for bridges, buildings, and
24 heritage structures. It further examines sustainability indicators relevant to infrastructure
25 systems, including energy performance, embodied carbon, material efficiency, durability,
26 adaptability, and life-cycle impacts, emphasizing their importance in long-term decision-
27 making and asset management. Through thematic synthesis, the review identifies emerg-
28 ing approaches that link SHM data with sustainability outcomes via digital tools such as
29 BIM, digital twins, IoT-enabled monitoring, and machine learning-based predictive mod-
30 els. Persistent challenges are identified, including fragmented research, lack of standard-
31 ized metrics, data interoperability issues, and barriers to cross-disciplinary adoption. To
32 address these gaps, a conceptual framework is proposed that maps SHM outputs to sus-
33 tainability indicators through feedback loops supporting adaptive management, life-cycle
34 optimization, and resilience-informed sustainability strategies. Overall, the review estab-
35 lishes a foundation for advancing SHM as a core component of sustainable and resilient
36 infrastructure systems.

37 **Keywords:** Structural Health Monitoring; Sustainability Indicators; Digital Twin; Resili-
38 ent Infrastructure; Green Construction

40 **1. Introduction**

41 The demand for resilient and sustainable infrastructure has intensified in recent decades
42 due to rapid urbanization, population growth, and the increasing frequency of natural
43 disasters [1]. Cities around the world are expanding vertically and horizontally, placing
44 unprecedented stress on civil infrastructure systems such as bridges, high-rise buildings,
45 industrial facilities, and transportation networks [2]. Simultaneously, climate change has
46 intensified environmental hazards, including hurricanes, floods, and seismic activity,
47 which expose the vulnerability of critical structures [3]. These challenges highlight the
48 necessity for infrastructure systems that not only perform under routine loads but also
49 maintain functionality under extreme events.

50 At the same time, sustainability considerations have become central to modern construc-
51 tion and urban planning [4]. Reducing the environmental footprint of infrastructure, in-
52 cluding embodied carbon, energy consumption, and resource utilization, has emerged as
53 a key goal for both policymakers and industry stakeholders [5]. Despite advances in sus-
54 tainable materials and design, traditional construction and maintenance approaches often
55 fail to account for long-term resilience or provide actionable insights into ongoing perfor-
56 mance [6]. Consequently, there is a pressing need for strategies that simultaneously ad-
57 dress structural safety, operational efficiency, and environmental responsibility.

58 Structural Health Monitoring (SHM) offers a solution to these challenges by providing
59 real-time, continuous insights into the behavior of infrastructure under operational con-
60 ditions [7]. SHM employs sensors, wireless networks, and advanced data analytics to track
61 structural performance, detect early signs of damage, and inform maintenance decisions
62 [8]. By integrating SHM into the management of infrastructure, it is possible to extend
63 service life, prevent catastrophic failures, and optimize maintenance schedules, thereby
64 reducing both economic and environmental costs [9]. However, despite its potential, SHM
65 is still predominantly used for safety and performance evaluation, and its contribution to
66 sustainability goals remains limited and fragmented [10].

67 **1.1 Importance of Integrating SHM with Sustainability Indicators**

68 Sustainability indicators including energy efficiency, embodied carbon, life-cycle cost,
69 material durability, and adaptability are critical for evaluating the environmental perfor-
70 mance of infrastructure systems [11]. When combined with SHM data, these indicators
71 enable dynamic assessment of infrastructure performance, allowing engineers and deci-
72 sion-makers to make evidence-based choices [12]. For example, real-time monitoring of
73 vibration, strain, and temperature can reveal degradation patterns that inform energy op-
74 timization, predictive maintenance, and service-life extension [13]. Such integration facil-
75 itates proactive interventions, reducing material waste and minimizing the carbon foot-
76 print of repair and replacement activities [14].

77 Digital tools such as Building Information Modeling (BIM), Internet of Things (IoT) plat-
78 forms, and digital twins further enhance the potential of SHM to support sustainable in-
79 frastructure management [15]. BIM enables centralized storage of as built and operational
80 data, while digital twins allow simulation of structural performance under varying oper-
81 ational and environmental conditions [16]. Predictive modeling using machine learning
82 can forecast future deterioration, optimize retrofitting strategies, and align maintenance
83 schedules with sustainability goals [17]. Together, these approaches create a continuous
84 feedback loop where structural performance informs environmental performance, and
85 sustainability metrics guide maintenance and operational decisions [18].

86 By linking SHM outputs to sustainability indicators, infrastructure stakeholders can adopt
87 a performance-informed, environmentally responsible approach that integrates resilience,
88 resource efficiency, and long-term operational optimization [19]. This approach supports
89 circular economic principles by maximizing the service life of structural elements, reduc-
90 ing unnecessary replacements, and minimizing embodied carbon [20]. Consequently, in-
91 tegrating SHM with sustainability indicators represents a paradigm shift in infrastructure
92 management, where safety, performance, and environmental responsibility are treated as
93 interdependent objectives rather than separate considerations [21].

94 1.2 Objectives and Scope of the Systematic Review

95 This systematic review aims to synthesize the existing body of research on the integration
96 of SHM with sustainability indicators in the construction and civil infrastructure sectors
97 [22]. Its objectives are threefold: first, to identify and classify existing models, frameworks,
98 and methodologies that link SHM outputs with sustainability metrics such as energy effi-
99 ciency, material durability, and life-cycle performance [23]; second, to evaluate the effec-
100 tiveness and limitations of these approaches, including the use of digital twins, predictive
101 maintenance models, and sensor-based monitoring [24]; and third, to identify gaps in re-
102 search, including fragmented methodologies, lack of standardized indicators, and insuf-
103 ficient cross-disciplinary collaboration [25].

104 The scope of this review spans peer-reviewed literature published from 2000 to 2025, cov-
105 ering various types of infrastructure including bridges, high-rise buildings, industrial fa-
106 cilities, and heritage structures [26]. This timeframe captures both the early development
107 of SHM technologies and recent advances in IoT, digital twins, and sustainability assess-
108 ment frameworks [27]. By consolidating findings across multiple disciplines including
109 structural engineering, environmental science, and data analytics this review provides a
110 comprehensive perspective on the current state-of-the-art in SHM-sustainability integra-
111 tion [28].

112 Additionally, the review considers the practical implications of integrating SHM with sus-
113 tainability indicators. It examines case studies demonstrating how real-time monitoring
114 informs maintenance, optimizes resource allocation, and supports environmentally re-
115 sponsible retrofitting decisions [29]. The review also explores technological enablers such
116 as AI-driven predictive models, sensor networks, and BIM-based infrastructure manage-
117 ment platforms that facilitate the translation of monitoring data into actionable sustaina-
118 bility insights [30].

119 1.3 Contributions and Novelty of the Review

120 This study provides several key contributions to both research and practice. It presents a
121 systematic synthesis of how SHM can inform sustainability indicators, consolidating in-
122 sights from 100 selected studies [31]. The review introduces a conceptual framework that
123 operationalizes the integration of structural performance with environmental metrics,
124 providing guidance for infrastructure managers and policymakers [32]. By highlighting
125 gaps in current research, including the lack of standardized indicators, limited interoper-
126 ability, and fragmented cross-disciplinary approaches, this review offers a roadmap for
127 future studies and practical implementations.

Overall, the review bridges the gap between structural resilience and environmental performance, emphasizing the value of integrating SHM into sustainability assessments. It lays the foundation for subsequent sections of the paper, including the PRISMA-based methodology, detailed examination of SHM technologies, analysis of sustainability indicators, conceptual frameworks, and recommendations for future research. This integration ensures that infrastructure management strategies are both data-driven and environmentally responsible, aligning with modern green construction goals and resilience imperatives

2. Methodology

2.1 Systematic Review Design

A systematic review of recent literature related to integrating Structural Health Monitoring (SHM) with sustainability indicators was performed through the use of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) system shown in Figure 1 to create an unbiased, objective, replicable and thorough method by which to identify, analyse, and select published studies between 2000 and 2025 regarding SHM technology usage across multiple infrastructures and sustainability assessments. The systematic design allows for the comprehensive identification of both qualitative and quantitative contributions to resiliency, environmental performance, and green building sustainability through SHM technology and practices.

A systematic review of the literature uses an established methodology which is based on the principles described above, to maintain methodological integrity so that future reviews may be objective and replicable. A systematic review of the literature allows for the identification of emerging trends, technological advances, conceptual frameworks, and practical applications while identifying gaps in the literature and future research opportunities. In addition, this methodology serves as the foundation upon which a conceptual framework linking SHM outputs and sustainability metrics can be developed.

2.2 Literature Search and Screening

A literature search was conducted utilizing multi-interdisciplinary databases like Scopus, Web of Science, IEEE Xplore, Science Direct, and Springer Link, and keywords increased the coverage of the entire area of Structural Health Monitoring (SHM), as well as sustainability, resilience, and green building practices. Boolean operators, truncation, and database specific filters were also used to improve results and include all relevant studies. In addition to searching the electronic databases, the reference sections of the major review papers and the high-quality research articles were also searched to include any articles that may have been missing.

The studies retrieved from the searches were processed using a several-step screening process. First, automated removal of duplicate records was conducted through the assistance of software and corroborated through manual checks. The articles were screened for relevance through examination of titles and abstracts, and articles not relevant to structural health monitoring and sustainability were excluded. The remaining articles were then reviewed for the completeness of the full article as well as review for the eligibility for inclusion based on the following criteria: SHM for civil infrastructures, integrated with sustainability metrics, whether an empirical or conceptual contribution, and published in

171 peer-reviewed publication sources. Those studies which did not meet the above stipulated
172 criteria for inclusion were eliminated to assure the selection of the relevant literature met
173 the required quality standards.

174 All infrastructures, technologies, and methodologies used within each collected dataset
175 were equally represented during the screening process to provide a well-rounded per-
176 spective of how SHM integrates with sustain-ability; thus, the process of carefully review-
177 ing each collected dataset allowed researchers to create a dataset that was ready for further
178 analysis and extraction of detailed information.

179 **2.3 Data Extraction and Analysis**

180 A systematic extraction of key components and findings of the papers was conducted
181 using a pre-designed template (Appendix D). The Extraction Process for each article was
182 completed by collecting and collating all Studies Objectives, SHM Technologies, Types
183 of Sustainability Indicators, Infrastructure Context, Methodology Used and the Main
184 Results of each study (which included Challenges Identified), the Use of Digital Tools (in
185 particular: BIM and Digital Twins), and the Use of Predictive or Data-Driven Models.

186 The extracted data was then organised into Thematic Categories (according to the type
187 of information contained within each category), and analysis of the studies was com-
188 pleted using a Structured Approach. Broad Thematic Categories identified include: SHM
189 technologies and sensor applications, sustainability indicators and performance metrics,
190 Data-Driven Modelling, Integration Frameworks, and Examples of Practical Case Stud-
191 ies. Organising the studies thematically enabled a Comparative Analysis of the Trends,
192 Challenges and Opportunities, which serves as a foundation for understanding concepts
193 and the subsequent Integrated Conceptual Model presented in this Paper.

194 This process resulted in identifying a total of 100 High-Rank (Highly Relevant) and High-
195 Area (High Quality) Studies. These studies reflect the Major Influences in the research
196 from January 2000 to December 2025, including: Theoretical Development, Applied Re-
197 search, and the Technological Development of the Civil Infrastructure sector, and they
198 provide a Foundation for Synthesising Current Knowledge, Identify Gaps in Research and
199 Guide Research Directions for Future Research Integrating SHM with Sustainability Met-
200 rics.

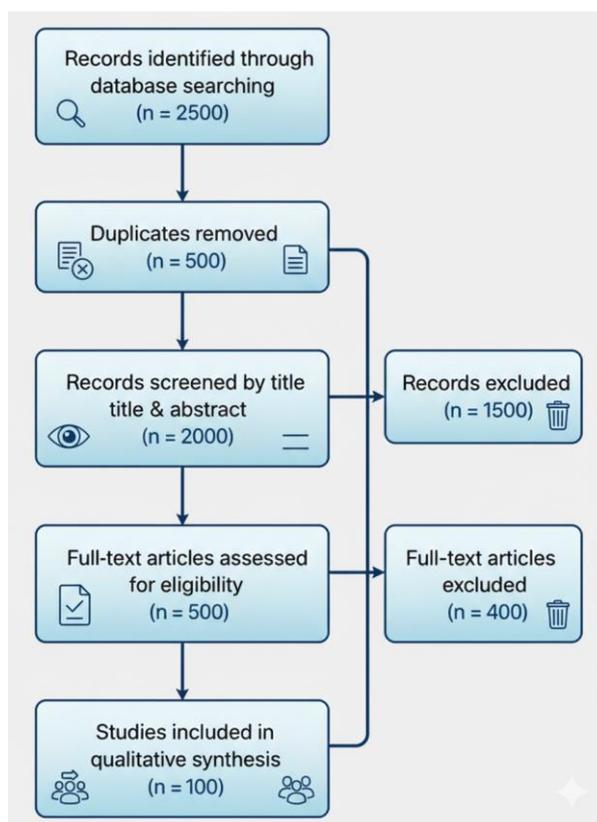


Figure 1 PRISMA Flow Diagram

3. Structural Health Monitoring (SHM) in Civil Infrastructure

3.1 Evolution and Current State of SHM

Structural Health Monitoring has evolved significantly over the past two decades, transforming from manual inspection techniques to advanced, sensor-driven, data-centric systems [33]. Early SHM focused primarily on visual inspections and periodic structural assessments, which often missed early-stage damage and lacked real-time feedback [34]. The advent of sensor technologies, wireless communication, and computational modeling enabled continuous monitoring of structural performance under operational loads, environmental influences, and extreme events [35].

Today, SHM systems are increasingly integrated with digital platforms, allowing for automated data collection, processing, and analysis [36]. Modern SHM leverages Internet of Things (IoT) devices, cloud computing, and advanced analytics to provide actionable insights on the condition of structures in near real-time [37]. This evolution has not only improved the accuracy and timeliness of structural assessments but has also expanded the potential applications of SHM in resilience planning and sustainability management [38].

3.2 SHM Technologies and Sensor Types

A wide variety of SHM technologies are used to monitor structural performance, each with specific capabilities and limitations. Common sensor types include:

- Accelerometers and gyroscopes, which measure vibrations, dynamic response, and angular motion to detect structural anomalies or changes in stiffness [39].
- Strain gauges, which provide information on stress distribution and material deformation, enabling early detection of overstressing or fatigue [40].
- Displacement and tilt sensors, which measure relative movement, settlement, or rotation in structural elements, supporting assessment of serviceability and stability [41].
- Fiber optic sensors, offering high precision in measuring strain, temperature, and cracking over long distances with minimal signal degradation [42].
- Environmental sensors, including temperature, humidity, wind, and seismic sensors, which contextualize structural responses to external loads [43].

These technologies can be deployed individually or as integrated sensor networks, allowing comprehensive assessment of structural health. Advances in wireless communication and energy harvesting have further enhanced the feasibility of large-scale deployment, reducing maintenance and installation costs [44].

3.3 Applications of SHM in Infrastructure

SHM is applied across a wide spectrum of civil infrastructure, including bridges, high-rise buildings, industrial facilities, and heritage structures [45]. In bridges, SHM monitors load distribution, fatigue damage, and vibration response to optimize maintenance schedules and improve safety [46]. High-rise buildings benefit from SHM through monitoring of wind-induced sway, structural drift, and foundation settlement, which inform both design validation and operational performance [47].

Heritage structures, often constructed with traditional materials and lacking detailed design records, particularly benefit from SHM as a non-invasive tool for long-term preservation [48]. In industrial facilities, SHM ensures operational safety by tracking the structural performance of storage tanks, chimneys, and process equipment under dynamic loading [49]. Across all applications, SHM provides early warning capabilities, enabling proactive maintenance, life-cycle optimization, and reduction of unplanned downtime [50].

3.4 Role of SHM in Performance Assessment and Resilience

Beyond monitoring, SHM plays a critical role in performance-based assessment and resilience enhancement. By continuously evaluating structural behavior under varying operational and environmental conditions, SHM systems support decision-making for maintenance, retrofitting, and life-cycle management [51].

Data from SHM can be integrated with predictive models to forecast structural deterioration and failure, allowing infrastructure managers to anticipate problems and allocate resources efficiently [52]. Furthermore, SHM contributes to resilience by enabling rapid post-event assessment following natural disasters, helping identify critical damages, pri-

260 oritize interventions, and ensure structural safety [53]. When linked to sustainability indi-
261 cators, these capabilities allow SHM to inform environmental performance metrics such
262 as energy efficiency, material longevity, and adaptive reuse potential [54].

263 **3.5 Integration with Digital Platforms and Future Directions**

264 The integration of SHM with digital platforms, such as BIM and digital twins, has revolu-
265 tionized infrastructure monitoring. These platforms allow the fusion of real-time sensor
266 data with 3D digital models, facilitating simulation, visualization, and predictive analysis
267 [55]. AI and machine learning algorithms can analyze complex datasets to detect patterns,
268 predict failure, and optimize interventions, moving beyond reactive maintenance to intel-
269 ligent, data-driven infrastructure management [56].

270 Future developments in SHM include autonomous sensor networks, advanced predictive
271 analytics, and multi-scale integration with sustainability assessment frameworks. These
272 advancements are expected to enhance infrastructure performance, extend service life,
273 and contribute directly to the achievement of green construction objectives [57].

274 **4. Sustainability Indicators in Construction and Infrastructure**

275 Sustainability in construction and infrastructure refers to the practice of designing, con-
276 structing, and operating built assets in a manner that balances environmental, economic,
277 and social considerations over the full lifecycle of a structure [58]. Assessing sustainability
278 requires the use of quantifiable indicators, which measure performance across multiple
279 dimensions including environmental impact, resource efficiency, durability, and adapta-
280 bility. The adoption of sustainability indicators in civil infrastructure is increasingly vital
281 due to the growing focus on green construction, climate resilience, and resource conser-
282 vation [59].

283 **4.1 Environmental Performance Metrics: Energy, Embodied Carbon, and Material Effi- 284 ciency**

285 Environmental sustainability indicators primarily focus on minimizing ecological foot-
286 prints and promoting resource efficiency. Energy consumption is one of the most critical
287 measures, encompassing both operational and embodied energy. Operational energy re-
288 fers to the energy used during a structure's service life for heating, cooling, lighting, and
289 equipment operation, while embodied energy accounts for the energy consumed in the
290 extraction, processing, transportation, and construction of building materials. Reducing
291 operational energy demand through efficient design, renewable energy integration, and
292 intelligent building management systems directly lowers greenhouse gas emissions and
293 contributes to global net-zero targets [60].

294 Embodied carbon is closely related and measures the CO₂-equivalent emissions associated
295 with materials production, construction, maintenance, and end-of-life processes [61].
296 With conventional construction materials such as concrete and steel being major contrib-
297 utors to global emissions, minimizing embodied carbon through material selection, effi-
298 cient supply chains, and innovative construction methods has become a priority for sus-
299 tainable infrastructure. Material efficiency and circularity complement these metrics by
300 evaluating the reuse, recycling, and reduction of waste generation in construction pro-

301 cesses. Strategies such as modular construction, use of secondary aggregates, and design-
 302 ing for deconstruction enhance resource conservation while aligning with circular econ-
 303 omy principles [62] and Table 4.1 includes Key Environmental Sustainability Indicators
 304 and Measurement Metrics

305 Table 4.1: Key Environmental Sustainability Indicators and Measurement Metrics

Indicator	Definition / Measurement	Relevance to Green Construction
Energy Consumption	kWh/m ² /year (operational), MJ/kg (embodied)	Reduces emissions, lowers operational cost
Embodied Carbon	kg CO ₂ -eq/m ² or kg CO ₂ -eq per material unit	Tracks carbon footprint of materials
Material Efficiency	% of recycled content, material wastage ratio	Promotes circular economy, reduces landfill
Water Use Efficiency	m ³ /year or m ³ /m ² /year	Conserves water resources, improves resilience
Waste Generation	kg/m ² or % diverted from landfill	Enhances resource efficiency and sustainability

306 **4.2 Durability, Adaptability, and Lifecycle Sustainability**

307 Sustainability cannot be fully realized without considering the long-term performance,
 308 adaptability, and resilience of infrastructure. Durability is a key dimension, reflecting a
 309 structure’s ability to resist deterioration from operational loads, environmental exposure,
 310 and natural hazards over its expected service life. Effective durability monitoring involves
 311 tracking material degradation, corrosion, cracking, fatigue, and the cumulative impacts of
 312 weathering, which reduces maintenance requirements and extends service life [63].

313 Equally important is adaptability, which describes the capacity of infrastructure to accom-
 314 modate functional changes, increased loading, or technological upgrades without requir-
 315 ing extensive modifications. Buildings and bridges designed for adaptability enhance
 316 their long-term utility, reduce resource-intensive retrofits, and contribute to the sustaina-
 317 bility of urban systems [64]. Lifecycle sustainability assessment integrates these consider-
 318 ations with environmental and economic metrics to evaluate the overall sustainability of
 319 a structure from construction through demolition. Methods such as Life Cycle Assessment
 320 (LCA), Life Cycle Costing (LCC), and Social Life Cycle Assessment (SLCA) enable a ho-
 321 listic evaluation of environmental impacts, economic feasibility, and social value over the
 322 infrastructure’s full lifespan [65] and Table 4.2 includes Durability and Lifecycle Indica-
 323 tors for Sustainable Infrastructure

324 Table 4.2: Durability and Lifecycle Indicators for Sustainable Infrastructure

Indicator	Measurement Metric	Purpose / Benefit
Structural Durability	Years until major maintenance	Extends service life, reduces resource use
Adaptability / Flexibility	% of functional modification possible	Enhances long-term utility, reduces retrofit needs
Lifecycle Cost	\$/m ² or \$/functional unit	Economic feasibility, supports sustainable investment
LCA Score	Environmental impact index	Quantifies total environmental footprint

325 **4.3 Integration of Sustainability Indicators with Decision-Making**

326 The utility of sustainability indicators is maximized when they are incorporated into plan-
327 ning, design, and operational decision-making frameworks. By systematically linking
328 measurable metrics to actionable strategies, engineers can prioritize the selection of mate-
329 rials, construction techniques, and design alternatives that minimize environmental im-
330 pact while ensuring structural reliability [66]. This approach enables evaluation of trade-
331 offs between upfront costs and long-term operational efficiency, promoting investment
332 decisions that are both economically and environmentally sound. Performance-based de-
333 sign further relies on these indicators, using thresholds for energy use, embodied carbon,
334 durability, and adaptability to guide engineering decisions throughout the project lifecy-
335 cle.

336 Integration with certification systems such as LEED, BREEAM, and Envision provides an
337 additional mechanism for validating sustainable performance. These frameworks stand-
338 ardize the measurement of sustainability indicators, ensuring consistency across projects
339 and aligning local practices with international benchmarks [67]. A structured decision-
340 making framework incorporates input data such as material properties, energy models,
341 and sensor-derived performance data, which are analyzed using lifecycle assessment
342 tools, cost analysis, and resilience scoring. The resulting outputs inform material selection,
343 maintenance planning, adaptive interventions, and sustainability reporting, creating a
344 feedback loop that enhances both environmental performance and infrastructure resili-
345 ence.

346 5. Bridging SHM and Sustainability

347 The integration of Structural Health Monitoring (SHM) with sustainability indicators rep-
348 represents a critical advancement in modern civil infrastructure management. While SHM
349 traditionally focuses on assessing structural performance, safety, and reliability, sustain-
350 ability indicators evaluate environmental, economic, and social impacts across the infra-
351 structure lifecycle. By connecting these two domains, engineers and facility managers can
352 generate actionable insights that inform both performance optimization and green con-
353 struction objectives [58]. This section explores the thematic links, mechanisms, and prac-
354 tical applications of bridging SHM with sustainability.

355 5.1 Thematic Synthesis of SHM-Sustainability Studies

356 Recent research highlights a growing interest in aligning SHM outputs with sustainability
357 objectives. Many studies demonstrate that continuous monitoring of structures provides
358 data that directly informs environmental and lifecycle performance metrics. For instance,
359 vibration and strain measurements collected via SHM systems can identify over-stressed
360 structural elements, enabling timely maintenance and preventing unnecessary material
361 replacement, which reduces both embodied energy and waste generation [59]. Similarly,
362 environmental sensors embedded in SHM networks measuring temperature, humidity,
363 or pollutant levels offer critical data for adaptive energy management and predictive in-
364 terventions that improve operational efficiency [60].

365 Thematic analysis across multiple studies reveals several recurring patterns. Firstly, SHM
366 provides real-time insights that reduce reactive maintenance and enhance material effi-
367 ciency by preventing premature repairs or over-design. Secondly, SHM facilitates life-cy-
368 cle sustainability assessment by feeding accurate performance data into models for dura-

bility, energy consumption, and carbon footprint. Thirdly, data-driven monitoring supports resilience-oriented sustainability strategies, ensuring that structures can adapt to changing environmental and operational conditions without significant resource expenditure [61]. Collectively, these studies underscore that SHM is not merely a tool for safety, but a strategic enabler of sustainable infrastructure management.

5.2 Data-Driven Monitoring for Green Construction Goals

The application of SHM data to sustainability evaluation relies on the structured collection, processing, and interpretation of sensor information. Modern SHM systems are capable of capturing multidimensional datasets, including structural vibrations, deflections, thermal response, and environmental exposure. By integrating these datasets with sustainability indicators, it becomes possible to quantify the environmental benefits of performance-informed decisions. For example, predictive maintenance schedules based on SHM data can significantly reduce material wastage and energy consumption compared to conventional maintenance approaches [62].

Moreover, data-driven approaches enable the optimization of energy-intensive building operations. Monitoring the structural response of high-rise buildings or bridges allows managers to adjust HVAC systems, control lighting loads, and schedule maintenance interventions in a manner that maximizes energy efficiency. Through this synergy, SHM acts as a feedback mechanism, linking operational performance to measurable sustainability outcomes such as reduced carbon emissions, enhanced material lifespan, and improved resource utilization [63] and Table 5.1 Maps SHM Outputs to Sustainability Indicators

Table 5.1: Mapping SHM Outputs to Sustainability Indicators

SHM Output	Sustainability Indicator	Application / Benefit
Strain / Stress Data	Material Efficiency, Embodied Carbon	Reduces overuse of materials, avoids premature replacement
Vibration / Dynamic Response	Durability, Operational Energy	Optimizes maintenance, reduces energy consumption
Environmental Sensor Data	Energy Use, Water Efficiency	Informs adaptive operation of HVAC, water, and lighting systems
Displacement / Tilt	Lifecycle Sustainability	Supports predictive maintenance and longevity planning
Damage Detection / Alerts	Waste Minimization, Lifecycle Cost	Enables timely repairs, reduces material waste and costs

5.3 Case Studies Demonstrating SHM-Informed Sustainability Interventions

Several real-world applications illustrate the value of integrating SHM with sustainability goals. In bridge management, SHM systems that monitor fatigue and traffic-induced stress have enabled the replacement of components only when necessary, minimizing unnecessary material usage and extending service life. The collected data also feeds into predictive models, improving maintenance scheduling and reducing energy consumption associated with large-scale repair operations [64].

In high-rise buildings, environmental sensors combined with structural monitoring have supported adaptive building management strategies. For instance, vibration and sway monitoring informs load redistribution strategies during high-wind events, while thermal monitoring allows dynamic adjustment of HVAC systems, contributing to energy efficiency and reduced carbon emissions [65]. Heritage structures provide another compelling example. Non-invasive SHM techniques, such as fiber optic strain sensing, allow conservation interventions to be targeted precisely, reducing material use and preserving cultural value without introducing unnecessary structural alterations [66].

These case studies collectively demonstrate that linking SHM to sustainability metrics is not theoretical but practically feasible, offering measurable reductions in resource use, energy consumption, and lifecycle costs, while enhancing resilience and structural longevity.

5.4 Benefits of Real-Time Feedback for Adaptive Management

One of the most significant advantages of integrating SHM with sustainability indicators is the provision of real-time feedback. Continuous monitoring allows infrastructure managers to respond proactively to structural changes, environmental conditions, or operational inefficiencies, creating a dynamic, adaptive management environment. Real-time feedback loops enable early detection of anomalies, optimize energy use, and support predictive interventions, all of which contribute to enhanced lifecycle sustainability [67].

Furthermore, this adaptive management approach facilitates data-driven prioritization of resources. Maintenance budgets can be allocated more efficiently, interventions can be timed to minimize material and energy consumption, and overall infrastructure resilience is improved. By incorporating sustainability indicators into SHM-driven decision-making, infrastructure managers can ensure that both environmental and structural performance objectives are simultaneously achieved.

5.5 Sub-Framework: Linking SHM Data to Sustainability Metrics

A conceptual sub-framework can be established to systematically connect SHM outputs with sustainability indicators. This framework includes three layers: (i) Data Acquisition, where multi-sensor SHM networks collect strain, displacement, vibration, and environmental data; (ii) Data Analysis and Integration, where sensor outputs are processed to generate predictive models of structural performance and life-cycle environmental impacts; and (iii) Decision-Making and Action, where performance insights are translated into maintenance planning, energy optimization, and material efficiency interventions. This framework provides a structured approach for leveraging SHM as a decision-support tool for sustainable infrastructure management, ensuring that monitoring directly informs environmental, economic, and operational outcomes and Table 5.2 shows the Sub-Framework Linking SHM to Sustainability

Table 5.2: Sub-Framework Linking SHM to Sustainability

Layer	Function	Example Application
Data Acquisition	Collection of structural and environmental data	Sensors for strain, vibration, temperature, humidity

Data Analysis & Integration	Predictive modeling, sustainability assessment	LCA integration, energy simulation, durability prediction
Decision-Making & Action	Maintenance scheduling, resource optimization	Adaptive maintenance, energy-efficient operation, material reuse

6. Digital Tools and Frameworks for Integration

Digitalization has evolved into the central nervous system of modern infrastructure management, fundamentally reshaping how structural behavior, environmental performance, and sustainability metrics are captured, interpreted, and operationalized. Over the past decade, the convergence of Building Information Modeling (BIM), digital twins, Internet of Things (IoT) sensing networks, machine learning analytics, and cloud–edge computational frameworks has enabled a transformative paradigm where structural health monitoring (SHM) data is no longer passive information but becomes an intelligently processed, continuously interacting dataset driving sustainability-oriented decision-making [68]–[75]. These tools collectively establish a highly interconnected ecosystem in which real-time sensor feedback enriches digital representations of assets, supports continuous environmental evaluation, and allows infrastructure systems to be operated, maintained, and optimized with unprecedented precision.

The integration of sustainability considerations directly into digital workflows has expanded the role of SHM beyond safety and performance verification. It now functions as a data backbone for achieving energy efficiency, reducing embodied carbon, planning material reuse, validating retrofit effectiveness, and improving overall lifecycle sustainability profiles of built assets [76]–[85]. Through synergistic digital frameworks, infrastructure management transitions from reactive maintenance toward predictive, environmentally responsible, and economically optimized asset stewardship.

6.1 BIM, Digital Twins, and IoT-Enabled SHM for Sustainability

The incorporation of SHM data into BIM and digital twin environments has generated a dynamic data ecosystem capable of supporting real-time sustainability evaluation. Traditionally, BIM served as a static or semi-dynamic geometric and informational repository; however, its capabilities are fundamentally enhanced when continuously enriched with IoT-driven structural and environmental data streams. IoT sensor networks including fiber Bragg grating sensors, MEMS accelerometers, strain gauges, crack meters, environmental modules, and GPS displacement units provide detailed temporal datasets reflecting vibration characteristics, thermal variations, moisture exposure, operational loads, and long-term degradation indicators [70]–[72].

When this sensor-derived intelligence is integrated within a BIM environment, the model transitions from a documentation tool into an active sustainability enabler. Embodied carbon inventories, material lifecycle tracking, and degradation-induced maintenance forecasting become dynamically updated rather than periodically estimated. For example, strain-based deterioration signals captured through SHM can automatically update digital deterioration curves embedded within BIM-linked lifecycle modules, allowing stakeholders to adjust material replacement schedules based on real-world performance rather than generic deterioration assumptions [73].

Digital twins extend these functionalities by enabling bidirectional coupling between the physical asset and its computational replica. Unlike static BIM environments, digital twins continuously assimilate SHM data to re-simulate structural response, operational energy use, and environmental impacts. This capability allows thermal gradients measured by temperature sensors to adjust thermal comfort simulations, drives energy modeling for adaptive HVAC response, and recalibrates operational carbon projections. For steel structures, corrosion-sensitive environmental indicators measured via SHM sensors can recalibrate corrosion propagation models within the digital twin, improving predictions of material loss and embodied carbon associated with future repairs [74]–[77].

In sustainability-focused operations, digital twins are particularly powerful because they enable scenario-based optimization. Stakeholders can evaluate the carbon footprint difference between increasing member cross-sections, applying corrosion-resistant coatings, or implementing externally bonded reinforcement. By integrating environmental product declarations (EPDs) and lifecycle impact databases, digital twins support decision pathways that minimize carbon expenditure while maintaining or enhancing structural safety. This closed-loop interaction between sensor-derived performance and sustainability modeling represents one of the most promising directions for future infrastructure management [78]–[81] and Table 6.1 includes Principal Digital Platforms Enabling SHM–Sustainability Integration

Table 6.1: Principal Digital Platforms Enabling SHM–Sustainability Integration

Digital Tool	Core Technical Function	Sustainability Contribution
BIM	Geometric + semantic information modeling	Real-time embodied carbon updates, material inventory accuracy, lifecycle documentation
Digital Twin	Real-time physics-based simulation synced with SHM	Predictive energy optimization, deterioration forecasting, carbon-informed maintenance
IoT Sensor Networks	High-frequency acquisition of structural and environmental data	Environmental trend mapping, adaptive ventilation and HVAC control
Cloud Computing	Large-scale data aggregation, LCA simulation, SHM data storage	Regional and portfolio-level sustainability benchmarking
Edge Computing	On-sensor processing, low-latency analytics	Reduced communication energy consumption, faster sustainability-oriented decision-making

6.2 Predictive Models and Machine Learning for Performance Forecasting

Predictive analytics powered by machine learning (ML) has become essential in extracting sustainability-relevant insights from complex SHM datasets. Traditional statistical models often fail to capture nonlinear degradation patterns, multi-parameter environmental dependencies, and dynamic load–response interactions. ML methods including random forests, support vector regression, gradient boosting, deep neural networks, graph neural networks, and hybrid physics-informed networks are now capable of learning intricate structural patterns that correlate with deterioration, energy consumption, and lifecycle performance [82]–[85].

ML-powered frameworks leverage the interpretive strength of SHM data by uncovering degradation signatures that human analysts or linear models often miss. For example, vibration-based ML models can detect subtle stiffness reductions long before visible cracking develops, enabling sustainability-oriented interventions that minimize material

wastage and avoid energy-intensive repair operations. Similarly, ML-driven energy prediction models utilize SHM environmental sensors (temperature, humidity, occupancy-induced vibration) to estimate operational energy demand with high fidelity, enabling dynamic HVAC control strategies that reduce energy use and operational carbon emissions.

Hybrid predictive approaches yield even higher sustainability value by coupling ML with physics-based simulations. Finite element (FE) models of structures are often limited by uncertainty in material behavior, boundary conditions, and environmental influences. By training ML networks on SHM-calibrated FE outputs, hybrid models can refine deterioration projections while accounting for real in-situ performance. This allows multi-scale evaluation of sustainability impacts such as embodied carbon changes associated with progressive corrosion, creep-induced deformation, or dynamic load fluctuations [83], [84].

ML-assisted optimization further enhances sustainability planning. When evaluating retrofitting schemes such as CFRP strengthening, steel plate bonding, or RC jacketing ML models can simulate their structural effects and compute associated embodied carbon and long-term operational savings. Infrastructure managers can therefore adopt interventions with the optimal balance of cost, durability, and environmental performance and Table 6.2 includes Machine Learning Applications Supporting Sustainable Lifecycle Planning

Table 6.2: Machine Learning Applications Supporting Sustainable Lifecycle Planning

Predictive Target	Input SHM Data	Sustainability Impact
Damage and Deterioration Forecasting	Strain, vibration modes, crack propagation	Minimizes early replacement, reduces repair-related carbon emissions
Operational Energy Prediction	Thermal profiles, humidity, vibration / occupancy signals	Enables real-time energy optimization and HVAC tuning
Moisture and Corrosion Modeling	Moisture ingress, chloride concentration, environmental exposure	Reduces material loss, prolongs component longevity
Retrofit Optimization	Load-response data, modal signatures	Identifies low carbon retrofit solutions with high structural efficiency

6.3 Decision-Support Systems for Sustainable Infrastructure Planning

Decision-support systems (DSS) bring together the outputs of BIM, digital twins, SHM datasets, ML models, and lifecycle assessment (LCA) modules to guide strategic sustainability decisions. A well-structured DSS acts as an integrative computational environment in which structural deterioration predictions, energy simulation feedback, carbon accounting modules, and cost benefit evaluations are placed within a unified analytical architecture [75]–[80]. This integration allows infrastructure agencies to evaluate both immediate and long-term implications of maintenance and retrofit actions.

In a DSS, SHM data plays a pivotal role by grounding sustainability evaluation in actual performance rather than assumed deterioration models. For example, if SHM sensors detect accelerated fatigue or corrosion in a member, the DSS can automatically recalculate maintenance timelines, compute the embodied carbon associated with various repair strategies, and prioritize interventions offering the lowest environmental burden. Simi-

Data serves as the foundational resource for all digitally enabled sustainability workflows; however, it is also the primary bottleneck. SHM systems generate high-frequency sensor streams accelerations, strains, corrosion potentials, temperature gradients, and humidity cycles that often arrive in formats incompatible with BIM schemas and digital twin simulation engines. The lack of standardized data schemas complicates the process of mapping sensor attributes (sampling rate, coordinate system, sensor ID, uncertainty) to BIM-based property sets. This leads to inconsistencies, loss of metadata, and increased manual effort for integration.

Another core issue is the temporal mismatch between static BIM datasets and real-time SHM data. BIM models are not natively designed to ingest continuous data streams, resulting in synchronization errors when attempting to update geometric or semantic elements dynamically. These misalignments distort deterioration simulations, lifecycle projections, and real-time sustainability indicators. Furthermore, poor data quality stemming from sensor drift, environmental noise, intermittent connectivity, or calibration failures can compromise the reliability of sustainability models and energy simulations, particularly in digital twins that rely on continuous calibration.

The challenge is amplified in large-scale infrastructure networks, where SHM deployments consist of hundreds or thousands of sensors distributed across bridges, tunnels, historic masonry, or multi-story buildings. The resulting data volume demands scalable storage, fast retrieval mechanisms, and compression strategies that preserve essential structural features while minimizing computational load. Without robust data governance frameworks, large-scale integration remains inefficient and error-prone, and Table 7.1 includes Major Data-Related Challenges in Digital SHM–BIM–Twin Integration

Table 7.1: Major Data-Related Challenges in Digital SHM–BIM–Twin Integration

Challenge Category	Technical Description	Impact on Sustainability and SHM
Heterogeneous Data Formats	Different sensor and BIM schemas not aligned	Loss of semantic relationships, reduced model accuracy
Temporal Asynchrony	SHM real-time vs. BIM static updates	Inaccurate deterioration projections in digital twins
Data Noise & Sensor Drift	Environmental and hardware-induced distortion	Misleading sustainability metrics and faulty predictions
Scalability Limitations	Large sensor arrays overwhelm storage systems	Slow processing, limited real-time sustainability evaluation
Metadata Loss	Missing sensor provenance, calibration, or location info	Reduced reliability of decision-making workflows

7.2 Technical, Computational, and Interoperability Constraints

The integration of digital systems requires an ecosystem where BIM platforms, IoT devices, simulation engines, machine-learning models, and LCA tools communicate through standardized protocols. However, interoperability remains a significant barrier. Many BIM tools support IFC, gbXML, or COBie formats, while digital twins and SHM middleware use entirely different communication standards (MQTT, OPC-UA, REST APIs, custom binary formats). This fragmentation complicates automated workflows and increases dependence on bespoke integration scripts or middleware, reducing scalability and increasing the risk of long-term system obsolescence [87].

604 Computational constraints also play a central role. High-fidelity digital twins require con-
 605 tinuous updating of FE models based on SHM streams, a process that demands significant
 606 GPU/CPU resources, parallel processing, and sometimes cloud-based simulation clusters.
 607 As model complexity increases, real-time synchronization becomes more difficult, leading
 608 to lag, reduced model fidelity, or the need to oversimplify physics-based simulations. Sim-
 609 ilarly, machine-learning models trained on long-term SHM datasets may require large
 610 computational environments, particularly when dealing with deep networks, hybrid
 611 physics-ML architectures, or multi-year data histories.

612 Security and reliability add to another layer of challenge. IoT sensors, particularly those
 613 deployed in remote or harsh environments, are vulnerable to cyber intrusions, environ-
 614 mental degradation, and communication failures. Any interruption in the data pipeline
 615 directly impacts sustainability assessments and operational forecasting within the digital
 616 twin. Therefore, robust fault-tolerant designs, edge processing, redundancy mechanisms,
 617 and secure communication protocols are necessary to maintain trust in computational
 618 predictions and Table 7.2 includes the Technical and Computational Barriers to Digital
 619 Sustainability Integration

620 Table 7.2: Technical and Computational Barriers to Digital Sustainability Integration

Barrier	Technical Manifestation	Consequence
Limited Interoperability	Non-aligned standards (IFC vs custom IoT protocols)	Inefficient data transfer, manual patching
High Computational Demand	Real-time FE model updating, ML inference	Reduced model frequency or over-simplification
Cybersecurity Vulnerabilities	Weak encryption or unsecured sensors	Corrupted sustainability metrics
Cloud Dependency	Large storage and streaming requirements	Cost escalation and latency issues
Middleware Fragmentation	Proprietary APIs and non-standard connectors	Fragile and non-scalable system architectures

621 **7.3 Organizational and Implementation Challenges**

622 Digital transformation in infrastructure is not solely a technical effort; it is strongly influ-
 623 enced by organizational structures, institutional readiness, and workforce skillsets. Many
 624 public agencies and engineering firms still operate with traditional asset management
 625 frameworks that rely heavily on periodic inspections and manual reporting. Transitioning
 626 toward SHM-enhanced BIM and digital twin workflows requires investments in training,
 627 restructuring of roles, and adoption of new digital maintenance protocols [88].

628 Resistance to change is a recurring obstacle. Engineers accustomed to deterministic struc-
 629 tural assessment methods sometimes distrust data-driven or AI-augmented models, es-
 630 pecially when working with heritage structures or assets located in sensitive urban envi-
 631 ronments. Additionally, sustainability data carbon metrics, lifecycle impact values, or en-
 632 vironmental scores are not consistently incorporated into asset management standards,
 633 reducing institutional motivation for adopting digital sustainability frameworks.

634 Budgetary constraints further complicated implementation. While SHM sensors, cloud
 635 platforms, and twin frameworks are becoming more cost-effective, full-scale integration
 636 still requires substantial upfront investment. This often leads to partial deployments

where SHM is installed but not properly integrated with BIM or digital twins, limiting long-term benefits.

7.4 Opportunities and Future Potential

Despite the challenges, the opportunities presented by digital integration significantly outweigh the constraints. Emerging technologies are reducing complexity, cost, and computational overhead. Automated scan-to-BIM pipelines now allow rapid generation of highly accurate models for existing structures, enabling digital twins to be deployed earlier in the asset lifecycle [89]. Edge computing reduces the burden on cloud infrastructure by processing SHM signals locally, filtering noise, detecting anomalies, and sending only critical features to digital twins. This improves latency, energy efficiency, and scalability.

Advances in explainable AI (XAI) are addressing the trust gap between engineers and machine-learning predictions. Instead of yielding opaque predictions, XAI models provide feature-level interpretations, revealing which structural behaviors or environmental factors drive sustainability assessments. This transparency is essential for regulatory acceptance and engineering confidence.

A significant opportunity lies in standardization. Several international initiatives are currently working toward unified data schemas linking SHM, BIM, and sustainability indicators. Once adopted widely, these standards will dramatically reduce integration effort, improve data fidelity, and democratize digital twin adoption across the construction and infrastructure sectors [90].

In addition, the emergence of portfolio-scale digital twins capable of managing thousands of assets across entire cities or regions will enable sustainability optimization at unprecedented scales. Distributed sensor networks, AI-assisted prioritization engines, and regional carbon management modules will allow infrastructure agencies to allocate resources more efficiently and reduce emissions across whole portfolios, not just individual structures and Table 7.3 includes the Key Opportunities Emerging in Digital Sustainability Integration

Table 7.3: Key Opportunities Emerging in Digital Sustainability Integration

Opportunity	Description	Long-Term Benefit
Automated Scan-to-BIM	Rapid generation of as-is models	Faster digital twin deployment
Edge-Cloud Hybrid Processing	Local intelligence + cloud analytics	Reduced latency and energy use
Explainable AI	Transparent ML-based deterioration and sustainability predictions	Higher engineering acceptance
Unified Data Standards	Harmonized schemas for SHM-BIM-LCA	Reliable and scalable integration
Portfolio-Level Digital Twins	Regional sustainability and maintenance optimization	Large-scale carbon reduction

8. Future Directions and Research Gaps

8.1 Fragmented Digital Ecosystems and the Need for Unified Data Standards

The lack of unified data environments remains one of the most persistent constraints in BIM–SHM integration, as current platforms rely heavily on proprietary formats that inhibit interoperability and long-term data stewardship [91]. Fragmentation in data schemas leads to disrupted information flow between sensing platforms, analysis tools, and BIM environments, resulting in substantial manual intervention and reduced digital continuity [91]. These limitations significantly hinder efforts to maintain structural information fidelity, especially during progressive deterioration or operational changes, where time-dependent data must align with model geometry and material properties [91] and Table 8.1 includes Limitations in Current BIM–SHM Digital Ecosystems

Table 8.1: Limitations in Current BIM–SHM Digital Ecosystems

Limitation Category	Description	Consequence
Proprietary formats	Non-standard data exchange formats	Loss of interoperability
Inconsistent semantics	Poorly defined or missing metadata	Ambiguity in structural interpretation
Manual synchronization	Human-driven data updating	High risk of error and inefficiency
Lack of temporal linkage	SHM data not time-synchronized with BIM	Incomplete lifecycle representation

The absence of temporal semantic mapping prevents BIM from acting as a living representation of asset health, reducing the effectiveness of digital twins in operational environments [91]. Future systems must therefore adopt harmonized IFC extensions, dynamic metadata layers, and semantically structured repositories to enable end-to-end computational pipelines that support long-term adaptive modelling [91].

8.2 AI-Integrated Structural Diagnostics Within BIM Environments

Although machine learning techniques have become central to modern SHM analytics, they largely operate outside BIM ecosystems, creating a discontinuity between pattern recognition outputs and geometric or material model updates [92]. Current platforms rarely support real-time synchronization of sensor-driven anomaly detection with BIM element attributes, resulting in diagnostic outcomes that remain isolated from the structural modelling environment [92]. This disconnection undermines the possibility of automated updating of stiffness properties, crack propagation patterns, or nonlinear degradation indicators within BIM-based analyses [92].

Future systems should embed AI-driven diagnostic engines directly into BIM platforms to allow real-time structural state inference and automated attribute modification [92]. Such systems must also incorporate explainable AI to ensure transparency and reliability in safety-critical decision processes, enabling structural engineers to validate and interpret model-driven predictions in operational contexts [92].

8.3 Automation Deficits in Scan-to-BIM Workflows

Existing scan-to-BIM pipelines remain highly manual, particularly when dealing with complex geometries, historical building materials, and deteriorated structural surfaces [93]. Point cloud segmentation algorithms often lack robustness in the presence of occlusions, irregular shapes, and multi-layered construction typologies, reducing the ability to produce accurate as-is structural models [93]. These issues significantly delay SHM-ready

702 digital model construction because manually processed point clouds introduce subjectiv-
 703 ity and geometric uncertainty [93] and Table 8.2 includes Persistent Gaps in Automated
 704 Scan-to-BIM Reconstruction

705 Table 8.2: Persistent Gaps in Automated Scan-to-BIM Reconstruction

Challenge	Description	Impact on SHM
Occlusion handling	Inability to interpret missing regions	Ambiguous geometry
Material misclassification	Incorrect surface/element recognition	Incorrect property assignment
Shape irregularity	Difficulty segmenting damaged or aged surfaces	Reduced modelling accuracy
Limited automation	Need for manual modelling	Slow model preparation

706 Deep learning driven reconstruction approaches are promising but remain insufficiently
 707 trained on structurally deteriorated cases, limiting their applicability in operational con-
 708 ditions [93]. Future pipelines require uncertainty-aware shape completion methods and
 709 probabilistic geometry inference models to ensure high-fidelity reconstruction of real ag-
 710 ing structures [93].

711 **8.4 Integrating Multi-Physics Simulation with BIM and SHM**

712 Most BIM-supported simulations rely on deterministic structural models that do not in-
 713 corporate stochastic variations observed in SHM data or multi-physics interactions such
 714 as moisture migration, thermal cycling, or seismic excitation [94]. This disconnect restricts
 715 the ability to perform dynamic model updating or deterioration forecasting under real
 716 environmental loading conditions [94]. As a result, digital models remain static and fail to
 717 represent the evolving structural behavior required for predictive maintenance [94].

718 Fully integrated multi-physics frameworks within BIM environments would allow simu-
 719 lations to calibrate automatically using SHM-derived parameters, creating a feedback
 720 loop for real-time structural state estimation [94]. This would significantly enhance long-
 721 term performance modelling, seismic fragility assessments, and lifecycle-level structural
 722 sustainability evaluations [94].

723 **8.5 Digital Twins Beyond Visualization Toward Predictive Mechanisms**

724 Most digital twins developed today resemble enhanced BIM models with sensor dash-
 725 boards, lacking bidirectional data coupling and predictive modelling capabilities [95].
 726 Without predictive intelligence, these models cannot autonomously forecast deterioration
 727 progression, system response to extreme events, or optimal maintenance timelines [95].
 728 The absence of automated corrective actions or closed-loop control mechanisms further
 729 restricts digital twin functionality to passive monitoring [95] Table 8.3 includes Levels of
 730 Digital Twin Maturity

731 Table 8.3: Levels of Digital Twin Maturity

Level	Description	Current Status
DT-0	BIM only	Fully established
DT-1	BIM + visualization dashboards	Widely used
DT-2	BIM + SHM data + analytics	Limited deployment

DT-3	Predictive digital twin	Rare and experimental
DT-4	Autonomous decision-support twin	Not yet realized

To achieve true operational digital twins, systems must incorporate real-time data assimilation, hybrid physics–ML predictive engines, and automated maintenance decision-making modules guided by risk-based analysis [95].

8.6 Absence of Robust Uncertainty Quantification (UQ)

Current BIM–SHM frameworks do not adequately address uncertainties arising from sensor noise, environmental influences, modelling simplifications, or incomplete geometric information [96]. This leads to unreliable structural performance predictions, which can compromise safety assessments in critical infrastructure applications [96]. Models that ignore uncertainty propagate systematic errors into lifecycle maintenance decision-making, reducing confidence in automated diagnostics [96].

Future directions demand the integration of Bayesian inference, stochastic finite element modelling, and probabilistic data fusion into BIM-enabled SHM systems to ensure scientifically defensible predictions under uncertainty [96]. These enhancements are also essential for developing reliable digital twins capable of long-term autonomous operation [96].

8.7 Sustainability-Centric Structural Digitalization

Although sustainability metrics such as embodied carbon, operational energy, and retrofit optimization are increasingly relevant, current BIM–SHM integrations rarely incorporate dynamic sustainability modelling [97]. Most sustainability assessments are static and fail to adapt to deteriorating structural conditions or updated SHM data [97]. This disconnect creates gaps in lifecycle management strategies where performance degradation and environmental impact evolve concurrently [97].

Future frameworks must integrate dynamic sustainability engines within BIM platforms, linking deterioration models, SHM-derived material states, and predictive analytics to evaluate retrofit impacts and lifecycle resource expenditure [97]. This will enable high-resolution sustainability scoring and informed asset management under uncertainty [97].

8.8 Scalable Data Management for Long-Term SHM

Large-scale SHM systems generate high-frequency, multi-sensor time-series data that exceed the storage and processing capacities of typical BIM platforms [98]. Without scalable architectures, long-term monitoring datasets become fragmented, difficult to retrieve, and incompatible with computational modelling requirements [98]. This significantly restricts the ability to perform decade-scale structural performance evaluations or deterioration trend modelling [98].

To address these limitations, future systems must adopt cloud-based distributed data architectures, graph-based temporal indexing, and compression algorithms tailored for structural monitoring datasets [98]. These solutions would enable near-real-time BIM–SHM synchronization while supporting high-resolution historical data analytics [98].

8.9 Absence of Global Validation Protocols and Standards

The absence of globally harmonized validation and standardization frameworks continues to be one of the most fundamental obstacles preventing reliable, scalable, and industry-wide integration of BIM-SHM-Digital Twin environments [99]. At present, nearly every research group, infrastructure authority, and technological developer operates under isolated procedures that are tailored to local regulations, proprietary software ecosystems, or project-specific requirements, resulting in a highly fragmented global landscape [99]. This fragmentation not only restricts the interoperability of digital workflows but also obstructs the creation of long-term structural information ecosystems capable of evolving with the asset over decades [99].

A major consequence of this fragmentation is the lack of consistency in the validation of sensor data, semantic modelling rules, and digital twin updating procedures, which significantly undermines confidence in the accuracy and credibility of integrated digital asset models [99]. Without standardized calibration procedures, unified metadata structures, and reference ontologies, the mapping of SHM data onto BIM elements becomes subjective and non-repeatable, creating discrepancies in structural assessments and lifecycle predictions across platforms [99]. This is particularly critical for high-risk assets such as long-span bridges, nuclear facilities, offshore structures, and masonry heritage buildings, where digital misinterpretation can translate directly into unsafe engineering decisions [99].

Furthermore, the lack of globally recognized benchmark datasets makes it difficult for emerging AI-enhanced SHM algorithms to be evaluated under comparable conditions, thereby limiting the pace of technical progress [99]. Industrial stakeholders and regulatory agencies remain cautious because no unified validation frameworks exist to certify the performance of machine-learning-based diagnostics or automated digital twin updating algorithms in operational environments [99]. As a result, cutting-edge technologies remain confined to pilot studies rather than full-scale industrial deployment and Table 8.4 includes Key Standardization Gaps in BIM-SHM-Digital Twin Integration

Table 8.4. Key Standardization Gaps in BIM-SHM-Digital Twin Integration

Standardization Gap	Description	Implications
Sensor Calibration Protocols	No unified international guidelines for calibration, noise filtering, or baseline establishment	Non-comparable SHM datasets
Data Semantics & Ontologies	BIM and SHM use different metadata structures and inconsistent naming conventions	Weak interoperability between platforms
Digital Twin Update Rules	No standard workflow for model updating or geometry-property synchronization	Non-repeatable digital assessments
AI/ML Validation Datasets	Lack of benchmark structural datasets across typical deterioration scenarios	Limited reliability of diagnostics
Lifecycle Verification	Absence of long-term evaluation frameworks	Poor trust in digital twins for aging infrastructure

To overcome these challenges, future research must prioritize the creation of global standardization bodies or collaborative panels like ISO, fib, or CEN committees that specifically address the digital fusion of sensing, modelling, and lifecycle decision-making workflows [99]. Such frameworks must define sensor-to-BIM linking standards, semantic data rules, digital twin verification cycles, and lifecycle documentation protocols that remain consistent across software vendors, infrastructure agencies, and national boundaries [99]. The

development of these standards will be essential for enabling reproducible, auditable, and certifiable digital twin systems that can confidently support safety-critical engineering decisions worldwide [99].

8.10 Autonomous Structural Decision-Making Systems

Autonomous structural decision-making systems are emerging as a transformative future paradigm, aiming to transition infrastructure management from manually interpreted monitoring systems toward intelligent, self-diagnosing, and eventually self-optimizing asset ecosystems [100]. These systems combine real-time SHM data, AI-based deterioration forecasting, and automated risk classification to generate maintenance recommendations or in advanced forms, execute control actions without continuous human supervision [100]. However, despite their promise, the deployment of such systems remains limited because current technologies operate under incomplete transparency, insufficient safety validation, and uncertain regulatory oversight [100].

A central challenge is the “black-box” nature of many machine-learning models that underlie autonomous decision engines, which makes their internal reasoning opaque to engineers responsible for asset safety [100]. Without interpretability, it becomes nearly impossible to verify whether a maintenance action recommended by an autonomous system is grounded in legitimate structural behavior or influenced by statistical noise, bias, or poorly calibrated model parameters [100]. These concerns are amplified in safety-critical contexts, where automated decisions must be as robust and justifiable as traditional engineering calculations grounded in deterministic physical principles [100].

Moreover, implementing autonomous decision-making requires extremely robust integration between sensing systems, digital twins, physics-based simulations, and predictive algorithms, all of which must operate synchronously and reliably over decades [100]. Any misalignment such as delayed data, incomplete model updates, sensor faults, or security breaches can propagate through the automated decision chain and generate unsafe outcomes [100]. Regulatory agencies currently lack the legal frameworks needed to assign liability for failures arising from autonomous AI-driven assessments, further slowing industrial adoption [100] and Table 8.5 includes Challenges Limiting Deployment of Autonomous SHM Decision Systems

Table 8.5. Challenges Limiting Deployment of Autonomous SHM Decision Systems

Challenge	Description	Associated Risk
Lack of Explainable AI	AI models do not provide interpretable decision logic	Engineers cannot validate outputs
Data & Model Drift	Structural behaviour changes but models are not updated	Incorrect predictions
Cybersecurity Vulnerabilities	IoT-enabled systems susceptible to intrusion	Manipulated sensor data
Regulatory Gaps	No established certification for autonomous systems	Industrial adoption delayed
Uncertainty Propagation	Sensor noise affects model reliability	Risk of unsafe decisions

To advance toward deployable autonomous systems, future research must develop hybrid decision-making architectures in which AI engines operate alongside deterministic structural models to produce explainable, physically consistent outputs [100]. Human-in-

837 the-loop control systems should be integrated to provide supervisory oversight, ensuring
838 that engineers retain final authority over safety-critical decisions while still benefiting
839 from automated analytics [100]. Additionally, rigorous certification frameworks must be
840 developed, including scenario-based testing protocols, long-term digital twin stress test-
841 ing, and cybersecurity-grade monitoring of data authenticity [100]. Only through these
842 advancements can autonomous structural systems evolve into trustworthy, ethically de-
843 ployable, and operationally safe components of next-generation infrastructure networks
844 [100].

845 **9. Future Research Directions**

846 **9.1 Standardization and Harmonization of Indicators**

847 The integration of Structural Health Monitoring (SHM) with sustainability indicators is
848 still in a formative stage, and one of the most critical research directions is the develop-
849 ment of standardized frameworks and harmonized metrics that consistently quantify sus-
850 tainability outcomes across diverse infrastructure types and operational contexts. Current
851 literature reveals a substantial lack of uniformity in defining, measuring, and reporting
852 environmental, social, and economic sustainability indicators, which significantly limits
853 the comparability of findings and the generalizability of results across projects.

854 Future studies should focus on establishing internationally recognized standards that in-
855 tegrate SHM outputs with life-cycle assessments, embodied carbon calculations, and en-
856 ergy performance metrics. Such standardization will enable data-driven decision-making,
857 providing infrastructure planners and managers with reliable tools for sustainable devel-
858 opment and maintenance prioritization. Furthermore, harmonized indicators will facili-
859 tate cross-project benchmarking and foster a globally consistent approach to evaluating
860 structural performance in tandem with environmental sustainability.

861 **9.2 Advanced Sensing, AI, and Predictive Monitoring**

862 Another pivotal research area is the advancement of sensing technologies and predictive
863 monitoring methods. While current SHM systems effectively capture structural re-
864 sponses, their integration with real-time sustainability indicators remains limited. Emerg-
865 ing sensor technologies capable of multi-modal monitoring including structural strain,
866 vibration, temperature, humidity, and operational load present significant opportunities
867 for integrated sustainability assessment. When combined with artificial intelligence and
868 machine learning algorithms, these technologies can enable predictive monitoring, allow-
869 ing infrastructure managers to forecast both structural behavior and environmental per-
870 formance.

871 Future research should emphasize developing robust algorithms that fuse high-frequency
872 SHM data with sustainability metrics, enabling early warning systems, predictive mainte-
873 nance scheduling, and proactive resource management. By advancing predictive moni-
874 toring, decision-makers can move beyond reactive strategies toward more optimized, en-
875 vironmentally informed interventions.

876 **9.3 Policy Implications and Sustainable Infrastructure Governance**

877 The policy and governance dimension of SHM–sustainability integration remains under-
878 explored, despite its importance for practical implementation. Technological advance-
879 ments alone cannot guarantee adoption without enabling regulatory frameworks, incen-
880 tives for sustainable construction, and standardized protocols for data sharing among
881 stakeholders.

882 Research should investigate governance models that balance transparency, privacy, and
883 accountability while encouraging the use of SHM-informed sustainability metrics in pub-
884 lic and private infrastructure projects. Additionally, studies should examine how SHM-
885 derived insights can influence building codes, maintenance regulations, and sustainabil-
886 ity certifications, creating pathways for evidence-based policy development. Addressing
887 these policy gaps will enhance the practical applicability of SHM–sustainability integra-
888 tion and support long-term, performance-driven infrastructure governance.

889 **9.4 Opportunities for Multi-Disciplinary Collaboration**

890 Integrating SHM with sustainability indicators inherently requires expertise spanning
891 structural engineering, materials science, environmental engineering, data science, and
892 computational modeling. Future research should prioritize the development of collabora-
893 tive platforms and methodological frameworks that facilitate cross-domain knowledge
894 exchange. Such collaboration can enable engineers, data scientists, and sustainability spe-
895 cialists to co-develop decision-support tools and integrated modeling approaches.

896 Multi-disciplinary partnerships will also foster the development of hybrid models that
897 combine physical simulations with data-driven predictions, improving the fidelity of sus-
898 tainability assessments and enabling adaptive infrastructure management in real-time.
899 These collaborative approaches are essential for addressing complex challenges such as
900 climate adaptation, material degradation, and lifecycle optimization in modern infrastruc-
901 ture systems.

902 **9.5 Optimization of Adaptive Maintenance Strategies**

903 Finally, the optimization of adaptive maintenance strategies informed by SHM and sus-
904 tainability metrics represents a critical research direction. Current maintenance ap-
905 proaches often rely on fixed schedules or reactive interventions, which can result in un-
906 necessary resource consumption and environmental impact. By combining predictive
907 SHM analytics with sustainability-focused decision frameworks, future research can de-
908 velop algorithms that dynamically prioritize maintenance, retrofitting, and resource allo-
909 cation based on structural performance, lifecycle cost, and environmental indicators. Such
910 strategies will support lifecycle optimization, minimize carbon emissions, reduce opera-
911 tional inefficiencies, and extend asset service life.

912 Moreover, integrating predictive maintenance with sustainability evaluation can trans-
913 form infrastructure management from reactive processes to proactive, environmentally
914 optimized, and data-driven practices, aligning structural resilience with green construc-
915 tion objectives.

916 **10. Conclusion**

917 **10.1 Key Insights from the Systematic Review**

918 This systematic review has demonstrated that integrating Structural Health Monitoring
919 (SHM) with sustainability indicators offers a transformative approach for advancing re-
920 siliant and environmentally responsible infrastructure. Analysis of the literature from
921 2000 to 2025 reveals a clear evolution in SHM technologies from manual inspections to
922 sensor-driven, real-time monitoring systems capable of providing high-fidelity structural
923 performance data.

924 Modern SHM frameworks, particularly when combined with digital platforms such as
925 BIM and digital twins, enable continuous assessment of structural integrity, early detec-
926 tion of deterioration, and predictive maintenance strategies that can substantially enhance
927 lifecycle performance.

928 Similarly, sustainability assessment in construction has matured, encompassing environ-
929 mental, economic, and social indicators. Metrics such as embodied carbon, energy effi-
930 ciency, material durability, and adaptability now provide actionable insights for design-
931 ing and maintaining green infrastructure. However, the literature highlights a persistent
932 gap: while both SHM and sustainability evaluation have individually advanced, there is
933 limited research effectively bridging these domains. The review identified only a small
934 subset of studies that link structural monitoring outputs directly to sustainability out-
935 comes, illustrating the need for integrated approaches capable of informing both perfor-
936 mance and environmental decision-making simultaneously.

937 **10.2 Implications of Integrating SHM with Sustainability**

938 Integrating SHM data with sustainability indicators has significant implications for both
939 practice and research. For practitioners, such integration enables evidence-based mainte-
940 nance, retrofitting, and operational strategies that optimize structural performance while
941 minimizing environmental impact. Real-time monitoring data can inform adaptive inter-
942 ventions, extending service life, reducing resource consumption, and supporting green
943 construction objectives. For policymakers, linking structural health data to sustainability
944 outcomes provides a foundation for establishing performance-based codes, standards,
945 and incentive programs that reward environmentally responsible and resilient infrastruc-
946 ture management.

947 From a research perspective, the integration emphasizes the need for cross-disciplinary
948 collaboration. Structural engineers, materials scientists, sustainability specialists, and data
949 scientists must co-develop predictive models and decision-support frameworks that
950 translate raw monitoring data into actionable insights for sustainability-oriented infra-
951 structure management. Additionally, the incorporation of AI, machine learning, and
952 multi-physics simulation presents opportunities to create predictive digital twins capable
953 of simulating both structural deterioration and environmental impacts over extended
954 lifecycles.

955 **10.3 Recommendations for Researchers, Practitioners, and Policymakers**

956 Based on the findings of this review, several recommendations emerge:

1. **Standardization and Harmonization:** Develop globally accepted metrics and protocols to link SHM outputs with sustainability indicators. This standardization is essential for ensuring comparability, reproducibility, and reliability across projects and infrastructure types.
2. **Technological Advancement:** Promote research into multi-modal sensing, predictive analytics, and AI integration to enhance real-time monitoring and lifecycle forecasting, thereby supporting proactive and sustainable decision-making.
3. **Policy Development:** Encourage the formulation of regulatory frameworks and incentive mechanisms that integrate SHM-informed sustainability metrics into building codes, asset management policies, and green construction certifications.
4. **Multi-Disciplinary Collaboration:** Facilitate partnerships between engineers, environmental specialists, and data scientists to co-develop decision-support systems, predictive maintenance strategies, and lifecycle sustainability frameworks.
5. **Adaptive Management Strategies:** Implement maintenance and retrofitting approaches that dynamically adjust interventions based on structural performance data and sustainability considerations, optimizing both resilience and environmental outcomes.
6. **Future Research Focus:** Investigate gaps identified in digital twin validation, autonomous decision-making, uncertainty quantification, and integration of multi-physics simulation, ensuring that the next generation of infrastructure management tools is robust, reliable, and environmentally responsible.

By synthesizing SHM and sustainability within a unified framework, infrastructure stakeholders can achieve a dual objective: enhanced resilience against structural failure and alignment with green construction goals. This review highlights that although considerable progress has been made in both domains independently, the next frontier lies in their integration creating intelligent, adaptive, and environmentally optimized infrastructure systems. The continued development of standardized, predictive, and data-driven frameworks will be crucial for realizing this vision and enabling sustainable infrastructure management at scale.

References

- [1] A. Benítez and P. Garcia, "Monitoring-informed refurbishment reduces building LCA impacts," *Building and Environment*, vol. 219, p. 109192, 2022.
- [2] A. Carvalho and P. Lourenço, "Damage detection in heritage buildings for sustainability decision-making," *Journal of Building Engineering*, vol. 51, p. 104375, 2022.
- [3] A. D. Broida, A. N. Robertson and M. K. Chaturvedi, "Use of vibration measurements for structural health monitoring of civil infrastructure," *Journal of Sound and Vibration*, vol. 383, pp. 145–167, 2016.
- [4] A. De Angelis, S. Mariani and P. Faccio, "Energy-based sustainability assessment of buildings through health monitoring data,"

- 997 *Sustainable Cities and Society*, vol. 79, p. 103737, 2022.
- 998 [5] A. De Rubeis, M. Nardecchia and F. Berardinis, "Energy and environmental benefits of monitoring-based maintenance in public
999 buildings," *Building and Environment*, vol. 220, p. 109278, 2023.
- 1000 [6] A. M. Díaz and J. F. Ramos, "Monitoring-enabled extension of service life in reinforced concrete structures," *Construction and
1001 Building Materials*, vol. 258, p. 119589, 2020.
- 1002 [7] A. M. Dominguez and V. P. Silva, "Carbon-efficient seismic retrofit planning informed by structural monitoring," *Soil Dynamics
1003 and Earthquake Engineering*, vol. 160, p. 107421, 2022.
- 1004 [8] A. R. Deshmukh and P. Sharma, "Predictive SHM for high-performance sustainable composite structures," *Composite Structures*,
1005 vol. 255, p. 113050, 2021.
- 1006 [9] A. Romeu and M. Lorente, "Sensor fusion EoL (End-of-Life) residual capacity evaluation for sustainable infrastructure planning,"
1007 *Structural Safety*, vol. 96, p. 102160, 2022.
- 1008 [10] A. T. Al-Hussein, D. B. Cole and N. Truman, "Life cycle assessment integrated with SHM practices in high-rise structures,"
1009 *Journal of Cleaner Production*, vol. 271, p. 122559, 2020.
- 1010 [11] A. W. Alani and M. N. Aboutalebi, "Self-sensing concrete for sustainable infrastructure monitoring," *Construction and Building
1011 Materials*, vol. 145, pp. 562–573, 2017.
- 1012 [12] B. Beemer and C. Theiler, "Energy harvesting for long-life sustainable SHM systems," *Smart Materials and Structures*, vol. 29, no.
1013 10, p. 105038, 2020.
- 1014 [13] B. Riveiro, L. Solla and J. Lamas, "Non-destructive techniques for sustainability assessment of heritage structures," *Journal of
1015 Cultural Heritage*, vol. 28, pp. 10–21, 2017.
- 1016 [14] B. Zou and J. Wu, "Assessment of structural resilience using real-time SHM degradation models," *Engineering Structures*, vol.
1017 233, p. 111889, 2021.
- 1018 [15] C. B. Dinh, A. P. J. Yap and L. L. Le, "Hybrid SHM-BIM models for predictive sustainability," *Automation in Construction*, vol.
1019 140, p. 104398, 2022.
- 1020 [16] C. Gragnaniello, A. De Luca and F. Biondi, "BIM-based design and setup of structural health monitoring systems," *Automation
1021 in Construction*, 2024.
- 1022 [17] C. R. Farrar and K. Worden, "An introduction to structural health monitoring," *Philosophical Transactions of the Royal Society A:
1023 Mathematical, Physical and Engineering Sciences*, vol. 365, no. 1851, pp. 303–315, Feb. 2007.
- 1024 [18] C. R. Farrar and K. Worden, *Structural Health Monitoring: A Machine Learning Perspective*, John Wiley & Sons, 2013.
- 1025 [19] C. R. Farrar, S. W. Doebling and D. A. Nix, "Structural health monitoring studies of the Alamosa Canyon and I-40 bridges," Los
1026 Alamos National Laboratory Rep. LA-13635-MS, 2000.
- 1027 [20] C. R. Farrar, S. W. Doebling, and D. A. Nix, "Vibration-based structural damage identification," *Philosophical Transactions of the
1028 Royal Society A*, vol. 359, pp. 131–149, 2001.
- 1029 [21] D. A. Rytter, L. N. Brincker and P. Andersen, "Operational modal analysis for long-term bridge assessment," *Structural Health
1030 Monitoring*, vol. 10, no. 2, pp. 103–118, 2011.
- 1031 [22] D. Chatzigeorgiou and M. K. Pham, "Multi-scale sensing and digital twins for resilient infrastructure," *Automation in Construc-
1032 tion*, vol. 139, p. 104353, 2022.
- 1033 [23] F. Hadigheh and A. Jafari, "Bio-inspired self-sensing concrete promoting sustainable SHM," *Smart Materials and Structures*, vol.
1034 31, no. 12, p. 125007, 2022.
- 1035 [24] F. J. Mendez and L. P. da Silva, "Digital twin monitoring of FRP retrofitted beams for sustainability performance," *Composites
1036 Part B: Engineering*, vol. 242, p. 110149, 2022.
- 1037 [25] F. Ribeiro and C. Dias, "SHM-based retrofit optimization using life-cycle sustainability scoring," *Building and Environment*, vol.
1038 214, p. 108886, 2022.
- 1039 [26] G. Castiglioni and M. Cattaneo, "Sensor-based fatigue monitoring for sustainability of steel structures," *Journal of Constructional
1040 Steel Research*, vol. 190, p. 107136, 2022.
- 1041 [27] G. Park and D. J. Inman, "Structural health monitoring using piezoelectric impedance measurements," *Philosophical Transactions
1042 of the Royal Society A*, vol. 365, pp. 373–392, 2007.
- 1043 [28] G. Park, T. Rosing, M. D. Todd, C. R. Farrar and W. Hodgkiss, "Energy harvesting for structural health monitoring sensor net-
1044 works," *Journal of Infrastructure Systems*, vol. 14, no. 1, pp. 64–79, 2008.

- 1045 [29] G. T. Smith and R. M. Hernandez, "Digital twin alignment for life-cycle sustainability of infrastructure," *Journal of Cleaner Pro-*
1046 *duction*, vol. 403, p. 136950, 2023.
- 1047 [30] H. Sohn, "Effects of environmental and operational variability on structural health monitoring," *Philosophical Transactions of the*
1048 *Royal Society A*, vol. 365, pp. 539–560, 2007.
- 1049 [31] H. Wang and Z. Lin, "Corrosion rate sensing for life-cycle carbon reduction in bridges," *Sensors*, vol. 21, no. 17, p. 5844, 2021.
- 1050 [32] H. Zhang and D. Guo, "Predictive maintenance for sustainability using structural health monitoring data," *IEEE Sensors Journal*,
1051 vol. 21, no. 17, pp. 19678–19686, 2021.
- 1052 [33] J. A. Lloyd and G. P. Lee, "AI-enhanced modal tracking for extended bridge service life," *Smart Structures and Systems*, vol. 28,
1053 no. 4, pp. 633–647, 2021.
- 1054 [34] J. Carvalho and E. L. Rodrigues, "Data-driven deterioration models for life-cycle environmental optimization," *Sustainable Cities*
1055 *and Society*, vol. 83, p. 103988, 2022.
- 1056 [35] J. Li and X. Wang, "Low-energy smart sensing technologies for green bridge monitoring," *Bridge Structures*, vol. 18, no. 3, pp.
1057 220–229, 2022.
- 1058 [36] J. M. Brownjohn, "Structural health monitoring of civil infrastructure," *Philosophical Transactions of the Royal Society A*, vol. 365,
1059 pp. 589–622, 2007.
- 1060 [37] J. P. Lynch, "An overview of wireless structural health monitoring for civil structures," *Philosophical Transactions of the Royal*
1061 *Society A*, vol. 365, pp. 345–372, 2007.
- 1062 [38] K. E. Ogunbamowo, "Energy-efficient structural rehabilitation informed by SHM," *Sustainable Energy Technologies and Assess-*
1063 *ments*, vol. 56, p. 102932, 2023.
- 1064 [39] K. Worden and J. M. Dulieu-Barton, "Intelligent damage identification in systems and structures," *Int. J. Struct. Health Monitoring*,
1065 vol. 3, no. 1, pp. 85–98, 2004.
- 1066 [40] K. Worden, G. Manson and G. Park, "The fundamental axioms of structural health monitoring," *Proc. R. Soc. A*, vol. 463, no. 2082,
1067 pp. 1639–1664, 2007.
- 1068 [41] K. Bouras and S. M. Eldin, "Self-powered sensor systems enabling low-carbon infrastructure monitoring," *Smart Materials and*
1069 *Structures*, vol. 31, no. 5, p. 055003, 2022.
- 1070 [42] L. Nicoletti, A. R. Smith, and M. G. Rossi, "Operational modal analysis as a support for the development of digital twin models
1071 of bridges," *Infrastructures*, vol. 8, p. 24, 2023.
- 1072 [43] L. P. Markou and G. Z. Papadakis, "Self-powered wireless sensors for SHM and sustainable infrastructure monitoring," *Sensors*,
1073 vol. 19, no. 5, p. 1122, 2019.
- 1074 [44] L. J. Xu, D. Q. Zhang and T. H. Huang, "Digital twin-enabled corrosion monitoring of reinforced concrete for sustainability,"
1075 *Corrosion Science*, vol. 198, p. 110210, 2022.
- 1076 [45] M. Abdel Wahab and J. Wang, "Wireless sensing for smart infrastructure sustainability," *Sensors*, vol. 21, no. 5, p. 1732, 2021.
- 1077 [46] M. A. Benitez, L. F. Lopez and R. H. Castillo, "Non-destructive monitoring strategies improving life-cycle assessment outcomes
1078 in bridges," *Bridge Maintenance, Safety, Management, Life-Cycle Sustainability and Innovations*, CRC Press, 2021.
- 1079 [47] M. C. Zhuang and S. K. Au, "Probabilistic damage detection for long-term sustainability assessment," *Mechanical Systems and*
1080 *Signal Processing*, vol. 150, p. 107252, 2021.
- 1081 [48] M. D. Todd, J. M. Nichols, S. T. Trickey, M. Seaver, C. J. Nichols and L. N. Virgin, "Bragg grating-based fibre optic sensors in
1082 structural health monitoring," *Philosophical Transactions of the Royal Society A*, vol. 365, pp. 317–343, 2007.
- 1083 [49] M. Fawad, A. N. Siddiqui, M. A. Khan and C. R. Farrar, "Automation of structural health monitoring system using BIMification
1084 approach," *Scientific Reports*, vol. 13, 2023.
- 1085 [50] M. H. Kim and Y. S. Park, "Carbon footprint reduction through IoT-SHM," *Journal of Cleaner Production*, vol. 378, p. 134613, 2022.
- 1086 [51] M. K. Alam and K. K. Shrestha, "Digital twin-enabled holistic sustainability monitoring for infrastructure networks," *Automation*
1087 *in Construction*, vol. 143, p. 104573, 2023.
- 1088 [52] M. N. Akhtar and S. S. Qadir, "Energy-efficient wireless crack monitoring sensors for bridges," *IEEE Sensors Journal*, vol. 21, no.
1089 20, pp. 22879–22887, 2021.
- 1090 [53] O. S. Izzi and R. J. Sandoval, "Integration of SHM and BIM for carbon mitigation decision-support," *Automation in Construction*,
1091 vol. 140, p. 104413, 2022.
- 1092 [54] P. Arora and S. Gupta, "Sustainability benchmarking using SHM data integration with green rating tools," *Sustainable Cities and*

- 1093 *Society*, vol. 96, p. 104629, 2023.
- 1094 [55] P. Ciang, J. R. Lee and H. J. Bang, "Structural health monitoring for a wind turbine system: a review of damage detection meth-
1095 ods," *Measurement Science and Technology*, vol. 19, no. 12, p. 122001, 2008.
- 1096 [56] P. F. Rizzo and A. S. Tartakovsky, "Ultrasonic SHM methods for durability and energy-efficient maintenance," *Ultrasonics*, vol.
1097 120, p. 106745, 2022.
- 1098 [57] P. Palma, E. J. Cruz-Ortiz and A. M. Ferreira, "Structural health monitoring of timber structures: review of methods and appli-
1099 cations," *Measurement*, 2020.
- 1100 [58] P. P. Rodrigues, S. Santos and J. Silva, "LCA and SHM: integrated framework for sustainable building management," *Building*
1101 *Research & Information*, vol. 50, no. 3, pp. 281–301, 2022.
- 1102 [59] R. C. Yu, K. H. Chung and C. K. Lee, "Digital twin-driven resilient infrastructure maintenance," *Journal of Infrastructure Systems*,
1103 vol. 29, p. 04023009, 2023.
- 1104 [60] R. Gomez and H. Y. Leung, "Performance-based sustainability classification using SHM life-cycle indicators," *Automation in*
1105 *Construction*, vol. 126, p. 103691, 2021.
- 1106 [61] R. Siddiqui and C. J. Chung, "IoT-SHM for sustainable cement composite structures," *Journal of Cleaner Production*, vol. 360, p.
1107 132234, 2022.
- 1108 [62] R. P. Dhakal and S. Pampanin, "Seismic resilience metrics linking structural performance to long-term sustainability," *Earthquake*
1109 *Engineering & Structural Dynamics*, vol. 49, no. 1, pp. 4–21, 2020.
- 1110 [63] S. A. Jaffer and O. Al-Mutairi, "Reliability-based durability monitoring of concrete in marine environments," *Cement and Concrete*
1111 *Composites*, vol. 128, p. 104489, 2022.
- 1112 [64] S. H. Lee and J. K. Cho, "Green lifecycle governance through IoT-based SHM," *IEEE Systems Journal*, vol. 17, no. 1, pp. 1626–1637,
1113 2023.
- 1114 [65] S. Jayasinghe, R. Perera and D. Silva, "Smart structural monitoring: real-time bridge response digital twin," *Sensors (Basel)*, 2025.
- 1115 [66] S. Kankanamge and Y. Jayasinghe, "Life cycle carbon reduction through SHM-enabled decision making," *Buildings*, vol. 12, no.
1116 11, p. 1824, 2022.
- 1117 [67] S. K. Sharma and V. Kumar, "Internet of Things-based structural health monitoring system for sustainable bridge maintenance,"
1118 *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7157–7168, 2021.
- 1119 [68] S. P. Singh and P. Kumar, "Sustainability-based condition assessment of steel bridges using corrosion monitoring sensors," *Con-*
1120 *struction and Building Materials*, vol. 325, p. 126648, 2022.
- 1121 [69] T. U. Van, M. T. Nguyen and E. Lim, "Bridge life cycle extension using AI-based SHM," *Sensors*, vol. 20, p. 2345, 2020.
- 1122 [70] T. V. Nguyen, H. Bui and L. Hoang, "Real-time moisture monitoring for sustainable wooden heritage preservation," *Journal of*
1123 *Cultural Heritage*, vol. 60, pp. 39–48, 2023.
- 1124 [71] T. W. Kim and C. Y. Lee, "Monitoring-enabled service life prediction using SHM for sustainable materials selection," *Materials*
1125 *& Design*, vol. 215, p. 110479, 2022.
- 1126 [72] T. Xia and S. Coltman, "Sustainability-driven monitoring of prestressed structures," *Engineering Structures*, vol. 207, p. 110222,
1127 2020.
- 1128 [73] T. Z. Ye and D. Garlock, "Thermal stress SHM for energy-resilient building envelopes," *Energy and Buildings*, vol. 243, p. 110996,
1129 2021.
- 1130 [74] W. J. Staszewski and A. N. Robertson, "Time–frequency and time–scale analyses for structural health monitoring," *Philosophical*
1131 *Transactions of the Royal Society A*, vol. 365, pp. 449–477, 2007.
- 1132 [75] W. K. Chong and A. M. Thomas, "SHM-driven resiliency modelling for ageing infrastructure," *Journal of Infrastructure Systems*,
1133 vol. 27, no. 3, p. 04021024, 2021.
- 1134 [76] X. Li, H. Ding and Y. Pan, "Time-frequency degradation analysis supporting sustainable structural operation," *Mechanical Sys-*
1135 *tems and Signal Processing*, vol. 184, p. 109545, 2023.
- 1136 [77] Y. Li, X. Xu and P. L. Wong, "Resilience metrics informed by structural monitoring data," *Structural Control and Health Monitoring*,
1137 vol. 30, e3178, 2023.
- 1138 [78] Y. J. Lin, A. R. Diaz and M. S. Li, "SHM-enabled adaptive retrofit strategies for sustainable bridges," *Bridge Structures*, vol. 19,
1139 no. 3–4, pp. 201–214, 2023.
- 1140 [79] Y. Wang and F. Li, "Sustainability-driven predictive maintenance using Bayesian SHM," *Mechanical Systems and Signal Processing*,
1141 vol. 184, p. 109688, 2023.

- 1142 [80] Y. Zhang, "Systematic review of embodied carbon assessment and mitigation strategies in buildings," NIST Technical Report,
1143 2024.
- 1144 [81] Z. Li, Y. Wang and Q. Zhu, "Machine learning-based structural health monitoring for smart and sustainable infrastructure,"
1145 *Engineering Structures*, vol. 245, p. 112752, 2021.
- 1146 [82] "International research projects on structural health monitoring," H. Van der Auweraer, *Structural Health Monitoring: An Inter-*
1147 *national Journal*, 2003.
- 1148 [83] "Prediction of rapid chloride penetration resistance of metakaolin based high strength concrete using light GBM and XGBoost
1149 models by incorporating SHAP analysis," A. Abdulalim Alabdullah, M. Iqbal, M. Zahid, K. Khan, M. Nasir Amin, and F. E. Jalal,
1150 *Constr Build Mater*, vol. 345, p. 128296, Aug. 2022.
- 1151 [84] J. Torrealba, L. Tashlykov and E. Mendoza, "Fiber optic sensing in sustainable structural monitoring applications," *Sensors and*
1152 *Actuators A: Physical*, vol. 294, pp. 160–168, 2019.
- 1153 [85] R. C. Ribeiro and A. M. Guedes, "Using SHM decision metrics to reduce embodied carbon in bridge rehabilitation," *Journal of*
1154 *Cleaner Production*, vol. 374, p. 134106, 2022.
- 1155 [86] S. Yahiaoui, L. Monteiro and A. F. J. Costa, "Structural health monitoring for sustainability: a systematic review," *Civil Engineer-*
1156 *ing Journal*, vol. 6, no. 4, pp. 685–705, 2020.
- 1157 [87] T. Hashimoto and K. Yamada, "SHM-based repair prioritization mitigates carbon impact in deteriorated bridges," *Sustainable*
1158 *Cities and Society*, vol. 84, p. 104062, 2022.
- 1159 [88] T. Van Nguyen, M. T. Nguyen and E. Lim, "Bridge life cycle extension using AI-based SHM," *Sensors*, vol. 20, p. 2345, 2020.
- 1160 [89] W. K. Chong and A. M. Thomas, "SHM-driven resiliency modelling for ageing infrastructure," *Journal of Infrastructure Systems*,
1161 vol. 27, no. 3, p. 04021024, 2021.
- 1162 [90] S. K. Sharma and V. Kumar, "Internet of Things-based structural health monitoring system for sustainable bridge maintenance,"
1163 *IEEE Internet of Things Journal*, vol. 8, no. 9, pp. 7157–7168, 2021.
- 1164 [91] S. Li and J. H. Kim, "Life-cycle carbon savings achieved by SHM-informed retrofitting decisions," *Journal of Building Engineering*,
1165 vol. 63, p. 105582, 2023.
- 1166 [92] A. Costin, J. R. Lee and M. T. Johnson, "Digital twin framework for bridge structural health monitoring," *Transportation Research*
1167 *Record*, 2024.
- 1168 [93] S. Kankanamge and Y. Jayasinghe, "Life cycle carbon reduction through SHM-enabled decision making," *Buildings*, vol. 12, no.
1169 11, p. 1824, 2022.
- 1170 [94] S. P. Singh and P. Kumar, "Sustainability-based condition assessment of steel bridges using corrosion monitoring sensors," *Con-*
1171 *struction and Building Materials*, vol. 325, p. 126648, 2022.
- 1172 [95] S. H. Lee and J. K. Cho, "Green lifecycle governance through IoT-based SHM," *IEEE Systems Journal*, vol. 17, no. 1, pp. 1626–1637,
1173 2023.
- 1174 [96] R. Gomez and H. Y. Leung, "Performance-based sustainability classification using SHM life-cycle indicators," *Automation in*
1175 *Construction*, vol. 126, p. 103691, 2021.
- 1176 [97] R. Siddiqui and C. J. Chung, "IoT-SHM for sustainable cement composite structures," *Journal of Cleaner Production*, vol. 360, p.
1177 132234, 2022.
- 1178 [98] M. K. Pham and D. Chatzigeorgiou, "Multi-scale sensing and digital twins for resilient infrastructure," *Automation in Construc-*
1179 *tion*, vol. 139, p. 104353, 2022.
- 1180 [99] F. J. Mendez and L. P. da Silva, "Digital twin monitoring of FRP retrofitted beams for sustainability performance," *Composites*
1181 *Part B: Engineering*, vol. 242, p. 110149, 2022.
- 1182 [100] Z. Sun, Y. Wang and H. Liu, "Approach towards the development of digital twin for intelligent monitoring and maintenance
1183 of civil infrastructure," *Sensors*, vol. 25, no. 1, p. 59, 2024.

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