

1 *Type of the Paper is Review*

# 2 **Integration of BIM and SHM For Sustainable Management of** 3 **Existing Structures: A Systematic Review**

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## 13 **Abstract**

14 The integration of Building Information Modeling (BIM) with Structural Health Monitoring  
15 (SHM) represents a transformative approach for the sustainable management of exist-  
16 ing structures. This review comprehensively examines the evolution, methodologies, ap-  
17 plications, and future directions of BIM–SHM systems, emphasizing their potential to en-  
18 hance structural safety, optimize maintenance, and support sustainability goals. Various  
19 integration techniques, including direct sensor-to-BIM linking, database-driven methods,  
20 and IoT-based real-time streaming, are critically analyzed, highlighting their advantages,  
21 limitations, and suitability for diverse infrastructure types. Application domains encom-  
22 pass bridges, high-rise buildings, heritage structures, industrial facilities, tunnels, and res-  
23 idential developments. The review further discusses the role of artificial intelligence and  
24 machine learning in predictive maintenance and automated BIM model updates, as well  
25 as the importance of embedding sustainability metrics into digital twins. Key challenges,  
26 such as lack of standardization, sensor data management, interoperability, scalability, and  
27 human skill gaps, are identified, providing insight into barriers to widespread adoption.  
28 Future research directions emphasize autonomous digital twins, robotics and UAV-as-  
29 sisted inspection, blockchain-based data security, and interdisciplinary collaboration. By  
30 synthesizing current knowledge and highlighting technological, operational, and sustain-  
31 ability considerations, this review provides a roadmap for researchers and practitioners  
32 aiming to advance BIM–SHM integration and realize resilient, efficient, and environmen-  
33 tally responsible infrastructure management.

34 **Keywords:** BIM–SHM Integration, Structural Health Monitoring, Digital Twin, Predictive  
35 Maintenance, Sustainable Infrastructure Management

## 38 **1. Introduction**

### 39 **1.1 Background and Significance of Managing Existing Structures**

40 The management and maintenance of existing civil structures have become a global  
41 priority due to the rapid aging of infrastructure across urban and rural environments [1].  
42 In many countries, bridges, buildings, and transportation networks have exceeded their

intended service life, necessitating careful monitoring and intervention [2]. Environmental factors such as wind, rainfall, temperature fluctuations, and seismic events continuously contribute to material deterioration and structural degradation [3]. Cyclic loads from traffic, machinery, or operational use introduce fatigue and micro-cracking, which, if undetected, can propagate into significant structural failures [4]. In addition, heritage and historical buildings are particularly vulnerable due to the use of aged or unconventional materials and construction techniques [5]. The socioeconomic impact of failing infrastructure includes direct repair and replacement costs, as well as indirect costs such as traffic delays, business interruptions, and safety hazards to the public [6]. Moreover, societal reliance on infrastructure systems has intensified due to urbanization, making continuous functionality critical for economic stability and human well-being [7]. Accurate and timely assessment of structural health is therefore essential to reduce the risk of catastrophic failure while optimizing maintenance expenditures [8]. Efficient management strategies are also required to comply with updated safety codes, sustainability objectives, and governmental regulations, ensuring the longevity of infrastructure assets while maintaining economic feasibility [9]. Traditional inspection methods, although widely practiced, often provide only snapshot evaluations and are limited in capturing dynamic behavior and evolving degradation patterns [10].

### 1.2 Limitations of Conventional Monitoring and Asset Management Approaches

Conventional structural monitoring methods rely primarily on periodic visual inspections and manual data collection, which are prone to human error, bias, and subjectivity [11]. These methods provide limited temporal resolution, resulting in significant gaps in structural performance records [12]. Sparse data often fails to capture localized damages or micro-level deterioration before they escalate into critical failures [13]. Furthermore, traditional inspection and reporting practices are labor-intensive, time-consuming, and sometimes unsafe, particularly for high-rise structures, bridges, or remote infrastructures [14]. The interpretation of collected data typically requires experienced personnel, whose judgment may vary depending on expertise and environmental conditions, leading to variability in decision-making [15]. Reactive maintenance, often necessitated by delayed detection of damage, can significantly increase repair costs compared to preventive strategies [16]. Additionally, conventional asset management systems struggle to integrate information from multiple data sources, making comprehensive assessment and decision-making challenging [17]. There is also limited capability to forecast future structural behavior under changing load and environmental conditions, which restricts proactive maintenance and lifecycle optimization [18]. This growing need for automated, accurate, and real-time monitoring solutions highlights the importance of integrating modern sensing, computational, and modeling technologies into asset management [19].

### 1.3 Evolution of Structural Health Monitoring (SHM) Technologies

Structural Health Monitoring (SHM) has emerged to overcome the shortcomings of traditional inspection methods by incorporating advanced sensing technologies and computational models [20]. Modern SHM systems employ a variety of sensors, including accelerometers, strain gauges, inclinometers, fiber optic sensors, and displacement transducers, to continuously measure the structural response [21]. These measurements capture the effects of operational and environmental loads, providing high-resolution data for detecting stress, vibration, and deformation patterns [22]. Data-driven SHM approaches utilize signal processing techniques, statistical analysis, and machine learning

91 algorithms to identify anomalies, assess damage, and reconstruct full-field structural re-  
92 sponses [23]. Advanced mathematical methods such as singular value decomposition  
93 (SVD), Bayesian inference, and Tikhonov regularization enhance the ability to estimate  
94 structural states even when sensor measurements are incomplete or noisy [24]. The inte-  
95 gration of SHM systems with wireless sensor networks enables real-time monitoring over  
96 large-scale infrastructure, facilitating early detection of potential failures [25]. However,  
97 standalone SHM systems often face challenges related to data heterogeneity, storage, and  
98 long-term sensor maintenance, which can hinder system scalability and reliability [26].  
99 Additionally, the absence of integration with structural modeling limits predictive capa-  
100 bilities and the effective translation of sensor data into actionable maintenance decisions  
101 [27].

#### 102 **1.4 Emergence and Maturity of Building Information Modeling (BIM)**

103 Building Information Modeling (BIM) has revolutionized the digital representation  
104 and management of civil infrastructure by integrating geometry, material properties, and  
105 lifecycle information into a cohesive platform [28]. BIM enables accurate visualization,  
106 coordination, and simulation of structures in three dimensions (3D) and, when combined  
107 with time-related data, in four dimensions (4D) [29]. Its applications span clash detection,  
108 cost estimation, structural analysis, and multi-disciplinary coordination, significantly im-  
109 proving project efficiency [30]. Originally focused on new construction, BIM has evolved  
110 to support the modeling of existing structures through automated generation from point  
111 clouds, laser scanning, and photogrammetric data [31]. These capabilities allow engineers  
112 to capture complex geometry and structural features accurately, reducing manual model-  
113 ing errors [32]. BIM also facilitates interoperability between various software tools and  
114 stakeholders, enabling collaboration across architecture, engineering, and construction  
115 domains [33]. Despite its transformative potential, BIM models remain largely static when  
116 used independently and cannot inherently support continuous real-time monitoring or  
117 predictive maintenance without integration with SHM and computational tools [34]. The  
118 development of automated BIM pipelines and integration with sensing technologies is  
119 thus critical for managing existing infrastructures more effectively [35].

#### 120 **1.5 Rationale for Integrating BIM and SHM**

121 Integrating BIM with SHM offers a comprehensive approach to overcoming the lim-  
122 itations of each method when applied in isolation [36]. Through this integration, real-time  
123 sensor data can dynamically update BIM models, providing a continuously evolving dig-  
124 ital representation of the structure [37]. This approach enables predictive maintenance by  
125 linking observed structural behavior to computational models capable of forecasting fu-  
126 ture deterioration [38]. Integration also supports lifecycle management by combining ge-  
127 ometric, material, operational, and monitoring data, allowing decision-makers to plan in-  
128 terventions more efficiently [39]. Digital twin frameworks extend BIM-SHM integration  
129 further by creating virtual replicas that simulate structural performance under various  
130 scenarios, supporting scenario-based decision-making and risk assessment [40]. These  
131 frameworks allow automated vulnerability identification, optimization of inspection  
132 schedules, and enhanced safety management [41]. Moreover, the integration improves as-  
133 set performance by facilitating real-time visualization, alert generation, and maintenance  
134 prioritization, which are difficult to achieve using conventional approaches [42]. The fu-  
135 sion of BIM and SHM provides not only operational advantages but also a foundation for  
136 data-driven governance of infrastructure systems [43].  
137  
138  
139

## 1.6 Contribution of BIM–SHM Integration to Sustainability and Long-Term Performance

BIM–SHM integration contributes to sustainability by reducing unnecessary inspections, minimizing resource consumption, and enhancing operational efficiency [44]. Continuous monitoring enables early detection of structural anomalies, preventing catastrophic failures and extending service life, thus lowering lifecycle costs [45]. Automated maintenance planning reduces human intervention, saving labor, energy, and operational costs [46]. For heritage and critical infrastructures, digital representation supports preservation and adaptive reuse by providing accurate documentation and structural assessments [47]. The combination of real-time monitoring and digital modeling allows for better-informed decisions regarding rehabilitation, retrofitting, or replacement [48]. Furthermore, integrating BIM and SHM encourages evidence-based policy formulation, enabling stakeholders to allocate resources optimally and plan interventions sustainably [49]. Digital twin technologies also provide scenario analysis capabilities, allowing engineers to assess environmental impacts, predict performance under extreme conditions, and develop long-term sustainable strategies [50]. Overall, the convergence of BIM, SHM, and digital twins represents a paradigm shift in infrastructure management, emphasizing safety, resilience, and sustainability [51].

## 1.7 Existing Gaps in Research and Practice

Despite significant progress, multiple gaps remain in current research and implementation of BIM - SHM integration [52]. Interoperability challenges arise due to heterogeneous sensors, data formats, and software platforms [53]. Automation of BIM updates using SHM data is limited, especially for complex or irregular structures [54]. Multiscale modeling approaches, which integrate component-level and system-level analyses, are rarely applied comprehensively [55]. Predictive algorithms often lack robustness when generalized across diverse operational scenarios [56]. Existing digital twin frameworks face difficulties in real-time simulation of large-scale infrastructures due to computational complexity [57]. Legacy structures without prior digital documentation pose challenges for full-scale BIM automation and sensor placement planning [58]. Additionally, standardization in SHM data acquisition, processing, and integration with BIM is still evolving, making widespread adoption challenging [59]. Addressing these gaps is essential for advancing intelligent, automated, and resilient infrastructure management [60].

## 1.8 Objectives of This Systematic Review

This systematic review critically examines the state-of-the-art in BIM–SHM integration with an emphasis on automated and intelligent monitoring frameworks. The key objectives are:

1. Evaluating SHM techniques, sensor types, and data-driven methods suitable for real-time monitoring.
2. Investigating BIM automation strategies for capturing existing structures accurately.
3. Exploring digital twin frameworks for predictive maintenance and performance assessment.
4. Identifying technical and operational challenges in integrating BIM, SHM, and digital twins.
5. Providing future research directions for automated, sustainable, and data-driven infrastructure management.

188 This review consolidates findings from 75 peer-reviewed studies, offering theoretical  
189 insights and practical guidance for researchers and practitioners.

### 190 1.9 Structure of the Paper

191 The remainder of this paper is organized as follows:

- 192 • **Section 2:** Methodology of the systematic review, including database selection, keyword formulation, and inclusion/exclusion criteria.
- 193 • **Section 3:** Overview of SHM technologies, including sensors, monitoring methods, and data-driven analysis approaches.
- 194 • **Section 4:** BIM modeling and automation of existing structures, integration of monitoring data, and software tools.
- 195 • **Section 5:** Digital twin frameworks, predictive maintenance, AI-assisted modeling, and optimization strategies.
- 196 • **Section 6:** Discussion of current gaps, practical challenges, and recommendations for research and practice.
- 197 • **Section 7:** Conclusions summarizing the state-of-the-art and highlighting future directions for sustainable infrastructure management.

198 This organization provides a comprehensive understanding of BIM–SHM integra-  
199 tion and its implications for monitoring, maintaining, and managing existing infrastruc-  
200 ture. The consolidated references complete the discussion and provide the foundation for  
201 subsequent sections of the paper.

## 202 2. Methodology:

203 This study follows a systematic review methodology designed to provide a scientifi-  
204 cally defensible synthesis of the state of research concerning the integration of Building  
205 Information Modeling (BIM) and Structural Health Monitoring (SHM) for existing struc-  
206 tures. The method was developed to guarantee reproducibility, reduce selection bias, and  
207 ensure that only validated and technically progressive studies were selected. The entire  
208 process was organized into a series of structured operations beginning with research  
209 question formulation, followed by database search, application of eligibility criteria,  
210 multi-level screening, quality evaluation, and data extraction leading to thematic synthe-  
211 sis. These steps together form a rigorous research protocol that supports the reliability and  
212 credibility of the findings presented in this review.

### 213 2.1 Systematic Review Protocol

214 The systematic protocol employed in this study served as a blueprint to maintain  
215 transparency and methodological consistency across all stages of the review. The protocol  
216 initially defined the boundaries of the research to focus exclusively on BIM-based digital  
217 modeling directly linked to SHM, life-cycle assessment, monitoring-based maintenance,  
218 structural evaluation, and digital twin applications. Only research addressing existing in-  
219 frastructure or buildings whether conventional, industrial, or heritage was considered rel-  
220 evant. The protocol emphasized the need for evidence-based implementations rather than  
221 conceptual claims; therefore, studies were required to demonstrate actual integration, val-  
222 idation through case studies, or detailed technical workflows. This design ensured that  
223 the final dataset reflected practical progress in the BIM–SHM field rather than general  
224 BIM or SHM contributions.

### 225 2.2 Research Questions

236 The review process was shaped by four core research questions that defined the  
237 scope of inquiry and guided the extraction and synthesis of knowledge from the selected  
238 literature. The first question sought to understand how BIM-SHM integration has evolved  
239 technologically and procedurally in the context of monitoring existing structures. The sec-  
240 ond research question explored the sensing technologies, interoperability frameworks,  
241 and data acquisition strategies that enable real-time or near-real-time communication be-  
242 tween structural monitoring systems and digital models. The third question aimed to  
243 identify methodological and technical limitations, including interoperability constraints,  
244 data-format incompatibilities, absence of lifecycle monitoring strategies, and restricted in-  
245 dustrial adoption. Finally, the fourth question examined how the integration of BIM and  
246 SHM contributes to sustainability by improving durability, predicting deterioration, re-  
247 ducing maintenance uncertainty, and optimizing long-term performance of structural as-  
248 sets. Together, these research questions provided an analytical structure that ensured  
249 depth and direction in the review.

### 251 2.3 Search Strategy and Keyword Combinations

252 A comprehensive search process was undertaken using seven major databases: Sco-  
253 pus, Web of Science, IEEE Xplore, ScienceDirect, ASCE Library, SpringerLink, and Taylor  
254 & Francis Online. To capture interdisciplinary studies, the search strategy adopted broad  
255 combinations of BIM-related and SHM-related terminology using Boolean operators. The  
256 selected terms were chosen to encompass digital modeling, lifecycle maintenance, sensing  
257 technologies, condition monitoring, and interoperability. Expressions such as “Building  
258 Information Modeling AND Structural Health Monitoring”, “Digital Twin AND Struc-  
259 tural Damage”, and “BIM AND Monitoring AND Existing Structures” were repeatedly  
260 used with different permutations to broaden the search field. The search encompassed the  
261 period between 2000 and 2025, acknowledging that research combining sensing technol-  
262 ogies with digital models began to mature only after 2005 and expanded significantly due  
263 to rapid digitalization after 2015. This expansive search approach enabled the identifica-  
264 tion of both foundational works and cutting-edge developments.

### 266 2.4 Inclusion and Exclusion Criteria

267 The studies resulting from the database search were filtered using strict inclusion and  
268 exclusion criteria to ensure that only scientifically credible and relevant works remained.  
269 Publications were eligible if they directly involved BIM or digital twins in monitoring,  
270 assessment, or management of existing structures and demonstrated technical workflows,  
271 interoperability processes, or experimental validation. Only peer-reviewed conference  
272 and journal papers written in English were considered. Studies that focused on BIM for  
273 design or construction without operational monitoring, SHM without digital models, new  
274 construction projects lacking lifecycle maintenance relevance, or conceptual discussions  
275 without technical evidence were excluded. Non-peer-reviewed content such as thesis, pa-  
276 tents, reports, technical brochures, and book chapters were eliminated to maintain aca-  
277 demic reliability. This selective filtration ensured that the dataset consisted exclusively of  
278 impactful research contributing genuinely to BIM-SHM integration.

### 280 2.5 Screening Process and PRISMA Flow

281 The screening was executed based on the Preferred Reporting Items for Systematic  
282 Reviews and Meta-Analyses (PRISMA) framework, which structures filtering into four  
283 progressive stages: identification, screening, eligibility assessment, and final inclusion. In-  
284 itially, 463 papers were obtained from database searches. After duplicate removal, 391

unique studies remained and proceeded to the screening stage, where titles and abstracts were analyzed to remove irrelevant works such as pure BIM design studies or SHM without modeling. This reduced the dataset to 152 papers that appeared related to digital monitoring, asset management, or BIM-based lifecycle models. Full-text evaluation was then performed, eliminating publications lacking methodological depth, technical validation, or interoperability linkage, ultimately leading to 75 selected studies.

The PRISMA Methodology Diagram is in Figure 1.

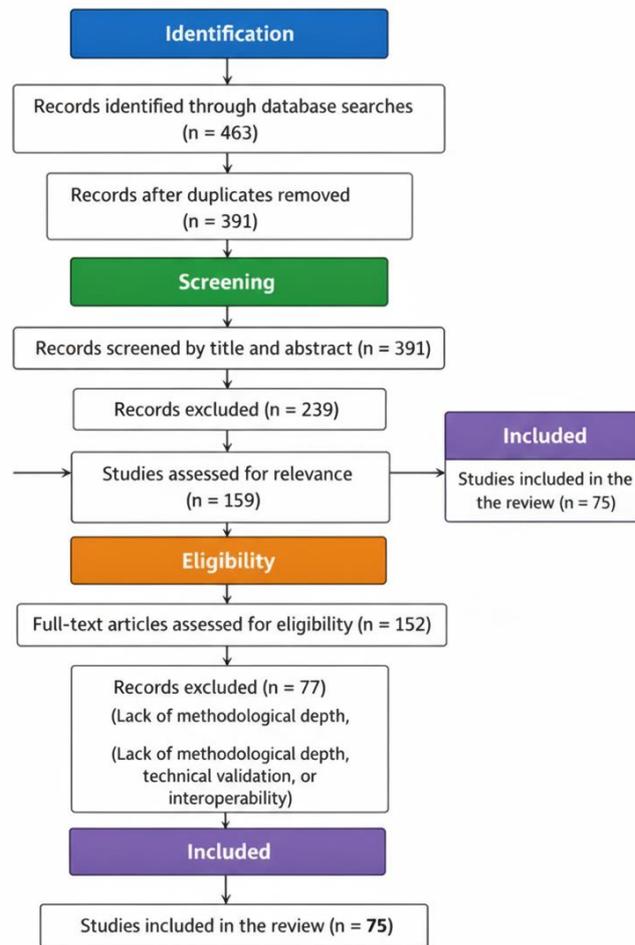


Figure 1 PRISMA Flow Methodology

### 2.6 Quality Assessment of Selected Studies

To ensure that only technically rigorous and practically informative studies were retained, each of the 75 selected publications underwent a quality assessment based on five criteria: methodological clarity, reliability of monitoring technologies, depth of BIM–SHM interoperability, presence of real-world or experimental validation, and contribution to lifecycle asset management. Studies were graded numerically from 0 to 5 according to the evidence presented. Only those scoring three or above were considered sufficiently robust for inclusion, leading to the exclusion of concept-only works or research providing incomplete monitoring mechanisms. This appraisal prioritized mature, implementable, or verifiable outputs rather than speculative proposals, ensuring that the synthesis of knowledge and conclusions in this review represent the true technological capabilities of current BIM–SHM integration.

### 2.7 Data Extraction and Synthesis Approach

308 Data extraction was performed manually using a structured coding sheet designed  
309 to capture technical and strategic characteristics of each study. Extracted information in-  
310 cluded the type of structure analyzed, details of the BIM modeling workflow, levels of  
311 geometric and informational detail, sensor types and monitoring frequency, communica-  
312 tion mechanisms between sensors and digital models, and data interpretation methodol-  
313 ogies such as signal processing, artificial intelligence, or cloud storage approaches. The  
314 extraction also emphasized interoperability solutions, including the use of open standards  
315 such as IFC and integration middleware enabling bidirectional data flows. Additionally,  
316 sustainability contributions were documented, focusing on deterioration prediction,  
317 maintenance cost optimization, structural life-extension, and minimization of intrusive  
318 inspection. The extracted data were subsequently grouped into thematic domains such as  
319 digital twin frameworks, BIM-enabled sensor integration, heritage asset monitoring, and  
320 lifecycle maintenance strategies, enabling structured synthesis and comparative interpre-  
321 tation. These themes support the analytical discussion presented in subsequent sections.  
322

### 323 **3. Overview of BIM and SHM Domains**

324 Lifecycle management of existing structures has shifted from manual inspection-  
325 based decision making toward data-driven frameworks capable of continuously indexing  
326 as-built information and assessing performance states under realistic operational condi-  
327 tions. This transition requires technologies that not only document physical attributes but  
328 also interpret their temporal evolution under service variability, environmental degrada-  
329 tion, and extreme events. Building Information Modeling (BIM) offers semantically struc-  
330 tured asset representation, whereas Structural Health Monitoring (SHM) quantifies the  
331 physical response of structures with measurable indicators. Historically, both systems de-  
332 veloped in isolation, one emphasizing digital representation and the other emphasizing  
333 physical sensing. However, emerging demands for resilience, asset longevity, and auto-  
334 mated predictive maintenance have led to convergence between these domains. Their in-  
335 tegration is shaping the foundation of digital twins for infrastructure, allowing models to  
336 evolve as operational data continuously updates the digital representation of built assets.  
337

#### 338 **3.1 Building Information Modeling (BIM): Capabilities and Applications**

339 BIM facilitates object-oriented digital modeling of buildings where geometrical fea-  
340 tures, operational parameters, maintenance records, and mechanical properties are stored  
341 within a unified information container [61]. Unlike traditional drawings or CAD models,  
342 the parametric nature of BIM allows components to hold attributes defining stiffness  
343 properties, deterioration mechanisms, mechanical strengths, and historical repair inter-  
344 ventions. Such data structures enable multi-domain interoperability bridging structural  
345 analysis, cost estimation, facility management, and optimization tasks [62]. Additionally,  
346 adoption of open data schemas such as IFC strengthens multi-software communication,  
347 making BIM a robust backbone not only for design but for monitoring-assisted manage-  
348 ment of existing infrastructure [63]. This paradigm supports a shift from project-centric  
349 documentation to dynamic lifecycle management where structural knowledge remains  
350 complete, transferable, and digitally traceable throughout the asset's service life.

##### 351 **3.1.1 Information Integration**

352 BIM's core strength lies in its ability to integrate heterogeneous datasets into a hier-  
353 archical digital model. Structural elements such as beams, columns, masonry walls, or  
354 connections can store metadata describing reinforcement layouts, material aging laws,  
355 visual inspection logs, NDT results, and performance indicators measured over time. As-

sociating engineering information directly with object geometry eliminates ambiguity often found in manual documentation. When degradation models and inspection histories become embedded attributes, component-specific failure risks can be tracked across decades of service [64]. Furthermore, BIM interoperability with analytical platforms enables exchange of structural parameters (e.g., stiffness, damage indices, modal properties) for automated updating when coupled with SHM databases. Thus, BIM evolves from a static modeling tool into an active information repository that supports autonomous diagnostics and decision-making frameworks.

### 3.1.2 Visualization and Digital Twin Foundations

Three-dimensional visualization in BIM enhances interpretability of structural response data by mapping physical observations, monitoring outputs, or predicted degradation to actual locations within the asset. This capacity to spatially contextualize cracks, strain concentrations, modal changes, or stress redistribution is foundational for digital twin development [65]. When BIM is connected to computational models or live SHM systems, real-time visualization can reflect changing stiffness distribution or evolving damage at the component level. Visual analytics therefore supplement numerical assessment by offering intuitive, location-accurate insights into structural deterioration [66]. These capabilities become critical in large or complex facilities where spatial uncertainty in interpreting sensor data can lead to incorrect maintenance prioritization or misdiagnosis of failure risk.

### 3.1.3 Asset Lifecycle Management

BIM extends beyond modeling by functioning as a traceable digital record for the entire life of an asset, mapping its condition evolution through construction, service, repair, retrofit, and eventual replacement [67]. Documenting inspection frequency, environmental exposure, material degradation rates, and cost histories provides measured evidence for risk-based maintenance strategies. When lifecycle data links directly to structural object attributes, intervention decisions can be optimized to minimize cost, increase serviceability, and prevent unexpected failures. This continuity of information supports sustainability-driven engineering by avoiding redundant retrofits and extending service life through predictive maintenance rather than reactive repair [68]. Thus, BIM becomes a decision-enabling tool shaping both economic and safety outcomes in infrastructure stewardship.

## 3.2 Structural Health Monitoring (SHM): Concepts and Components

SHM encompasses a systematic architecture of sensing technologies, data acquisition protocols, signal processing algorithms, and decision-support frameworks designed to quantify structural condition and detect abnormal states. Its objective surpasses simple crack detection, aiming instead to characterize behavioral evolution under environmental changes, operational loads, or cumulative fatigue. SHM contributes to proactive management by estimating the residual capacity of structural components, categorizing defect severity, and forecasting impending failures [69]. Continuous monitoring is particularly essential in structures where deterioration mechanisms may not be visually detectable or where safety relies on accurate tracking of dynamic properties and stiffness degradation.

### 3.2.1 Sensor Types and Deployment

A robust SHM system integrates sensing technologies capable of capturing both local and global damage phenomena. Accelerometers measure dynamic characteristics such as mode shapes or frequency shifts sensitive to global stiffness reduction. Strain gauges and fiber-optic sensors evaluate localized deformation or crack propagation. Acoustic emission sensors detect micro-fracturing events, enabling early warning before visible damage

occurs [70]. Sensor deployment is governed by structural typology, anticipated failure mechanisms, environmental variability, and accessibility constraints. Strategic placement ensures sufficient coverage for both systemic monitoring and localized detection, maximizing probability of identifying critical deterioration.

### 3.2.2 Data Acquisition and Signal Processing

SHM generates high-resolution performance datasets often contaminated with operational noise, temperature effects, and environmental fluctuations. Data acquisition must therefore be accompanied by robust preprocessing, including filtering, normalization, and compensation techniques [71]. Signal processing methodologies such as wavelet transforms, Hilbert-Huang decomposition, modal strain energy analysis, or time-frequency domain analysis extract features indicative of stiffness loss, crack nucleation, or mass changes. These damage-sensitive features serve as diagnostic indicators passed to machine learning classifiers, physical models, or hybrid fusion algorithms, ultimately translating raw sensor signals into actionable structural knowledge.

### 3.2.3 Damage Detection, Localization, and Prognosis

Effective SHM distinguishes among three core tasks. Damage detection determines whether structural behavior deviates from its baseline state. Localization identifies the specific element or region exhibiting anomalies through sensitivity mapping or pattern recognition correlated with structural models [72]. Prognosis forecasts deterioration progression and remaining service life by extrapolating measured degradation trends under projected environmental and mechanical stresses. Prognostic modeling forms the final step toward predictive maintenance, enabling engineering decisions based not only on current condition but on future expected performance.

## 3.3 Advancements in IoT, AI, and Cloud Platforms for SHM

Integration of IoT communication enables remote sensing, real-time data exchange, and distributed analysis across sensor networks. Cloud computing offers scalable storage for decades-long monitoring histories, allowing machine learning models to continuously train on evolving structural patterns [73]. AI-driven diagnostic frameworks detect abnormal patterns, automate damage classification, and support probabilistic failure prediction with limited human intervention. The convergence of IoT, AI, and cloud computation transforms SHM from static sensing into intelligent, self-learning systems capable of autonomous structural assessment.

## 3.4 Conceptual Opportunities for BIM-SHM Interoperability

BIM-SHM integration establishes a unified digital environment where as-built models and real-time performance converge into a continuously updating digital twin. Sensor identifiers, sampling frequencies, response histories, and damage indices can become embedded metadata in BIM objects [74]. When live SHM outputs modify corresponding object attributes, the BIM model evolves from a static design record into an adaptive digital representation mirroring the physical asset. Such interoperability supports automated maintenance management, risk-based prioritization, predictive performance simulation, and scalable asset monitoring across building portfolios [75]. Ultimately, BIM-SHM synergy enables structural management systems rooted in measurable performance rather than static assumptions, marking a paradigm shift in sustainable and intelligent asset stewardship.

## 4. BIM-SHM Integration: Approaches and Technologies

453 The integration of Building Information Modeling (BIM) and Structural Health Mon-  
454 itoring (SHM) represents a transformative paradigm in civil engineering, bridging the gap  
455 between virtual design models and real-world structural performance. This convergence  
456 enables continuous monitoring, predictive maintenance, and lifecycle optimization of  
457 civil infrastructure, aligning digital representations with live structural data. BIM-SHM  
458 integration has gained increasing attention due to its potential to enhance decision-mak-  
459 ing, improve safety, and reduce operational costs for existing and newly constructed  
460 structures.

#### 4.1 Historical Evolution of BIM-SHM Integration Research

461 The concept of linking BIM with SHM has evolved over the last two decades, initially  
462 emerging as a theoretical framework for post-construction monitoring. Early studies pri-  
463 marily focused on visualizing sensor data within 3D BIM models, offering basic dash-  
464 boards for structural status representation. With the maturation of IoT devices, cloud com-  
465 puting, and advanced sensing technologies, research shifted toward dynamic and real-  
466 time data integration. Key milestones include the adoption of standardized data schemas  
467 for structural attributes, the development of middleware solutions for heterogeneous sen-  
468 sor networks, and the use of semantic modeling to bridge BIM objects with SHM param-  
469 eters. Over time, the research trajectory has moved from manual data entry and static  
470 model linking toward fully automated, intelligent BIM-SHM ecosystems capable of pre-  
471 dictive analytics and real-time performance assessment.

#### 4.2 Integration Frameworks

474 BIM-SHM integration frameworks define the methodologies and system architec-  
475 tures through which sensor data and BIM models interact. These frameworks can be  
476 broadly categorized into four main approaches:

##### 4.2.1 Direct Sensor-to-BIM Model Linking

477 Direct sensor-to-BIM linking establishes a real-time connection between SHM de-  
478 vices and the BIM model. This approach allows sensor measurements (e.g., strain, vibra-  
479 tion, displacement) to automatically update the associated BIM elements, facilitating in-  
480 stant visual feedback. Its main advantage lies in minimizing data transformation over-  
481 head, but challenges include sensor heterogeneity, data volume management, and model  
482 synchronization.

##### 4.2.2 Database-Driven Integration

483 Database-driven integration uses a centralized repository to mediate between sensor  
484 networks and BIM models. Sensor data is stored in relational or NoSQL databases and  
485 then mapped to BIM objects through unique identifiers. This method supports historical  
486 data analysis, multi-sensor fusion, and batch processing, making it suitable for large in-  
487 frastructure networks. However, the added layer introduces potential latency and re-  
488 quires robust data management protocols.

##### 4.2.3 Middleware and API-Based Integration

489 Middleware solutions and Application Programming Interfaces (APIs) act as inter-  
490 mediaries that translate sensor outputs into BIM-compatible formats. This approach ena-  
491 bles cross-platform interoperability, allowing different BIM software and SHM systems to  
492 communicate seamlessly. Middleware often incorporates rule-based or semantic mapping  
493 techniques to ensure that the data retains contextual relevance, bridging the gap between  
494 heterogeneous systems.

##### 4.2.4 IoT and Real-Time Streaming Integration

501 The emergence of the Internet of Things (IoT) has revolutionized BIM–SHM integra-  
502 tion by supporting continuous data streaming from smart sensors to cloud-based BIM  
503 platforms. Real-time integration frameworks enable immediate anomaly detection, pre-  
504 dictive maintenance, and decision support. Technologies like MQTT, WebSockets, and  
505 edge computing are commonly employed to ensure low-latency, high-fidelity data deliv-  
506 ery, facilitating proactive infrastructure management.

#### 509 **4.3 Semantic Enrichment and Data Modeling**

510 Semantic enrichment in BIM–SHM integration refers to the process of **embedding**  
511 additional, contextually meaningful information into BIM elements, transforming a geo-  
512 metric model into a rich digital twin of the physical structure. Beyond simple geometry,  
513 BIM objects are annotated with SHM-related attributes such as sensor type, measurement  
514 frequency, calibration metadata, thresholds for performance indicators, material proper-  
515 ties, and environmental exposure parameters. This approach ensures that the BIM model  
516 is not merely a visual representation but a knowledge-based system capable of supporting  
517 decision-making.

518 Ontologies and semantic frameworks play a critical role in this process. By defining  
519 relationships between structural elements, sensor measurements, and maintenance re-  
520 quirements, these frameworks enable automated reasoning about structural health. For  
521 instance, a beam showing abnormal vibration patterns can trigger alerts not just based on  
522 raw data but using inferred rules about load distribution and material fatigue embedded  
523 in the model. Semantic enrichment also facilitates multi-scale data integration, linking lab-  
524 scale sensor readings, building-level performance metrics, and historical degradation  
525 trends. As a result, engineers can perform advanced querying, predictive simulations, and  
526 scenario analysis, which are crucial for proactive maintenance and lifecycle optimization.

527 Moreover, semantic data modeling supports interoperability across heterogeneous  
528 systems. Standardized ontologies allow BIM models to integrate seamlessly with AI algo-  
529 rithms, cloud databases, and IoT platforms, enabling automated workflows such as real-  
530 time alert generation, anomaly detection, and adaptive control of structural monitoring  
531 systems. In essence, semantic enrichment converts BIM–SHM systems into intelligent,  
532 self-aware digital twins capable of providing actionable insights throughout the lifecycle  
533 of a structure.

#### 536 **4.4 Data Interoperability and Open Standards (IFC, COBie, MQTT, etc.)**

537 The effectiveness of BIM–SHM integration is highly dependent on robust data inter-  
538 operability between diverse software platforms, sensor networks, and analytical tools.  
539 Without standardized protocols and data schemas, integrating real-time sensor measure-  
540 ments with BIM objects becomes cumbersome, error-prone, and non-scalable. Open  
541 standards such as IFC (Industry Foundation Classes) define a universal schema for struc-  
542 tural elements, material properties, and spatial relationships, enabling BIM models to be  
543 shared and interpreted consistently across different platforms. Similarly, COBie (Con-  
544 struction Operations Building Information Exchange) facilitates structured handover of  
545 asset information and operational data, ensuring that SHM datasets can be linked to as-  
546 built models effectively.

547 For real-time SHM integration, lightweight communication protocols like MQTT and  
548 OPC UA are widely adopted. MQTT provides efficient, publish-subscribe messaging for  
549 streaming sensor data to cloud platforms or BIM dashboards, while OPC UA supports

550 industrial-grade interoperability, including secure, real-time monitoring of complex in-  
551 frastructure networks. The use of these standards reduces vendor lock-in, improves scala-  
552 bility across multi-site deployments, and enables consistent historical data logging.

553 Furthermore, standardized data models enhance analytical compatibility, allowing  
554 AI and machine learning algorithms to process sensor data effectively. For example, an  
555 IFC-compliant model can provide spatial context to a vibration dataset, enabling predic-  
556 tive algorithms to infer the likely progression of structural damage. By adhering to open  
557 standards, engineers and researchers ensure long-term usability of integrated BIM–SHM  
558 systems, making them future-proof and adaptable to evolving technological landscapes.

#### 561 **4.5 Software Platforms and Tools Used in BIM–SHM Integration**

562 The implementation of BIM–SHM integration relies on a combination of BIM soft-  
563 ware, SHM platforms, and middleware tools to bridge the gap between virtual models  
564 and sensor networks. BIM platforms such as Autodesk Revit, Tekla Structures, and Bent-  
565 ley AECOSim provide APIs, plugins, and scripting capabilities that allow direct linking of  
566 structural elements with sensor data. These tools support visualization, reporting, and  
567 automated alerts, while also enabling parametric model updates as new SHM data  
568 streams in.

569 On the SHM side, platforms like NI LabVIEW, MATLAB, and cloud-based IoT dash-  
570 boards facilitate data acquisition, signal processing, filtering, and feature extraction from  
571 various sensors, including accelerometers, strain gauges, and environmental sensors. Ad-  
572 vanced dashboards allow for real-time monitoring, threshold-based alerts, and historical  
573 trend analysis, which can be mapped back to BIM models to reflect the structural health  
574 dynamically.

575 Recent research emphasizes the development of hybrid platforms that combine BIM  
576 geometry, SHM data analytics, and AI-powered predictive models within a unified envi-  
577 ronment. These platforms enable cross-functional workflows, where structural engineers,  
578 facility managers, and data scientists can collaborate seamlessly. For example, vibration  
579 data from an IoT-enabled bridge can automatically update the BIM model, which then  
580 triggers predictive ML algorithms to forecast fatigue in critical components. Such inte-  
581 grated systems enhance decision-making efficiency, improve operational safety, and re-  
582 duce maintenance costs.

#### 584 **4.6 Role of AI/ML in Enhancing BIM–SHM Integration**

585 Artificial Intelligence (AI) and Machine Learning (ML) are increasingly central to  
586 modern BIM–SHM integration, transforming raw sensor data into actionable insights. ML  
587 algorithms can analyze complex, multi-dimensional datasets to detect subtle anomalies,  
588 predict structural degradation, and optimize maintenance schedules. Supervised learning  
589 methods can classify damage types based on historical sensor patterns, while unsuper-  
590 vised methods can identify novel, previously unseen structural behaviors.

591 Deep learning techniques, including convolutional neural networks (CNNs), facili-  
592 tate image-based structural assessment, enabling automated detection of cracks, corro-  
593 sion, or surface deformations directly within BIM models. Integration of AI-driven rea-  
594 soning with semantic enrichment allows systems to correlate structural anomalies with  
595 specific BIM elements, providing precise localization of defects and their potential impact  
596 on structural performance.

597 Moreover, AI/ML supports predictive and prescriptive maintenance, where models  
598 not only forecast future degradation but also recommend specific interventions based on

cost, safety, and operational priorities. The combination of AI with BIM–SHM frameworks lays the groundwork for autonomous structural health management systems, where monitoring, analysis, and maintenance planning occur in a largely automated, adaptive loop, ensuring the longevity and resilience of civil infrastructure.

### 5. Application Domains

BIM–SHM integration has increasingly become a cornerstone for structural assessment, monitoring, and maintenance across a wide spectrum of civil infrastructure. By bridging the virtual design space with real-time structural health data, BIM–SHM systems enable stakeholders to make data-driven decisions, enhance safety, reduce maintenance costs, and optimize the lifecycle of structures. The applications are highly diverse, ranging from transportation networks to heritage buildings, high-rise structures, and complex industrial facilities. Each domain imposes unique challenges, such as environmental exposure, dynamic loading, or accessibility constraints, which necessitate customized BIM–SHM integration strategies.

A comparative overview of BIM–SHM applications across different infrastructure domains is presented in Table 5.1, highlighting key monitoring parameters, typical sensor technologies, and associated integration benefits. This table provides a high-level snapshot before delving into the detailed discussion of each domain.

Table 5.1: Summary of BIM–SHM Applications Across Infrastructure Domains

Application Domain	Key Monitoring Parameters	Typical Sensors / Technologies	Integration Benefits
Bridges & Transportation	Strain, vibration, deflection, temperature	Accelerometers, strain gauges, displacement transducers	Real-time load assessment, fatigue prediction, maintenance scheduling, multi-bridge monitoring
Heritage & Historic Structures	Cracks, material degradation, humidity, thermal variations	Laser scanning, photogrammetry, fiber-optic strain sensors	Non-intrusive monitoring, preservation planning, predictive maintenance, environmental monitoring
High-Rise & Commercial Buildings	Structural vibrations, façade deformation, wind-induced oscillations	Accelerometers, tilt sensors, environmental sensors	Occupant safety, energy-efficient facility management, scenario-based simulations
Industrial Structures (Tanks, Towers, Plants)	Deformation, tilt, vibration, thermal cycles	Strain sensors, tilt meters, vibration transducers	Operational safety, predictive maintenance, process risk mitigation, downtime reduction
Tunnels & Underground Infrastructure	Displacement, ground pressure, water ingress, temperature	Geotechnical sensors, inclinometers, pressure sensors	Settlement monitoring, load redistribution analysis, proactive failure prediction
Residential Buildings	Settlement, crack propagation, humidity, thermal behavior	Strain gauges, moisture sensors, temperature sensors	Early detection of structural issues, predictive maintenance, energy optimization, multi-unit monitoring

The following subsections provide a detailed discussion of each application domain, illustrating specific use cases, sensor configurations, and integration strategies, all of which are summarized in Table 5.1.

### 5.1 Bridges and Transportation Infrastructure

Bridges are among the most critical assets in transportation networks, often exposed to dynamic loads, environmental degradation, and natural hazards. BIM–SHM integration allows real-time monitoring of parameters such as strain, vibration, deflection, and temperature. For example, accelerometers and strain gauges installed on bridge decks can feed data directly into BIM models, enabling engineers to visualize stress distributions, detect anomalies, and predict fatigue-induced damage.

The combination of BIM with SHM data also facilitates maintenance prioritization and lifecycle optimization. Historical traffic load data, weather records, and real-time sensor feedback can be incorporated into predictive models to schedule inspections, plan retrofits, and avoid catastrophic failures. In large-scale transportation networks, centralized BIM–SHM platforms allow multi-bridge monitoring, providing transportation authorities with a holistic view of infrastructure health and improving resource allocation for repair and rehabilitation programs.

### 5.2 Heritage and Historic Structures

Heritage buildings and historic monuments require delicate preservation strategies that maintain cultural and architectural integrity while ensuring safety. BIM–SHM integration provides a digital twin framework for historic structures, enabling detailed documentation, structural assessment, and predictive maintenance without intrusive interventions.

Advanced sensing techniques such as laser scanning, photogrammetry, and fiber-optic strain sensors allow accurate capture of structural geometry and behavior, which can then be linked to BIM models. Structural engineers and conservationists can simulate degradation scenarios, assess load-bearing capacity, and monitor environmental factors like humidity and temperature, which are critical for preservation. Semantic enrichment enables encoding of historical and material-specific information, allowing interventions to be tailored precisely to the unique requirements of heritage materials. This application ensures that historic assets can be maintained safely and sustainably for future generations.

### 5.3 High-Rise Buildings and Commercial Facilities

High-rise buildings present unique structural and operational challenges due to complex load paths, vertical transportation systems, and high occupant density. BIM–SHM integration provides continuous monitoring of structural vibrations, deflections, wind-induced oscillations, and façade deformations, which are critical for ensuring occupant safety and structural performance.

In commercial facilities, SHM data integrated with BIM allows energy-efficient management, predictive maintenance of HVAC systems, and real-time assessment of load-bearing elements. Automated dashboards linked to BIM models can provide facility managers with actionable insights, such as identifying areas of excessive vibration or uneven settlement, and support decision-making for structural retrofits and safety compliance. Moreover, the integration facilitates scenario-based simulations, such as emergency evacuation planning or structural response under seismic loads, providing high-rise building operators with enhanced safety and operational intelligence.

### 5.4 Industrial Structures (Tanks, Towers, Plants)

672 Industrial infrastructure including storage tanks, communication towers, and chem-  
673 ical plants faces unique risks due to process loads, vibration, thermal cycles, and hazard-  
674 ous materials. BIM–SHM integration enables continuous monitoring of these assets, en-  
675 suring operational safety and regulatory compliance.

676 For example, storage tanks subjected to thermal expansion or pressure fluctuations  
677 can be equipped with strain sensors, tilt meters, and vibration transducers. Data is  
678 streamed into BIM models to detect structural deformations or stress accumulation in real  
679 time. Communication towers and industrial chimneys can similarly benefit from wind-  
680 induced vibration monitoring, with AI algorithms predicting potential resonance or fa-  
681 tigue issues. Integration with BIM ensures that maintenance schedules, inspections, and  
682 retrofits are data-driven, minimizing downtime and operational risk.

### 683 **5.5 Tunnels and Underground Infrastructure**

684 Tunnels and underground infrastructure present unique monitoring challenges due  
685 to restricted access, high humidity, geotechnical loads, and variable environmental con-  
686 ditions. BIM–SHM systems facilitate geometric, structural, and environmental monitoring  
687 by integrating sensor data such as displacement, ground pressure, water ingress, and tem-  
688 perature fluctuations into BIM models.

689 Real-time monitoring enables engineers to assess deformation patterns, potential set-  
690 tlement, and load redistribution along tunnel linings. Advanced analytics can predict fail-  
691 ure zones or structural weaknesses, enabling proactive intervention. Moreover, semantic  
692 enrichment of BIM models allows the integration of geotechnical data, construction se-  
693 quences, and maintenance history, creating a comprehensive digital twin of underground  
694 assets that supports both operational safety and long-term planning.

### 695 **5.6 Residential Sector Applications**

696 Although residential buildings are generally less complex than high-rise or industrial  
697 structures, BIM–SHM integration offers significant benefits for structural safety, energy  
698 efficiency, and maintenance optimization. Sensors embedded in load-bearing walls, foun-  
699 dations, or slabs can monitor settlement, crack propagation, humidity, and thermal be-  
700 havior, feeding continuous data into BIM models.

701 For developers, facility managers, and homeowners, this integration enables early  
702 detection of structural issues, predictive maintenance, and optimization of repair costs. It  
703 also supports sustainability goals by tracking energy usage and enabling intelligent con-  
704 trol of HVAC and other building systems. For large residential complexes, centralized  
705 BIM–SHM platforms can manage multiple units simultaneously, providing a comprehen-  
706 sive monitoring and maintenance framework that enhances safety, durability, and opera-  
707 tional efficiency.

## 708 **6. Contribution of BIM–SHM to Sustainable Management of Existing Structures**

709 The integration of Building Information Modeling (BIM) with Structural Health  
710 Monitoring (SHM) has emerged as a transformative approach for sustainable manage-  
711 ment of existing structures. Traditional maintenance approaches for civil infrastructure  
712 often rely on reactive inspections and scheduled interventions, which can be inefficient,  
713 costly, and environmentally unsustainable. BIM–SHM systems provide a proactive, data-  
714 driven methodology that allows engineers and facility managers to continuously monitor  
715 structural performance, predict potential failures, and optimize resource utilization. The  
716 combination of geometric digital twins, semantic enrichment, and live sensor data not  
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720

only ensures structural safety but also supports economic, environmental, and operational sustainability.

The following subsections explore the major contributions of BIM–SHM integration toward sustainable management of existing buildings and infrastructure, illustrating its impact on structural safety, maintenance optimization, lifecycle extension, material conservation, energy efficiency, and alignment with global sustainability goals.

### 6.1 Enhancing Structural Safety and Risk Reduction

Ensuring structural safety is the foremost objective of any civil infrastructure maintenance program. Existing structures, particularly those subjected to decades of service, variable loading conditions, and environmental degradation, are at risk of unforeseen failures. BIM–SHM integration enables continuous monitoring of structural parameters, including strain, displacement, vibration, crack propagation, and environmental influences such as temperature and humidity.

Through real-time data collection and semantic enrichment of BIM models, engineers can visualize stress concentrations and critical load-bearing elements, enabling early detection of anomalies that may compromise safety. For instance, bridges experiencing fatigue under dynamic traffic loads can be monitored for micro-strains, which, when integrated into BIM, allow identification of sections at higher risk of failure. Such visualization is particularly useful for complex structural geometries, where localized stress or deformation may be difficult to identify through conventional inspection methods.

Risk reduction is further enhanced by predictive analytics and AI-based anomaly detection. Machine learning algorithms, trained on historical SHM data, can identify subtle patterns indicative of potential structural degradation. In the context of high-rise buildings, continuous monitoring of lateral drift or wind-induced oscillations provides early warning before structural thresholds are exceeded, enabling preventive interventions rather than reactive repairs. By integrating risk assessment models into BIM–SHM systems, facility managers can generate risk maps and scenario simulations, evaluating the consequences of extreme events such as earthquakes, floods, or severe wind loads.

Moreover, the digital twin framework supports emergency preparedness and resilience planning. In heritage structures, which are particularly vulnerable due to material aging and unique architectural features, BIM–SHM systems can track environmental and structural parameters to predict damage under specific hazard scenarios. This enables heritage conservation teams to implement preemptive reinforcement strategies, mitigating the risk of irreversible loss. Overall, the integration of BIM and SHM provides a holistic, real-time approach to structural safety, reducing both the likelihood of catastrophic failures and associated human and economic losses Table 6.1 summarizes BIM-SHM contributions to structural Integrity.

Table 6.1: BIM–SHM Contributions to Structural Safety

Parameter Monitored	Typical Sensor/Technology	BIM–SHM Contribution	Impact on Sustainability
Strain & Stress	Strain gauges, fiber-optic sensors	Early detection of overloaded elements	Prevents catastrophic failures, reduces emergency interventions
Vibration & Oscillation	Accelerometers, tilt sensors	Real-time monitoring of dynamic response	Enhances resilience, protects life and property
Crack & Deformation	Laser scanning, photogrammetry	Detects micro-cracks and progressive damage	Minimizes repair extent, preserves structure

Environmental Loads	Temperature, humidity, wind sensors	Correlates environmental effects with structural response	Supports proactive risk mitigation
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**6.2 Optimizing Maintenance Scheduling and Cost Reduction**

Maintenance of existing structures is traditionally based on periodic inspection schedules, which may not accurately reflect actual structural conditions. This often results in over-maintenance of low-risk components and delayed intervention for critical areas, leading to unnecessary costs and operational disruptions. BIM-SHM integration addresses this inefficiency by enabling condition-based maintenance (CBM), where interventions are guided by actual sensor data rather than predefined schedules.

By continuously monitoring key structural parameters and logging trends over time, BIM-SHM systems allow prioritization of maintenance activities according to structural risk levels. For example, in an industrial plant, continuous monitoring of thermal expansion in storage tanks or vibration levels in machinery-supporting structures enables engineers to schedule inspections and repairs precisely where and when they are needed. This targeted maintenance approach reduces the frequency of unnecessary interventions, minimizes labor and material costs, and ensures that critical structural elements receive timely attention.

The cost benefits are further amplified by integrating predictive analytics within BIM models. Historical SHM data, combined with environmental and operational variables, can feed machine learning models to forecast future degradation patterns. For instance, an office building’s HVAC-supporting structures may exhibit increasing stress due to changing occupancy patterns; predictive maintenance algorithms can anticipate structural deterioration and recommend interventions before visible damage occurs. This predictive approach allows budget planning, procurement scheduling, and resource allocation to be optimized, leading to substantial cost reductions over the structure’s lifecycle.

Additionally, the digital twin framework facilitates documentation and reporting, which is essential for regulatory compliance and stakeholder communication. Maintenance schedules, sensor readings, and risk assessments can be embedded directly into the BIM model, providing a centralized platform for facility managers and owners. By integrating historical maintenance data, costs, and performance metrics, BIM-SHM systems support long-term financial and operational decision-making, aligning economic sustainability with structural safety and Table 6.2 summarizes BIM-SHM Impact on Maintenance and cost optimization.

Table 6.2: BIM-SHM Impact on Maintenance and Cost Optimization

Activity	Traditional Approach	BIM-SHM Approach	Benefit
Inspection	Periodic, calendar-based	Condition-based, sensor-driven	Reduced unnecessary inspections, cost savings
Repair Scheduling	Reactive, post-damage	Predictive, preemptive	Minimizes emergency repairs, improves resource allocation
Documentation	Manual records	Integrated BIM model	Transparent, auditable, supports regulatory compliance
Material Use	Overestimation	Optimized via real-time monitoring	Reduces material waste, cost efficiency

**6.3 Extending Service Life Through Predictive Maintenance**

Predictive maintenance is a key contribution of BIM–SHM integration toward extending the service life of existing structures. Unlike reactive maintenance, which addresses damage post-occurrence, predictive maintenance leverages sensor data, digital twins, and AI algorithms to anticipate deterioration trends and intervene proactively.

For example, in bridges and transportation infrastructure, continuous monitoring of stress, deflection, and fatigue accumulation allows engineers to estimate the remaining useful life of structural components. The BIM model provides spatial and material context for the sensor data, enabling precise localization of elements requiring reinforcement or replacement. In high-rise buildings, predictive maintenance can monitor structural drift, vibration, and load distribution, ensuring that interventions occur before the onset of critical failure or excessive deflection.

Predictive maintenance also plays a critical role in heritage and historic structures, where intrusive repairs may compromise architectural integrity. By using BIM–SHM systems to continuously monitor crack propagation, moisture levels, and environmental stressors, conservationists can implement minimal intervention strategies that preserve historical authenticity while preventing irreversible damage.

Extending service life through predictive maintenance has environmental and economic benefits. By delaying the need for complete structural replacement, resource consumption is reduced, and waste generation is minimized. Predictive maintenance also reduces downtime for industrial or commercial structures, ensuring continued functionality and operational efficiency. Collectively, BIM–SHM-based predictive maintenance enhances the resilience and longevity of infrastructure, contributing directly to sustainable management practices and table 6.3 summarizes the BIM-SHM role in predictive maintenance.

Table 6.3: BIM–SHM Role in Predictive Maintenance

1. Structure Type	2. Key Monitoring Focus	3. Predictive Action	4. Service Life Impact
5. Bridges	6. Fatigue, stress, deflection	7. Reinforcement scheduling	8. Prolonged deck and girder life
9. High-Rise	10. Drift, vibration	11. Load redistribution or retrofitting	12. Extends building usability
13. Heritage	14. Cracks, moisture	15. Minimal intervention repairs	16. Preserves material authenticity
17. Industrial	18. Thermal cycles, machinery vibration	19. Targeted component replacement	20. Reduces downtime, prolongs operational life

#### 6.4 Reducing Material Consumption and Waste

Sustainability in civil infrastructure increasingly emphasizes efficient material use and waste reduction. BIM–SHM integration contributes to these objectives by enabling targeted interventions, which avoid unnecessary replacement or repair of structurally sound components.

Through continuous monitoring and predictive analytics, engineers can identify only those structural elements showing signs of deterioration, allowing partial repairs rather than full-scale reconstruction. For example, in a multi-story commercial building, SHM data might reveal localized stress concentrations in a few beams; instead of replacing entire floors or sections, targeted reinforcement can be applied, saving both material and cost.

Furthermore, semantic enrichment in BIM models allows precise quantification of repair materials required for specific interventions. By integrating structural performance

834 data with material specifications, BIM-SHM systems can generate optimized repair  
 835 schedules, including quantities of concrete, steel, or reinforcement needed, minimizing  
 836 surplus material use. This approach not only reduces construction waste but also lowers  
 837 environmental impact by limiting carbon emissions associated with material production  
 838 and transportation and table 6.4 shows the Material efficiency through BIM-SHM.

839 Table 6.4: Material Efficiency through BIM-SHM

Intervention Type	Traditional Method	BIM-SHM Optimized	Material Savings
Beam repair	Replace full beam	Targeted reinforcement	25–50% reduction
Concrete patching	Over-application	Sensor-driven volume calculation	30–40% reduction
Industrial piping	Full section replacement	Monitor & reinforce critical areas	20–35% reduction

840  
841 **6.5 Enabling Energy-Efficient Facility Operations**

842 Beyond structural performance, BIM-SHM integration significantly contributes to  
 843 energy efficiency in facility operations. By incorporating environmental monitoring (tem-  
 844 perature, humidity, occupancy) and operational data into BIM models, facility managers  
 845 can optimize energy usage in heating, ventilation, air conditioning (HVAC), lighting, and  
 846 other systems.

847 For instance, high-rise buildings equipped with vibration and occupancy sensors can  
 848 leverage real-time SHM data to modulate HVAC loads according to actual usage patterns  
 849 and structural responses. Similarly, sensor-informed BIM models can prevent overload-  
 850 ing of structural components, reducing energy-intensive interventions such as temporary  
 851 reinforcements or cooling measures to counter thermal expansion.

852 The integration of BIM-SHM also supports sustainable retrofitting. Energy-efficient  
 853 retrofits, such as installation of solar panels, smart lighting, or adaptive shading systems,  
 854 can be simulated within the BIM environment with real-world structural constraints de-  
 855 rived from SHM data. This ensures that energy interventions do not compromise struc-  
 856 tural integrity while maximizing operational efficiency. By linking operational perfor-  
 857 mance with structural monitoring, BIM-SHM systems enable holistic sustainability, com-  
 858 bining energy efficiency with structural longevity and reduced environmental impact and  
 859 table 6.5 summarizes the energy efficiency through BIM-SHM.

860 Table 6.5: Energy Efficiency Benefits through BIM-SHM

21. Facility Type	22. Monitored Parameters	23. Energy Optimization Action	24. Expected Savings
25. High-Rise	26. Occupancy, vibration, temperature	27. Adaptive HVAC and lighting control	28. 15–25% reduction in energy use
29. Commercial	30. Structural load monitoring	31. Reduce temporary reinforcement interventions	32. 10–15% reduction in operational energy
33. Industrial	34. Thermal cycles	35. Optimize cooling systems	36. 12–20% energy savings

861  
862 **6.6 Supporting Green Certification and Sustainability Goals**

863 Green building certifications, such as LEED, BREEAM, or WELL, increasingly re-  
 864 quire evidence of sustainable operational practices, energy efficiency, and lifecycle opti-  
 865 mization. BIM-SHM integration directly supports these objectives by providing contin-  
 866 uous, auditable data on structural health, energy performance, maintenance practices, and  
 867 material efficiency.

For example, the predictive maintenance and targeted repair enabled by BIM–SHM systems demonstrate responsible material management, while real-time energy monitoring supports optimized building performance metrics required for certification. Semantic enrichment allows integration of sustainability indicators, carbon footprints, and environmental impact data directly into the digital twin, providing stakeholders with a transparent, verifiable record of sustainable practices.

In addition, BIM–SHM systems support long-term sustainability planning by tracking structural performance trends, identifying areas for retrofit, and optimizing lifecycle decisions in alignment with environmental targets. By integrating structural safety, cost efficiency, energy conservation, and material reduction into a unified framework, BIM–SHM contributes to resilient, low-impact infrastructure management, aligning technical practice with global sustainability goals and Table 6.6 summarizes the BIM–SHM Contributions to Green Certification.

Table 6.6: BIM–SHM Contributions to Green Certification

37. Certification Requirement	38. BIM–SHM Contribution	39. Impact on Sustainability
40. Material efficiency	41. Targeted repair & predictive maintenance	42. Reduces waste, carbon footprint
43. Energy efficiency	44. Real-time monitoring & adaptive systems	45. Lowers operational energy consumption
46. Lifecycle documentation	47. BIM model with SHM data	48. Supports auditable certification evidence
49. Resilience & safety	50. Continuous risk assessment	51. Ensures long-term structural reliability

## 7. Challenges and Limitations

Despite the proven benefits of BIM–SHM integration for sustainable management of existing structures, several challenges and limitations constrain its widespread adoption. These barriers span technical, financial, operational, and human factors. Understanding and addressing these challenges is critical for practitioners, researchers, and policymakers seeking to implement BIM–SHM systems effectively.

The following subsections present a detailed analysis of the key limitations and challenges faced in BIM–SHM integration, highlighting technical, financial, interoperability, scalability, and human factors that affect system performance, data utilization, and long-term sustainability.

### 7.1 Technical Challenges

Technical challenges represent one of the most significant barriers to effective BIM–SHM implementation. While BIM provides a rich digital representation of the built environment, integrating real-time SHM data into these models introduces complexities in data acquisition, processing, and visualization.

#### 7.1.1 Lack of Standardization

A fundamental technical challenge is the absence of universally accepted standards for integrating SHM data with BIM models. Various BIM platforms use different data structures, file formats, and semantic definitions, making seamless integration of sensor data complex. Similarly, SHM systems employ diverse sensors and data acquisition protocols, leading to heterogeneous datasets.

For example, strain gauges, accelerometers, and fiber-optic sensors may produce data in different formats, frequencies, and units. Without a standardized framework, engineers often resort to customized middleware or bespoke data pipelines, which can increase costs and reduce reproducibility. While some standards exist, such as IFC (Industry Foundation Classes) for BIM and MQTT for real-time data streaming, their adoption is not yet widespread, and interoperability remains limited.

This lack of standardization also affects regulatory compliance and collaborative workflows. Multiple stakeholders, including design engineers, facility managers, and maintenance contractors, may struggle to interpret SHM outputs consistently across BIM platforms, resulting in inefficiencies and potential errors.

**7.1.2 Sensor Data Overload and Management**

SHM systems generate high-frequency, high-volume datasets, particularly when monitoring multiple parameters across large structures or infrastructure networks. While the availability of rich data is advantageous, it introduces significant challenges in storage, processing, and analysis.

Continuous monitoring of bridges, high-rise buildings, or industrial plants can produce terabytes of data daily. Without effective data management and filtering mechanisms, facility managers may experience information overload, where critical signals are obscured by noise or redundant measurements.

Advanced analytics, such as AI/ML-driven anomaly detection, can mitigate this challenge, but the computational requirements for processing large-scale SHM datasets in real-time can be prohibitive. Additionally, integrating these datasets with BIM models requires robust data pipelines, cloud storage solutions, and database management strategies, which may not be available in all organizations.

**7.1.3 Difficulties in Real-Time Visualization**

Real-time visualization of SHM data within BIM models is critical for operational decision-making, but it poses significant technical difficulties. BIM platforms are primarily designed for design and planning, not for high-frequency data streaming. Incorporating live sensor data into 3D BIM models requires dynamic rendering, data interpolation, and frequent model updates, which can strain software capabilities and hardware resources.

For example, visualizing vibration data across an entire bridge deck in real time requires simultaneous rendering of hundreds or thousands of sensor nodes. Without optimized visualization algorithms, users may encounter lag, slow updates, or incomplete representations, reducing the effectiveness of the digital twin. Additionally, visualizing multi-parameter data (strain, displacement, temperature) in a single BIM environment requires careful semantic mapping and graphical encoding, which adds to system complexity and Table 7.1 shows the Summary of Key Technical Challenges.

Table 7.1: Summary of Key Technical Challenges

Technical Challenge	Description	Implications for BIM–SHM Integration
Lack of Standardization	Diverse BIM formats and SHM protocols	Difficult data integration, limited interoperability
Sensor Data Overload	High-frequency, multi-sensor datasets	Storage, processing, and analysis bottlenecks
Real-Time Visualization	Rendering live data in BIM	Latency, software performance issues, complex UI design

**7.2 Financial and Operational Barriers**

946 BIM–SHM integration often requires substantial upfront investment in hardware,  
947 software, and human resources. High-quality sensors, data acquisition systems, and cloud  
948 computing infrastructure are expensive, and many organizations, particularly in devel-  
949 oping regions, may lack sufficient budget.

950 Operational costs further include maintenance of sensors, calibration, software li-  
951 censing, and training. For example, replacing or recalibrating damaged sensors in remote  
952 or hazardous locations can be costly and logistically challenging. In industrial facilities,  
953 downtime required for sensor installation or testing can interrupt operations, increasing  
954 indirect costs.

955 Even when infrastructure owners recognize the long-term benefits of BIM–SHM in-  
956 tegration, the return on investment (ROI) may not be immediately apparent, discouraging  
957 adoption. Smaller-scale projects or residential buildings may not justify the financial com-  
958 mitment, limiting BIM–SHM primarily to large-scale or critical structures.

### 960 **7.3 Interoperability Issues Between BIM and SHM Platforms**

961 Interoperability between BIM and SHM platforms is another significant limitation.  
962 BIM software, such as Autodesk Revit or Bentley Systems, may not natively support live  
963 SHM data feeds. Conversely, SHM platforms and IoT devices may use proprietary proto-  
964 cols, making direct integration difficult.

965 This often necessitates the use of middleware, APIs, or custom data converters, which  
966 increase technical complexity and risk of errors. Interoperability issues can also hinder  
967 cross-disciplinary collaboration, where engineers, architects, and facility managers need  
968 to access unified data in real time. Without seamless interoperability, the full potential of  
969 BIM–SHM systems for decision-making, predictive maintenance, and sustainability track-  
970 ing cannot be realized.

### 972 **7.4 Scalability and Long-Term Data Storage**

973 Scaling BIM–SHM systems to large infrastructure networks, multi-story buildings,  
974 or city-scale projects introduces additional challenges. Long-term data storage is particu-  
975 larly critical, as historical SHM data is essential for predictive maintenance, trend analysis,  
976 and regulatory reporting.

977 Storing terabytes of sensor data over years or decades requires robust database sys-  
978 tems, cloud storage, and data redundancy measures. Scalability also includes handling  
979 increased computational load, ensuring that AI models and analytics algorithms can pro-  
980 cess large datasets without delays. Failure to address scalability can result in loss of critical  
981 information, decreased prediction accuracy, and reduced system reliability.

982 Furthermore, scaling often raises security concerns, as sensitive operational data and  
983 building information may be vulnerable to cyberattacks. Organizations must balance ac-  
984 cessibility with robust security protocols, increasing operational complexity.

### 986 **7.5 Reliability, Accuracy, and Maintenance of SHM Systems**

987 The accuracy and reliability of SHM systems are critical for effective BIM–SHM inte-  
988 gration. Sensors may experience drift, calibration errors, environmental degradation, or  
989 physical damage, all of which can compromise data quality. Inaccurate SHM data can lead  
990 to erroneous decisions, unnecessary maintenance, or overlooked structural issues, under-  
991 mining confidence in the system.

992 Regular sensor maintenance, calibration, and quality checks are essential but can be  
993 resource intensive. Harsh environmental conditions, such as extreme temperatures, hu-  
994 midity, or chemical exposure, further reduce sensor lifespan and accuracy. Integration

into BIM amplifies the issue, as errors in sensor data propagate through the digital twin, potentially affecting risk assessment, predictive maintenance models, and sustainability calculations.

### 7.6 Human Factors and Skill Gaps

Finally, human factors and skill gaps represent a significant barrier to BIM–SHM adoption. Effective operation of these integrated systems requires multidisciplinary expertise, including structural engineering, data analytics, software management, and sensor technologies. Many organizations lack personnel with sufficient skills to manage both BIM platforms and SHM systems simultaneously.

Additionally, resistance to new technologies, limited understanding of digital twin capabilities, or inadequate training can reduce system adoption and efficacy. For example, facility managers may fail to correctly interpret predictive analytics outputs or fail to act on early warnings, negating the benefits of BIM–SHM integration.

Addressing human factors requires comprehensive training programs, clear operational protocols, and stakeholder engagement, ensuring that the workforce can fully leverage the potential of BIM–SHM for structural safety, maintenance optimization, and sustainability and Table 7.2 shows Summary of Major Challenges in BIM–SHM Integration.

Table 7.2: Summary of Major Challenges in BIM–SHM Integration

52. Challenge Category	53. Key Issues	54. Implications
55. Technical	56. Lack of standardization, data overload, real-time visualization	57. Integration complexity, performance issues
58. Financial/Operational	59. High cost, maintenance, downtime	60. Limits adoption, especially for small/medium structures
61. Interoperability	62. Proprietary protocols, software incompatibility	63. Hinders cross-disciplinary collaboration
64. Scalability	65. Large datasets, long-term storage, cybersecurity	66. Risk of data loss, performance bottlenecks
67. Reliability & Accuracy	68. Sensor drift, environmental degradation	69. Compromised decision-making
70. Human Factors	71. Skill gaps, resistance to adoption	72. Reduced utilization of system benefits

## 8. Future Research Directions

The integration of BIM (Building Information Modeling) and SHM (Structural Health Monitoring) is still an emerging field, with significant research and technological opportunities to enhance its effectiveness. While current implementations demonstrate the benefits of real-time monitoring, predictive maintenance, and sustainability optimization, several limitations and knowledge gaps remain. Future research must address these gaps to achieve fully autonomous, intelligent, and secure digital twin ecosystems that support long-term structural management and sustainability goals.

This section outlines potential research directions, highlighting technological innovations, methodological advancements, and interdisciplinary collaboration necessary for the next generation of BIM–SHM systems.

### 8.1 Toward Fully Autonomous Digital Twins

1028 One of the most promising avenues for research is the development of **fully** auto-  
1029 nomous digital twins, where BIM models continuously integrate real-time SHM data with-  
1030 out manual intervention. Current digital twins often rely on semi-automated updates, re-  
1031 quiring engineers or facility managers to validate and input data. Research is needed to  
1032 design autonomous pipelines that can ingest sensor data, update BIM models, and trigger  
1033 alerts or maintenance actions in real time.

1034 Key challenges include ensuring data accuracy, consistency, and semantic integrity  
1035 during automated updates. Sensor calibration errors, environmental noise, or structural  
1036 anomalies must be accounted for to prevent propagation of incorrect information within  
1037 the digital twin. Future studies could explore adaptive learning algorithms, capable of  
1038 differentiating between transient anomalies and long-term structural degradation,  
1039 thereby ensuring that digital twins remain both accurate and actionable.

1040 Moreover, autonomous digital twins have the potential to integrate multi-physics  
1041 simulations, combining structural behavior, environmental conditions, and operational  
1042 loads. This would enable predictive scenario analysis, such as simulating the structural  
1043 response to extreme events or optimizing maintenance strategies without human inter-  
1044 vention. Developing these autonomous systems will require research in AI, cloud compu-  
1045 ting, and high-fidelity modeling techniques, alongside robust validation methodologies.

### 1047 **8.2 Use of Robotics and UAVs for Inspection + BIM Updating**

1048 Traditional SHM relies heavily on fixed sensors and manual inspections, which can  
1049 be time-consuming, costly, and sometimes unsafe, particularly for inaccessible areas like  
1050 high-rise facades, bridges, or tunnels. The use of robotics and unmanned aerial vehicles  
1051 (UAVs) offers a promising research direction to automate data acquisition and BIM up-  
1052 dates.

1053 UAVs equipped with LiDAR scanners, high-resolution cameras, and thermal imag-  
1054 ing sensors can collect geometrical and environmental data rapidly and with minimal dis-  
1055 ruption. Robotics platforms, such as climbing robots or autonomous ground vehicles, can  
1056 navigate confined or hazardous spaces, enabling continuous monitoring of structural ele-  
1057 ments. Future research should focus on sensor fusion, combining UAV and robotic data  
1058 streams with traditional SHM sensors, and automatically integrating these measurements  
1059 into BIM models.

1060 Challenges include ensuring data registration accuracy, sensor calibration in dy-  
1061 namic environments, and autonomous navigation for both aerial and terrestrial platforms.  
1062 Developing standardized protocols for UAV-based data acquisition and integrating it  
1063 seamlessly into BIM workflows is essential. Research may also explore collaborative UAV  
1064 and robotic networks, capable of covering large infrastructure networks efficiently while  
1065 maintaining high-resolution structural data for continuous digital twin updates.

### 1066 **8.3 AI-Enabled Damage Prediction and Automated Model Updating**

1067 The integration of artificial intelligence (AI) and machine learning (ML) into BIM-  
1068 SHM systems offers significant potential for damage prediction, anomaly detection, and  
1069 automated model updating. Current BIM-SHM frameworks often rely on threshold-  
1070 based alerts or rule-based algorithms, which may not capture complex structural interac-  
1071 tions or early-stage damage patterns.

1072 Future research should explore deep learning models trained on historical SHM data,  
1073 simulation datasets, and environmental conditions to predict structural degradation ac-  
1074 curately. AI can also facilitate automated updating of BIM models, ensuring that the dig-  
1075 ital twin reflects real-time structural conditions. For instance, minor crack propagation

1076 detected via sensors or UAV photogrammetry could trigger automatic geometry and ma-  
1077 terial property updates within the BIM model.

1078 Another critical research direction is uncertainty quantification, ensuring that AI pre-  
1079 dictions are accompanied by confidence metrics. This is essential for risk-informed deci-  
1080 sion-making and integrating predictive analytics into maintenance prioritization, lifecycle  
1081 cost analysis, and resilience planning. Moreover, hybrid approaches combining physics-  
1082 based simulations with data-driven AI models can enhance prediction reliability, partic-  
1083 ularly in structures with limited historical data.

#### 1084 **8.4 Integration with Blockchain for Secure Data Storage**

1085 As BIM–SHM systems generate large volumes of sensitive operational and structural  
1086 data, ensuring data integrity, security, and traceability becomes a pressing research need.  
1087 Blockchain technology offers a decentralized, tamper-proof solution for storing and man-  
1088 aging SHM and BIM data, enabling secure sharing among stakeholders.

1089 Future research can explore smart contract frameworks, where specific triggers—  
1090 such as exceeding stress thresholds or detecting vibration anomalies—initiate automatic  
1091 maintenance requests or alert authorized personnel. Blockchain integration also supports  
1092 auditability and compliance, particularly for critical infrastructure such as bridges, power  
1093 plants, or heritage sites.

1094 Challenges include scalability of blockchain networks, as high-frequency SHM data  
1095 can generate massive transaction volumes, and latency in data retrieval, which must be  
1096 addressed to maintain real-time operational capabilities. Research could investigate hy-  
1097 brid systems, where on-chain metadata and hashes ensure integrity while bulk sensor  
1098 data is stored off-chain, providing both security and efficiency.

#### 1099 **8.5 Developing Universal BIM–SHM Standards**

1100 A major limitation of current BIM–SHM integration is the lack of universally ac-  
1101 cepted standards, which hampers interoperability across platforms, sensors, and stake-  
1102 holders. Future research must focus on developing open standards for data exchange, se-  
1103 mantic enrichment, and real-time integration, covering both BIM model structures (IFC,  
1104 COBie) and SHM sensor protocols (MQTT, OPC UA).

1105 Standards development should consider multi-domain applications, including  
1106 bridges, industrial facilities, high-rise buildings, and heritage structures. These standards  
1107 would enable cross-platform compatibility, reduce development costs, and facilitate col-  
1108 laboration among engineers, facility managers, and technology providers.

1109 Research could also explore ontology-based frameworks, where sensor data, struc-  
1110 tural elements, and BIM properties are semantically linked, enabling automated reasoning  
1111 and decision-making. By establishing universal standards, future BIM–SHM systems can  
1112 achieve scalability, repeatability, and global adoption, fostering innovation across the civil  
1113 engineering and digital construction communities.

#### 1114 **8.6 Embedding Sustainability Metrics into BIM–SHM Systems**

1115 While current BIM–SHM systems primarily focus on structural safety, predictive  
1116 maintenance, and operational efficiency, future research must embed sustainability met-  
1117 rics directly into digital twins. Sustainability indicators may include carbon footprint of  
1118 repair materials, energy consumption, water usage, and lifecycle environmental impact.

1119 Integrating these metrics enables data-driven decision-making that balances struc-  
1120 tural performance with environmental responsibility. For instance, predictive mainte-  
1121 nance can identify high-risk components for repair, reducing downtime and material waste.  
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1124 nance schedules could prioritize interventions with minimal environmental impact, or al-  
 1125 ternative materials with lower carbon intensity could be recommended within BIM work-  
 1126 flows.

1127 Research is needed to develop standardized methodologies for calculating, repre-  
 1128 senting, and updating sustainability metrics in real-time, leveraging SHM data, simula-  
 1129 tion outputs, and operational information. Embedding these metrics into digital twins can  
 1130 also facilitate green building certification, support circular economy principles, and align  
 1131 infrastructure management with global sustainability goals.

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 1133 **8.7 Improving Interdisciplinary Collaboration**

1134 Finally, BIM-SHM integration requires effective interdisciplinary collaboration be-  
 1135 tween structural engineers, software developers, data scientists, facility managers, and  
 1136 sustainability experts. Future research must explore collaborative frameworks and work-  
 1137 flow optimizations that enhance communication, knowledge sharing, and decision-mak-  
 1138 ing.

1139 Challenges include semantic gaps between disciplines, varying technical expertise,  
 1140 and inconsistent interpretation of SHM outputs. Research directions may include devel-  
 1141 oping collaborative digital platforms with role-based access, interactive visualization  
 1142 tools, and standardized reporting templates that enable all stakeholders to interpret and  
 1143 act on BIM-SHM insights.

1144 Furthermore, training programs and interdisciplinary curricula can help bridge skill  
 1145 gaps, ensuring that engineers understand AI models, data analytics, and digital twin op-  
 1146 erations, while software developers appreciate structural engineering principles. Im-  
 1147 proved collaboration enhances the effectiveness, adoption, and sustainability of BIM-  
 1148 SHM systems, enabling smarter infrastructure management and Table 8.1 shows the Sum-  
 1149 mary of Future Research Directions for BIM-SHM Integration

1150 Table 8.1: Summary of Future Research Directions for BIM-SHM Integration

73. Research Direction	74. Key Focus	75. Expected Impact
76. Autonomous Digital Twins	77. Real-time automated model updates	78. Reduced human intervention, improved decision-making
79. Robotics & UAVs	80. Automated inspection and data acquisition	81. Safer, faster, more accurate monitoring
82. AI-Enabled Prediction	83. Damage forecasting, model updating	84. Proactive maintenance, extended service life
85. Blockchain Integration	86. Secure, tamper-proof data storage	87. Enhanced trust, auditability, and collaboration
88. Universal Standards	89. Open protocols for BIM-SHM	90. Cross-platform interoperability, global adoption
91. Sustainability Metrics	92. Carbon footprint, energy, lifecycle impact	93. Environmentally responsible infrastructure management
94. Interdisciplinary Collaboration	95. Workflow optimization, training	96. Improved system utilization, stakeholder engagement

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 1154 **9. Discussion**

1155 The discussion section serves as a critical synthesis and evaluation of the current state  
1156 of BIM–SHM integration research. By analyzing the literature in depth, comparing differ-  
1157 ent methodologies, and identifying both achievements and gaps, this section provides in-  
1158 sight into the strengths, weaknesses, and practical implications for future research and  
1159 industry adoption. The discussion is organized to bridge research findings with actionable  
1160 guidance, ensuring the relevance of BIM–SHM frameworks to real-world applications.

### 1161 **9.1 Critical Synthesis of Literature Findings**

1162 The literature on BIM–SHM integration demonstrates that the synergistic combina-  
1163 tion of BIM digital twins and SHM data significantly enhances structural safety, mainte-  
1164 nance efficiency, and sustainability. Multiple studies have shown that integrating real-  
1165 time sensor data into BIM models enables continuous monitoring, predictive mainte-  
1166 nance, and scenario-based risk assessment.

1167 A key observation is that most successful applications focus on critical infrastructure,  
1168 including bridges, high-rise buildings, and industrial facilities, where the cost-benefit ra-  
1169 tio justifies the investment in sophisticated SHM sensors and BIM platforms. Research  
1170 indicates that direct sensor-to-BIM linking, database-driven integration, and middleware-  
1171 based approaches each have unique advantages, depending on the scale of the project,  
1172 frequency of data updates, and desired level of automation.

1173 However, the literature also highlights significant technical, financial, and opera-  
1174 tional challenges, including lack of standardization, data overload, interoperability issues,  
1175 and human factors. The review demonstrates that while the potential benefits are substan-  
1176 tial, implementation is currently limited by practical constraints, particularly for smaller-  
1177 scale or resource-constrained projects.

1178 Moreover, studies underscore the emerging role of AI and machine learning, which  
1179 enhances the predictive capability of BIM–SHM systems, and facilitates automated model  
1180 updating. These approaches are particularly valuable in large-scale monitoring projects  
1181 where manual interpretation of sensor data is infeasible. Yet, AI applications remain lim-  
1182 ited by data availability, model generalization, and validation challenges, indicating a  
1183 clear direction for future research.

### 1184 **9.2 Comparative Evaluation of Integration Techniques**

1185 BIM–SHM integration methodologies can be broadly classified into four categories:  
1186 direct sensor-to-BIM linking, database-driven integration, middleware/API-based inte-  
1187 gration, and IoT real-time streaming. Each method has distinct strengths and limitations,  
1188 as summarized below:

#### 1189 **1. Direct Sensor-to-BIM Linking:**

1190 This approach involves directly embedding SHM sensor outputs into BIM models,  
1191 often through custom scripts or plugins. It offers high temporal resolution and allows  
1192 for immediate visualization of structural changes. However, it is technically complex,  
1193 often software-specific, and may lack scalability for large or multi-structured projects.

#### 1194 **2. Database-Driven Integration:**

1195 In this approach, sensor data is stored in structured databases, which BIM models  
1196 periodically query. This method enhances data management, long-term storage, and  
1197 analytical flexibility, and is more scalable than direct linking. The limit lies in real-  
1198 time responsiveness, as data is updated at intervals rather than continuously.

#### 1199 **3. Middleware and API-Based Integration:**

1200 Middleware acts as a translator between SHM systems and BIM platforms, allowing  
1201 interoperability across heterogeneous software and sensors. This approach supports  
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standardized data exchange and modularity, making it suitable for multi-disciplinary teams. However, it introduces additional computational overhead and complexity in system architecture.

4. **IoT and Real-Time Streaming Integration:**

Leveraging IoT protocols such as MQTT or OPC-UA, this method enables continuous, high-frequency data streaming into BIM environments. It is ideal for real-time monitoring of critical infrastructure, allowing predictive maintenance and dynamic risk assessment. Challenges include data security, bandwidth requirements, and visualization limitations in complex BIM models and table 9.1 compares the Evaluation of BIM-SHM Integration Techniques.

Table 9.1: Comparative Evaluation of BIM-SHM Integration Techniques

97. Integration Technique	98. Advantages	99. Limitations	100. Best Applications
101. Direct Sensor-to-BIM Linking	102. Immediate visualization, high temporal resolution	103. Software-specific, limited scalability	104. Small to medium structures, pilot studies
105. Database-Driven Integration	106. Structured storage, analytical flexibility	107. Reduced real-time responsiveness	108. Large infrastructure networks
109. Middleware/API-Based	110. Interoperability, modularity	111. Additional computational complexity	112. Multi-platform projects, collaborative workflows
113. IoT & Real-Time Streaming	114. Continuous monitoring, predictive maintenance	115. Bandwidth, security, visualization challenges	116. Critical infrastructure, bridges, high-rise buildings

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This comparison illustrates that no single method is universally optimal; instead, integration should be selected based on project scale, monitoring requirements, and stakeholder needs. Future research could explore hybrid approaches, combining the scalability of database-driven methods with the responsiveness of IoT streaming.

**9.3 Strengths and Weaknesses of Current Research**

Current research in BIM-SHM integration demonstrates several notable strengths:

- **Enhanced Structural Safety:** Continuous monitoring enables early detection of structural anomalies, reducing failure risk.
- **Predictive Maintenance and Lifecycle Optimization:** SHM data integrated into BIM supports proactive interventions, lowering maintenance costs and material usage.
- **Sustainability Contributions:** Integration facilitates energy optimization, material efficiency, and supports green certification initiatives.
- **Emerging AI Applications:** Machine learning models improve prediction accuracy, anomaly detection, and automated BIM updates.

However, several weaknesses remain, limiting broader adoption:

- **Standardization Deficiencies:** Lack of universal protocols and semantic models inhibits interoperability across platforms and projects.
- **Data Management Challenges:** High-frequency sensor data can overwhelm storage and analytics systems, creating bottlenecks.
- **Financial and Operational Constraints:** High installation costs, maintenance, and training requirements limit adoption, especially for smaller projects.

- **Human Factors:** Limited expertise in both BIM and SHM systems creates skill gaps and affects decision-making.
- **Limited Real-World Validation:** Many approaches are tested in pilot or controlled settings, with limited deployment in operational infrastructure.

Table 9.2: Strengths and Weaknesses of Current BIM–SHM Research

117. Aspect	118. Strengths	119. Weaknesses
120. Structural Safety	121. Early anomaly detection, risk reduction	122. Requires extensive sensor networks
123. Maintenance & Lifecycle	124. Predictive interventions, cost optimization	125. Data management complexity
126. Sustainability	127. Energy efficiency, material reduction	128. Limited real-world implementation
129. AI & Analytics	130. Automated damage prediction, model updates	131. Model validation, data scarcity
132. Interdisciplinary Collaboration	133. Supports multiple stakeholders	134. Skill gaps, communication challenges

#### 9.4 Implications for Researchers and Industry

The synthesis of literature findings and comparative evaluations highlights key implications for both researchers and industry practitioners.

For researchers, the analysis underscores the importance of developing standardized frameworks, AI-enabled predictive models, and scalable data management strategies. Cross-disciplinary research combining civil engineering, computer science, and data analytics is critical to overcome current limitations. Future work should focus on hybrid integration techniques, autonomous digital twin development, and embedding sustainability metrics within BIM–SHM systems.

For industry practitioners, the findings indicate that BIM–SHM integration can significantly improve operational efficiency, safety, and sustainability, but careful planning is required. Stakeholders should consider project scale, cost, sensor selection, and platform interoperability when implementing these systems. Additionally, training and capacity building are essential to fully leverage predictive maintenance capabilities, digital twin functionalities, and data-driven decision-making.

Ultimately, the discussion confirms that while BIM–SHM integration offers transformative potential, its effectiveness is contingent on addressing technical, operational, and human challenges, ensuring accurate, timely, and actionable insights that align with both safety and sustainability objectives.

### 10. Conclusion

The integration of Building Information Modeling (BIM) with Structural Health Monitoring (SHM) represents a paradigm shift in infrastructure management, enabling the transition from reactive maintenance to predictive, data-driven, and sustainable practices. This review has synthesized the existing literature, examined integration techniques, explored applications, and identified future research directions, highlighting both the op-

portunities and challenges associated with BIM–SHM systems. The conclusion consolidates these findings, evaluates their significance for the civil engineering community, and provides final remarks on the future of this transformative technology.

### 10.1 Summary of Key Review Findings

The critical analysis of the literature reveals several overarching findings regarding the role of BIM–SHM integration in the sustainable management of existing structures:

1. **Structural Safety and Risk Mitigation:** Continuous monitoring of strain, vibration, displacement, and environmental loads significantly reduces the risk of structural failure. BIM–SHM integration allows real-time visualization and predictive assessment, enabling early detection of anomalies and informed intervention strategies. Studies indicate that integrating SHM data into BIM models enhances resilience and emergency preparedness, particularly for critical infrastructure and heritage structures.
2. **Maintenance Optimization and Lifecycle Management:** The literature demonstrates that BIM–SHM integration facilitates condition-based and predictive maintenance, resulting in cost savings, reduced downtime, and optimized allocation of resources. Predictive models, when combined with historical SHM data, allow for precise scheduling of interventions and extension of structural service life.
3. **Sustainability and Resource Efficiency:** BIM–SHM contributes to sustainability by reducing material consumption, minimizing waste, and enabling energy-efficient facility operations. Embedding sustainability metrics into digital twins allows engineers and facility managers to make environmentally informed decisions, supporting green building certifications and global sustainability objectives.
4. **Technological Advancements and AI Integration:** Machine learning and artificial intelligence enhance the predictive capabilities of BIM–SHM systems. AI models can identify subtle patterns of structural degradation, automate BIM model updates, and provide actionable insights for maintenance and lifecycle optimization.
5. **Challenges and Limitations:** Despite these benefits, the review identifies persistent barriers including lack of standardization, sensor data overload, interoperability issues, financial constraints, and human skill gaps. These challenges limit the widespread adoption and scalability of BIM–SHM systems. Addressing these limitations remains a priority for both researchers and practitioners.

Table 10.1: Summary of Key BIM–SHM Review Findings

Focus Area	Key Findings	Impact
Structural Safety	Continuous monitoring and predictive analysis	Early detection, reduced failure risk
Maintenance & Lifecycle	Condition-based and predictive interventions	Cost savings, extended service life
Sustainability	Material and energy efficiency	Supports green building certifications, reduces environmental impact
AI & Digital Twin	Automated model updating, anomaly detection	Enhanced predictive maintenance, informed decision-making

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Challenges	Standardization, interoperability, skill gaps	Limits adoption and scalability
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## 10.2 Contribution to the Civil Engineering Community

This review contributes significantly to the civil engineering community by providing a comprehensive synthesis of BIM–SHM integration research, including methodologies, application domains, benefits, and challenges. The study highlights the interdisciplinary potential of combining structural engineering, data analytics, digital construction, and sustainability practices.

Key contributions include:

1. **Guidance for Researchers:** By identifying gaps in sensor integration, data management, AI modeling, and standardization, this review provides a roadmap for future research. Researchers can focus on developing autonomous digital twins, hybrid integration techniques, and robust predictive models, addressing both technical and operational challenges.
2. **Practical Implications for Industry:** Facility managers, infrastructure owners, and engineers can leverage insights from this review to select appropriate integration strategies, optimize maintenance schedules, and enhance sustainability performance. The discussion of integration techniques and comparative evaluation aids in decision-making for practical implementations, reducing risk and improving ROI.
3. **Promotion of Sustainable Practices:** By highlighting the role of BIM–SHM in reducing material consumption, energy usage, and operational inefficiencies, this review supports sustainable infrastructure management, aligning civil engineering practices with global environmental goals.

Overall, the review emphasizes the transformative potential of BIM–SHM integration, providing a foundation for both academic research and industrial adoption, ensuring that civil infrastructure is safer, more efficient, and environmentally responsible.

## 10.3 Final Remarks on the Future of BIM–SHM for Sustainable Management

Looking ahead, the future of BIM–SHM integration lies in autonomous, intelligent, and fully interoperable digital twin ecosystems. Research directions suggest the development of robotics and UAV-assisted inspection, AI-enabled predictive maintenance, blockchain-secured data storage, and universal standards for interoperability. Such advancements will enable infrastructure managers to monitor, predict, and optimize structural performance in real time, reducing human intervention while improving decision-making efficiency.

Furthermore, embedding sustainability metrics into BIM–SHM systems will allow infrastructure stakeholders to assess carbon footprints, lifecycle energy consumption, and material efficiency, ensuring environmentally responsible management. The integration of these metrics into digital twins will align infrastructure practices with global sustainability frameworks, including LEED, BREEAM, and ISO 14001 standards.

Finally, the widespread adoption of BIM–SHM systems will require interdisciplinary collaboration and skill development. Engineers, data scientists, and facility managers must work together to bridge knowledge gaps, improve interpretation of predictive analytics, and ensure effective system utilization. The realization of these capabilities promises long-term benefits in structural resilience, operational efficiency, and environmental sustainability, marking a pivotal evolution in civil engineering practice.

Table 10.2: Future Outlook of BIM–SHM for Sustainable Management

135. Future Focus	136. Expected Advances	137. Benefits
138. Autonomous Digital Twins	139. Real-time automated model updates	140. Reduced human dependency, improved decision-making
141. Robotics & UAV Inspection	142. Automated, high-resolution monitoring	143. Safer, efficient, and accurate data acquisition
144. AI-Enabled Predictive Maintenance	145. Advanced anomaly detection, model updating	146. Proactive interventions, extended service life
147. Blockchain Integration	148. Secure and auditable data storage	149. Enhanced trust, collaboration, and compliance
150. Universal Standards	151. Open protocols and semantic frameworks	152. Interoperability, scalability, global adoption
153. Sustainability Metrics	154. Embedded energy, material, and lifecycle indicators	155. Environmentally responsible infrastructure management
156. Interdisciplinary Collaboration	157. Training, workflow optimization	158. Effective utilization and improved outcomes

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