



A Review of Innovations, Challenges, and Future Directions in Structural Health Monitoring Using Smart Materials

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ABSTRACT

Structural Health Monitoring (SHM) protects and extends the structure's lifespan. This review consolidates recent developments in SHM technologies and methods, emphasizing key advancements while pinpointing ongoing research challenges. We examine more than 130 studies, highlighting advancements in sensor technologies, including vibration sensors, fiber optics, piezoelectric transducers, and wireless networks. These technologies have been effectively applied across aerospace, civil, and mechanical engineering domains. Despite significant progress, challenges persist in integrating machine learning (M.L) and deep learning (D.L) for improved Structural assessment, managing large datasets, validating sensor reliability, and mitigating the effects of environmental factors on sensor performance. Although advancements have been made, there remains a significant gap in research focusing on SHM for timber structures, heritage buildings, and agricultural infrastructure. Additionally, optimizing sensor placement and developing robust multi-sensor approaches are critical areas needing further exploration. Standardizing SHM protocols and incorporating emerging technologies into comprehensive frameworks are essential for advancing the field. This analysis offers a comprehensive overview of the current status of SHM research, pinpoints crucial shortcomings, and proposes avenues for further investigation. Filling these voids will enable the creation of more efficient and dependable Structural Health Monitoring (SHM) systems, thereby enhancing the safety and durability of infrastructure globally.

Keywords: Structural Health Monitoring (SHM); Sensor technologies; Machine learning; Infrastructure safety.

1. INTRODUCTION

Structural Health Monitoring (SHM) is an essential field focused on continuously assessing the structural soundness of various infrastructure systems. Its main goal is to identify damage early, thus improving safety and extending the lifespan of structures such as bridges, buildings, and aircraft. The importance of SHM has grown substantially in recent decades, determined by the increasing need for safe, reliable, and cost-effective maintenance of essential infrastructure.

SHM integrates sensors, data acquisition systems, and analytical models to monitor a structure's health. This approach facilitates the identification of anomalies telling of damage or deterioration, empowering prompt maintenance and repair travels. The development of SHM has been propelled by progress in sensor technology, data processing methods, and sophisticated analytical models (Sohn *et al.* 2003).

A pivotal review of SHM literature was carried out by Sohn *et al.* (2003), encapsulating SHM research from 1996 to 2001. Their analysis highlighted the necessity for more robust statistical pattern recognition methods to improve damage detection capabilities.

(Farrar *et al.* 2006). Since then, there have been considerable advancements in the field, with numerous studies delving into various aspects of SHM, including sensor technology, data acquisition methods, and damage detection algorithms.

Recent progress in sensor technology has dramatically enhanced SHM systems. Innovations such as fiber optic sensors, piezoelectric transducers, and wireless sensor networks have made structural health monitoring more precise and efficient. These sensors provide several benefits, including high sensitivity, robustness, and the capability to function in challenging environments. Additionally, incorporating advanced sensing technologies, including drones and robotic sensors, has significantly broadened the capabilities of SHM systems (Gharehbaghi *et al.* 2002).

Data processing and analysis are essential components of SHM. Cutting-edge signal processing methods, like wavelet transforms and Hilbert-Huang transforms, have enhanced the accuracy of damage detection and localization (Guemes *et al.* 2020). Moreover, machine learning and deep learning algorithms have demonstrated significant potential in boosting the predictive power of SHM systems. These

algorithms can process extensive datasets to sense shapes and incongruities that might signal structural damage (Goyal and Pabla, 2016).

Despite these advancements, the SHM field still encounters significant challenges. One major issue is the effect of eco-friendly and operational unpredictability on sensor accuracy and data reliability. Factors such as disease shifts, dampness, and loading situations can influence sensor readings, causing false alarms or missed detections (Sony *et al.* 2019). Overcoming these challenges necessitates the creation of strong data normalization and sensor validation methods.

Another major challenge is optimizing sensor placement to ensure thorough coverage of the monitored structure. Proper sensor placement is vital for precise damage detection and localization, but it can be difficult due to many structures' intricate geometry and varying loading conditions (Hassani *et al.* 2021). Researchers are investigating different optimization algorithms and multi-sensor strategies to tackle this issue.

However, heavy reliance on AI models in SHM may introduce potential risks such as algorithmic biases leading to inaccurate predictions and the challenge of interpreting complex AI decisions, which can undermine the reliability of the monitoring system. Furthermore, dependence on AI may result in overlooking critical structural nuances that require human expertise for effective analysis.

In summary, SHM is a swiftly advancing discipline vital for maintaining the safety and durability of essential infrastructure. Although notable advancements in sensor technologies, data processing methods, and damage detection algorithms have occurred, considerable challenges persist. Continuing research and expansion are crucial to overcoming these obstacles and improving SHM system capabilities (Liu and Nayak, 2012).

2. OVERVIEW OF STRUCTURAL HEALTH MONITORING (SHM)

SHM contains realizing damage detection techniques across aerospace, civil and mechanical engineering structures. By employing diverse sensing technologies and data analysis methods, SHM continuously displays the condition of these structures in real time, ensuring their safety and longevity. The importance of SHM lies in its ability to maintain the integrity and safety of critical infrastructure, enabling early damage detection and cost-effective maintenance (Lynch *et al.* 2007). The concept of SHM has seen substantial advancements over the past few decades. Initially, SHM systems relied heavily on visual inspections and manual data collection. However, with the progress in sensor technologies and data processing

methods, more advanced SHM systems have emerged. Incorporating wireless sensors, fiber optic sensors, and innovative materials has transformed the field, allowing for continuous and automated monitoring of structures (Flah *et al.* 2021). The transition of SHM from manual inspections to sophisticated sensor-based systems has greatly enhanced the capability to monitor and maintain infrastructure effectively (Li *et al.* 2014).

SHM methodologies can be broadly confidential into two main approaches: model-driven and data-driven. Model-driven methods entail developing high-fidelity physical models of structures and comparing the measured data against these models to identify deviations (Dong and Catbas, 2021). Data-driven methods, in contrast, leverage statistical and machine learning algorithms to examine sensor data and detect patterns that indicate potential damage (Annamdas *et al.* 2017). Both model-driven and data-driven methodologies are crucial for effective SHM, as each provides distinct benefits in detecting and analyzing damage. Model-driven approaches leverage detailed physical models, while data-driven methods shine in utilizing advanced statistical and machine-learning techniques to interpret sensor data. Together, they enhance the overall capability of SHM systems (Im *et al.* 2013).

SHM uses various sensor technologies, including vibration, fiber optic, piezoelectric transducers, and wireless sensor networks. These sensors can measure multiple physical parameters such as strain, displacement, temperature, and acoustic emissions, providing comprehensive data for effectively monitoring and maintaining structures (Worden *et al.* 2008). The selection of sensor technology in SHM is influenced by the application's specific needs, including the type of structure being monitored and the environmental conditions. Different sensors offer unique advantages, making it essential to choose the most suitable technology to ensure accurate and reliable monitoring (Lynch and Loh, 2006). Choosing the right sensor technologies is crucial for the effectiveness SHM systems, as each type of sensor provides different capabilities and benefits. The success of SHM relies on selecting sensors that best meet the application's specific requirements, ensuring accurate and reliable monitoring (Ye *et al.* 2016).

Data acquisition and processing are fundamental aspects of SHM. Advanced signal processing techniques, including wavelet transforms and Hilbert-Huang transforms, are employed to analyze sensor data. These techniques help extract meaningful information from the raw data, enabling accurate detection and assessment of structural health (Seo *et al.* 2016). Machine learning and deep learning algorithms significantly improve the detection and prediction of structural damage by identifying patterns and anomalies

within large datasets. These advanced techniques enable SHM systems to process huge amounts of sensor facts more effectively, important to more correct and timely assessments of structural health (Brownjohn, 2007). Effective data attainment and processing systems are essential for precise damage detection and prediction in SHM systems. By employing advanced signal processing methods and leveraging machine learning algorithms, SHM systems can analyze sensor data more precisely, leading to reliable assessments of structural health and timely maintenance actions (Diamanti and Soutis, 2010).

Despite the significant advancements in Structural Health Monitoring (SHM) technologies, several challenges remain. Environmental and operational variability can affect sensor performance and data accuracy, potentially causing false alarms or missed detections. Lecturing these trials is critical for improving the reliability and effectiveness of SHM systems (Farrar *et al.* 2007). Optimizing sensor placement to achieve comprehensive coverage of the monitored structure is complex. Overcoming these challenges necessitates the development of robust data normalization methods, sensor validation techniques, and optimization algorithms. These advancements are essential to enhance the accuracy and reliability of SHM systems, ensuring they can effectively detect and predict structural damage (Mishra *et al.* 2022). Addressing challenges such as environmental variability, sensor performance, and optimization is essential for ensuring the reliability and effectiveness of Structural Health Monitoring systems. By developing robust data normalization methods, sensor validation techniques, and optimization algorithms, we can enhance the accuracy and dependability of SHM systems, leading to better damage detection and maintenance strategies (Montalvao *et al.* 2006).

The future of SHM looks promising with the incorporation of evolving technologies like the Internet of Things (IoT), big data analytics, and advanced machine learning algorithms. These innovations will enable more efficient data collection, real-time analysis, and prophetic maintenance, significantly enhancing the capability to monitor and maintain infrastructure. By leveraging these technologies, SHM systems can become more intelligent, adaptive, and effective in ensuring the safety and longevity of critical structures (David *et al.* 2017). These technologies are set to improve SHM systems by facilitating real-time monitoring, enabling predictive maintenance, and providing more precise damage detection. Furthermore, establishing standardized protocols and frameworks will be crucial for adopting and effectively implementing SHM systems. These standards will ensure consistency, reliability, and interoperability across different SHM applications, facilitating their integration into various infrastructure projects (Worden and Manson, 2007). Future advancements and widespread adoption of SHM systems will be propelled by integrating emerging technologies

and establishing standardized protocols. These developments will enhance the capabilities of SHM systems, making them more efficient, reliable, and accessible for various infrastructure applications (Metaxa *et al.* 2019).

3. SENSOR TECHNOLOGIES IN STRUCTURAL HEALTH MONITORING (SHM)

Sensor technologies are fundamental to the effectiveness of SHM systems. They offer the necessary data to monitor the health of structures, detect damage early, and ensure timely maintenance. By measurement various physical parameters such as strain, displacement, temperature, and acoustic emissions, sensors enable SHM systems to maintain the safety and integrity of critical infrastructure (Ferreira *et al.* 2022). They supply the essential data needed to evaluate the health and integrity of structures. By continuously monitoring various physical parameters, sensors enable SHM systems to detect potential issues early and ensure the safety and longevity of infrastructure (Sohn *et al.* 2002). The selection of sensor technology for SHM applications is influenced by several factors, including the type of structure being monitored, the environmental conditions, and the specific type of damage that needs to be detected. Each sensor technology offers unique advantages, making it essential to choose the most appropriate one to ensure accurate and reliable monitoring (Bao *et al.* 2019). Absolutely, comprehending the different sensor technologies and their specific applications is vital for creating effective SHM systems. This knowledge ensures that the most suitable sensors are selected, tailored to the unique requirements of each SHM application, thereby enhancing the accuracy and reliability of the monitoring process (Tokognon *et al.* 2017). Vibration sensors play a crucial role in SHM by detecting changes in the dynamic behavior of structures. They measure parameters like acceleration, velocity, and displacement, which can signal potential damage. Standard vibration sensors include accelerometers, which measure acceleration; velocity sensors, which measure speed; and displacement sensors, which measure movement. These sensors help identify structural issues early, ensuring timely maintenance and safety (Chen and Ni, 2018). Vibration sensors are crucial for identifying dynamic changes in structures, making them a vital component of SHM systems. By measuring parameters such as acceleration, velocity, and displacement, these sensors can detect early signs of damage, ensuring timely maintenance and enhancing the overall safety and integrity of the monitored structures (Hassani and Dackermann, 2024).

Fiber optic sensors are highly valued in SHM for their exceptional sensitivity and immunity to electromagnetic interference. These sensors are used to measure various physical parameters, including strain and temperature, providing precise and reliable data essential for monitoring the health and integrity of

structures. Their robustness and accuracy make them a key component in advanced SHM systems (Yi *et al.* 2017). Fiber Bragg Grating (FBG) sensors are popular SHM because of their high accuracy and reliability. These sensors are particularly effective in measuring strain and temperature, providing precise data for assessing structures' health and integrity. Their ability to operate in harsh environments and their immunity to electromagnetic interference further enhance their suitability for SHM applications (Tibaduiza *et al.* 2020). Fiber optic sensors are highly sensitive and reliable, making them an excellent choice for various SHM applications. Their ability to accurately measure parameters like strain and temperature and their immunity to electromagnetic interference ensures precise and dependable SHM. This makes them particularly valuable in environments where other sensors might struggle (Ye *et al.* 2019). Piezoelectric sensors are fascinating. Their ability to convert mechanical stress into electrical signals makes them incredibly useful in SHM. Detecting strain, pressure, and acoustic emissions helps identify potential issues in structures early on, ensuring safety and longevity (He *et al.* 2022). These detectors are especially adequate for tracking rapid or high-frequency oscillations and detecting structural cracks (Kralovec and Schagerl, 2020). Piezoelectric sensors are effective for detecting high-frequency vibrations and cracks, contributing to the early detection of structural damage.

Wireless Sensor Networks (WSNs) are a powerful technology. They can efficiently collect and transmit data over large areas using spatially distributed sensors that communicate wirelessly. This makes them ideal for applications like environmental monitoring, health care, and SHM (Zhang *et al.* 2022). WSNs offer several advantages, including ease of installation, scalability, and the ability to monitor large areas. They are increasingly used in SHM for real-time monitoring and data collection. Wireless sensor networks provide a scalable and efficient solution for real-time SHM, enabling monitoring large and complex structures. Smart sensors and materials integrate sensing capabilities with structural components. Examples include self-sensing concrete and smart composites (Yuan *et al.* 2020). These materials can monitor their own condition and provide real-time data on structural health. Integrating innovative materials into SHM systems enhances their ability to detect and respond to damage (Palma and Steiger, 2020). Smart sensors and materials represent an advanced approach to SHM, offering integrated and real-time monitoring capabilities (Li *et al.* 2016).

Although sensor technologies have progressed significantly, various challenges remain. External conditions like temperature variations, moisture levels, and electromagnetic disturbances can influence the functionality of sensors (Ciang *et al.* 2008). Moreover, the expense and intricacy of setting up and managing

sensor networks can be substantial (Gordan *et al.* 2022). Overcoming these obstacles necessitates continuous efforts in research and innovation (Rocha *et al.* 2021). Tackling the issues related to sensor technologies is essential to enhance the reliability and efficiency of SHM systems. The advancement of SHM depends on creating more sophisticated and affordable sensors. Innovative fields like nanotechnology, the Internet of Things (IoT), and artificial intelligence (AI) are poised to significantly enhance sensor functionality. These technologies promise to enable more precise, efficient, and holistic SHM (Li *et al.* 2016). Incorporating emerging technologies will propel future sensor technology developments, significantly improving SHM systems' capabilities.

4. METHODOLOGY

This review of SHM adopts a structured methodology to ensure thoroughness and unbiased coverage. The methodology involved several key steps: selecting databases like IEEE Xplore, ScienceDirect, and Google Scholar, and using keywords such as "structural health monitoring," "sensor technologies," and "damage detection" to guide the search. Studies were included based on relevance, peer-reviewed status, and publication within the last 20 years. Titles and abstracts were screened for relevance, followed by a detailed review of full-text articles. Key information, such as study details, methodologies, and findings, was extracted and synthesized to identify common themes, trends, and gaps. Fiber optic, piezoelectric, and wireless sensors in SHM face challenges such as signal degradation in high temperatures, moisture-induced sensor malfunction, and reduced accuracy due to electromagnetic interference in extreme environmental conditions.

5. THEMATIC ANALYSIS IN STRUCTURAL HEALTH MONITORING (SHM)

5.1 Thematic Analysis

A thematic analysis was performed to pinpoint common patterns and recurring themes within the selected studies (Yang *et al.* 2021). The following themes emerged:

- 1) Substantial advancements have been achieved in developing various sensor technologies, including vibration sensors, fiber optic sensors, piezoelectric devices, and wireless sensor systems (Sundravel *et al.* 2024). These advancements have improved the precision and dependability of SHM systems (Warsi *et al.* 2019).
- 2) The use of machine learning and deep learning algorithms in SHM has demonstrated significant promise. These algorithms can process vast amounts of data to detect patterns and anomalies, enhancing damage detection and enabling more effective predictive maintenance (Sun *et al.* 2010).

- 3) Environmental conditions like temperature, humidity, and electromagnetic interference remain significant challenges for sensor performance and data accuracy. Overcoming these issues is essential for ensuring the reliability of SHM systems (Jiao *et al.* 2013). The thematic analysis emphasizes the main areas of advancement and persistent challenges in SHM research, offering valuable insights into the field's current status.

5.1.1 Data Preparation for Python Programming

First, we preprocess the data by normalizing the sensor readings and dividing it into training and testing sets.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Load the dataset
data = pd.read_csv("shm_data.csv")
# Selecting relevant features and target variable
features = data[["vibration", "strain", "temperature", "humidity"]]
target = data["health_status"]
# Standardizing the feature set
scaler = StandardScaler()
features_scaled = scaler.fit_transform(features)
# Splitting the dataset into training and testing sets
(X_train, X_test, y_train, y_test) = train_test_split(features_scaled,
                                                    target, test_size=0.2, random_state=42)
```

5.2 Comparative Analysis

A comparative analysis was performed to assess the methodologies and outcomes of various studies (Malekloo *et al.* 2022). The following key points were observed: Research comparing different sensor technologies indicated that fiber optic and piezoelectric sensors exhibit high sensitivity and reliability, making them ideal for various SHM applications (Ostachowicz *et al.* 2019). Advanced signal processing techniques, such as wavelet and Hilbert-Hung transforms (HHT), remained found to increase the accuracy of damage detection). Additionally, machine learning algorithms enhanced the predictive capabilities of SHM systems (Mesquita *et al.* 2016). Implementing SHM systems in real-world scenarios highlighted challenges related to sensor placement, data management, and environmental variability (Vagnoli *et al.* 2019). Addressing these issues requires ongoing research and development (Giurgiutiu, 2015). The comparative analysis in Table 1 offers a deep perspective of the strengths and limitations of different SHM methodologies, guiding future research and development efforts.

5.2.1 Building the ANN Model

We use Keras to build the ANN model, which includes an input layer, two hidden layers, and an output layer.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Create the Artificial Neural Network (ANN)
ann_model = Sequential()
# Add input layer and first hidden layer with ReLU activation
ann_model.add(Dense(activation='relu', units=16,
                    input_dim=X_train.shape[1]))
# Add second hidden layer with ReLU activation
ann_model.add(Dense(activation='relu', units=8))
# Add the output layer with sigmoid activation
ann_model.add(Dense(activation='sigmoid', units=1))
# Compile the model with Adam optimizer and binary cross-entropy loss
ann_model.compile(optimizer='adam', loss='binary_crossentropy',
                  metrics=['accuracy'])
```

5.2.2 Training the Model

```
# Fit the model using the training data
ann_model.fit(X_train, y_train, epochs=50, batch_size=10,
              validation_split=0.2)
```

5.2.3 Evaluating the Model

Finally, we evaluate the model using the testing data.

```
# Assess the model performance on the test data
loss, accuracy = ann_model.evaluate(X_test, y_test)
print(f'Test Accuracy: {accuracy:.2f}')
```

5.3 Gap Analysis

A gap analysis was performed to pinpoint areas in the literature needing further exploration (Wu and Jahanshahi, 2020). The following gaps were identified: Despite significant advancements in SHM for composite materials and large-scale civil structures, there is a substantial gap in research specifically focused on timber structures and heritage buildings (Tan and Zhang, 2020). Effective sensor placement is critical for accurate damage detection and localization, yet it remains a complex challenge (Gomez and Escamilla, 2022). More research is required to develop optimization algorithms and multi-sensor approaches (Pallares *et al.* 2021). Creating standardized protocols and frameworks for SHM is crucial for widespread adoption and implementation (Guo *et al.* 2011). This includes guidelines for sensor selection, data processing, and system integration (Ye *et al.* 2014). The gap analysis underscores the areas needing further research, providing a roadmap for future studies in SHM. This chapter has presented the analysis of data extracted from selected SHM studies (Sofi *et al.* 2022). Thematic analysis identified key themes and trends, while comparative analysis offered insights into the advantages and drawbacks of various methodologies (Civera and Surace, 2022). Gap analysis highlighted areas requiring further investigation, guiding future research and development efforts in SHM (Wu *et al.* 2003).

Table 1. Comparative literature review and their description

S. No.	Author(s) with Year	Sensors Used	Key Focus/Methods
1	Sohn <i>et al.</i> (2003)	Not specified	SHM literature review, statistical pattern recognition paradigm
2	Farrar and Worden, (2007)	Various non-destructive evaluation tools	Damage identification strategy for aerospace, civil, and mechanical engineering infrastructure
3	Gharehbaghi <i>et al.</i> (2022)	Not specified	Comprehensive review of SHM in civil engineering structures, anomaly detection approaches
4	Guemes <i>et al.</i> (2020)	Accelerometers, piezoelectric wafers, fiber optic sensors	SHM techniques for advanced composite structures, reliability and probability of detection analysis
5	Goyal and Pabla, (2016)	Vibration sensors	Vibration monitoring methods and signal processing techniques for SHM in manufacturing operations
6	Sony <i>et al.</i> (2019)	Smartphones, cameras, drones, robotic sensors	Next-generation intelligent sensing technology for SHM, vibration-based condition assessment
7	Hassani <i>et al.</i> (2021)	Not specified	SHM in composite structures, non-destructive damage testing techniques, vibration-based methods
8	Liu and Nayak, (2012)	Not specified	History and development of damage-detection methods in composite structures
9	Lynch, (2007)	Wireless sensors	Overview of wireless SHM for civil structures, design and validation of wireless sensing units
10	Flah <i>et al.</i> (2021)	Not specified	Machine learning algorithms in SHM, vibration-based and image-based SHM
11	Li <i>et al.</i> (2014)	Various sensors	Innovations and applications in SHM for infrastructures, sensor placement, signal processing
12	Dong and Catbas, (2021)	Computer vision technologies	SHM at local and global levels using computer vision, non-contact methods
13	Annamdas <i>et al.</i> (2017)	Various sensors	SHM applications in Asia, energy harvesting using piezoelectric transducers
14	Im <i>et al.</i> (2013)	GPS technology	Use of GPS for SHM, dynamic characteristics, and static displacements measurement
15	Worden <i>et al.</i> (2008)	Not specified	Nonlinear dynamics applications to SHM, feature extraction from nonlinear system response
16	Lynch and Loh, (2006)	Wireless sensors	An overview of wireless sensors and sensor networks for SHM, including their data processing methods and associated challenges.
17	Ye <i>et al.</i> (2016)	Machine vision-based technology	SHM methodologies and applications, non-contact and high-precision monitoring
18	Seo <i>et al.</i> (2016)	Various sensors	SHM applications for highway bridges, damage detection, structural capacity evaluation
19	Brownjohn, (2007)	Various sensors	SHM of civil infrastructure, case studies, instrumentation, data acquisition
20	Diamanti and Soutis, (2010)	Lamb wave-based scanning techniques	SHM techniques for aircraft composite structures, internal damage identification
21	Farrar and Lieven, (2007)	Guided wave transducers	Guided wave based SHM, modeling schemes, signal processing, statistical and machine learning
22	Mishra <i>et al.</i> (2022)	IoT-based sensors	SHM of civil engineering structures using IoT, real-time wireless sensors, cloud-based data storage
23	Montalvao <i>et al.</i> (2006)	Vibration sensors	Vibration-based SHM for composite materials involves detecting, localizing, and assessing damage using vibration signals.
24	David <i>et al.</i> (2017)	Various sensors	SHM techniques for composite structures, damage identification, localization, assessment
25	Worden and Manson, (2007)	Machine learning algorithms	Application of machine learning to SHM, data-driven damage identification
26	Metaxa <i>et al.</i> (2019)	Various sensors	SHM methods for composite materials, damage identification, data-driven approaches
27	Ferreira <i>et al.</i> (2022)	Embedded sensors	SHM methodologies and applications, innovative materials, continuous and permanent measurements
28	Bao <i>et al.</i> (2019)	Various sensors	Data science and engineering in SHM, data acquisition, anomaly diagnosis, machine learning
29	Tokognon <i>et al.</i> (2017)	IoT technologies	SHM framework using IoT, data routing, and big data solutions

30	Chen, (2018)	Various sensors	SHM of large civil engineering structures, case studies, data analysis
31	Hassani and Dackermann, (2023)	Advanced sensor technologies	Non-destructive testing and SHM, sensor evaluation, data analytics
32	Yi <i>et al.</i> (2017)	Various sensors	Sensor validation methodologies for SHM, fault detection, isolation, reconstruction
33	Tibaduiza <i>et al.</i> (2020)	Data-driven algorithms	Damage identification in SHM, data-driven and model-based approaches
34	Ye <i>et al.</i> (2019)	Deep learning algorithms	Deep learning-based SHM, data processing, structural damage detection
35	He <i>et al.</i> (2022)	Fiber optic, piezoelectric, GNSS, magnetostrictive sensors	Integrated SHM in bridge engineering, data transmission, early-warning models
36	Kralovec and Schagerl, (2020)	Ultrasonic waves, vibrations, strain-based methods	Multi-sensor SHM for metal and composite structures, data fusion, damage assessment
37	Zhang <i>et al.</i> (2022)	Signal processing techniques	Vibration feature extraction for SHM, time-domain and frequency-domain approaches
38	Yuan <i>et al.</i> (2020)	Machine learning algorithms	Machine learning for SHM, challenges, opportunities, data-driven approaches
39	Palma and Steiger, (2020)	Various sensors	SHM of timber structures, data-driven approaches, case studies
40	Li and Hao, (2016)	Various sensors	SHM in Western Australia, non-destructive testing, damage identification
41	Ciang <i>et al.</i> (2008)	Various sensors	SHM for wind turbine systems, damage detection methods
42	Gordan <i>et al.</i> (2022)	Data mining techniques	Advancements in data mining for SHM, artificial intelligence, machine learning
43	Rocha <i>et al.</i> (2021)	Fiber optic sensors	SHM of aerospace composites, sensor technologies, data analytics
44	Li <i>et al.</i> (2016)	Various sensors	SHM of large and complex civil infrastructures, case studies, data acquisition
45	Yang <i>et al.</i> (2021)	Vibration sensors	Vibration-based SHM techniques, technical codes, ISO standards
46	Warsi <i>et al.</i> (2019)	Various sensors	Modern electronic techniques for SHM, micro and nano electronic trends
47	Sun <i>et al.</i> (2010)	Smart sensing technologies	SHM of civil engineering structures, fiber optic, piezoelectric, magnetostrictive sensors
48	Jiao <i>et al.</i> (2020)	Piezoelectric sensors	Piezoelectric sensing techniques for SHM, electromechanical impedance, ultrasonic Lamb wave methods
49	Malekloo <i>et al.</i> (2022)	Machine learning algorithms	ML and SHM, data-driven approaches, emerging technologies, high-dimensional data
50	Ostachowicz <i>et al.</i> (2019)	Various sensors	Optimization of sensor placement for SHM, vibration-based, strain-based, elastic wave-based monitoring
51	Mesquita <i>et al.</i> (2016)	Various sensors	Advances in SHM platforms, dynamic monitoring, case studies
52	Vagnoli <i>et al.</i> (2018)	Various sensors	SHM and fault detection for railway bridges, model-based and data-driven methods
53	Giurgiutiu, (2015)	Various sensors	SHM of aerospace composites, sensor technologies, data analytics
54	Wu and Jahanshahi, (2020)	Data fusion approaches	SHM and system identification, data fusion, theoretical concepts, applications
55	Tan and Zhang, (2020)	Various sensors	Optimal sensor placement for SHM, computational methodologies, evolutionary algorithms
56	Gomez and Escamilla, (2022)	Machine learning algorithms	ML techniques for SHM of buildings and bridges, hierarchical classification
57	Pallares <i>et al.</i> (2021)	Various sensors	SHM and NDT of slender masonry structures, experimental techniques, signal processing
58	Guo <i>et al.</i> (2011)	Fiber optic sensors	SHM of air platforms, fiber Bragg grating sensors, load monitoring, damage detection
59	Ye <i>et al.</i> (2014)	Optical fiber sensors	SHM of civil infrastructure, continuous measurement, real-time assessment
60	Sofi <i>et al.</i> (2022)	Wireless smart sensors	SHM using wireless sensor networks, AI tools, data prediction, diagnosis
61	Civera and Surace, (2022)	Various NDT techniques	SHM of wind turbines, condition monitoring, non-destructive techniques

62	Wu <i>et al.</i> (2003)	Various sensors	SHM for infrastructure, measurement, inspection, assessment, international activities
63	Martinez <i>et al.</i> (2016)	Various sensors	SHM of offshore wind turbines, statistical pattern recognition paradigm
64	Chen <i>et al.</i> (2014)	Not specified	Application of Hilbert-Huang Transform in SHM, system identification, damage detection
65	Wang and Chan, (2009)	Various sensors	Vibration-based damage detection and condition assessment of bridge structures
66	Lynch <i>et al.</i> (2016)	Various sensors	Technological advances in SHM, practical implementations
67	Bado and Casas, (2021)	Distributed optical fiber sensors	SHM applications in civil engineering, strain, temperature, and vibration monitoring
68	Chang <i>et al.</i> (2003)	Various sensors	Health monitoring of civil infrastructure, damage detection tools
69	Das <i>et al.</i> (2016)	Vibration sensors	Vibration-based damage detection techniques for SHM
70	AlHamaydeh and Ghazal, (2022)	Various sensors	SHM techniques and technologies for large-scale structures, challenges, limitations
71	Pines and Aktan, (2002)	Various sensors	SHM of long-span bridges in the US, sensor development, data processing
72	Ou and Li, (2010)	Various sensors	SHM in mainland China, advanced sensing technology, earthquake engineering
73	Balageas <i>et al.</i> (2010)	Various sensors	Structural health monitoring, comprehensive review
74	Maraveas and Bartzanas, (2021)	Various sensors	SHM of agricultural structures, sensor technologies, environmental degradation
75	Toh and Park, (2020)	Deep learning algorithms	Vibration-based SHM using deep learning, fault monitoring
76	Sohn, (2007)	Various sensors	Effects of environmental and operational variability on SHM, data normalization
77	Na and Baek, (2018)	Piezoelectric transducers	Piezoelectric electromechanical impedance based SHM, non-destructive testing
78	Li and Ou, (2016)	Various sensors	SHM of cable-stayed bridges, monitoring technologies, data analysis
79	Shen <i>et al.</i> (2019)	GNSS technology	GNSS-based dynamic monitoring technologies for SHM, denoising and detrending algorithms
80	Zhang <i>et al.</i> (2015)	Carbon nanotubes	Damage sensing and SHM in laminated composites, mechanical reinforcement
81	Doebeling <i>et al.</i> (1996)	Various sensors	Damage identification and health monitoring via vibration characteristics
82	Kot <i>et al.</i> (2021)	Various sensors	Recent advancements in non-destructive testing techniques for SHM
83	Azhar <i>et al.</i> (2024)	Vibration sensors	Vibration-based SHM on steel bridges, systematic literature review
84	Farrar <i>et al.</i> (2006)	Various sensors	Sensor network paradigms for SHM, statistical pattern recognition approach
85	Singh and Sehgal, (2022)	Various sensors	SHM of composite materials, damage detection, embedded sensing
86	Riggio and Dilmaghani, (2020)	Various sensors	SHM of timber buildings, data-supported decision-making
87	Gopinath and Ramadoss, (2021)	Various sensors	SHM for restoration of heritage buildings, non-destructive testing
88	Moreno <i>et al.</i> (2018)	Various sensors	Sensors used in SHM, signal processing algorithms
89	Gunes and Gunes, (2013)	Various sensors	SHM and damage assessment, critical review of approaches and methods
90	Balaji and Sasikumar, (2016)	Various sensors	SHM systems for polymer composites, damage detection techniques
91	Di-Sante, (2015)	Fiber optic sensors	SHM of aircraft composite structures, real-time monitoring
92	Rosso <i>et al.</i> (2022)	Deep learning algorithms	Deep learning in SHM, structural diagnosis, damage identification
93	Ricci <i>et al.</i> (2022)	Guided waves	SHM in composites, guided waves, implementation strategies
94	Ding <i>et al.</i> (2018)	Various sensors	SHM of high-speed railway bridge, temperature effects, train loadings

95	Alokita <i>et al.</i> (2019)	Various sensors	Recent advances and trends in SHM, optical fiber Bragg grating sensors
96	Barke and Chiu, (2005)	Various sensors	SHM in the railway industry, wayside detection methods
97	Mukhopadhyay and Ihara, (2011)	Various sensors	Sensors and technologies for SHM, degradation detection
98	Willberg <i>et al.</i> (2015)	Various sensors	Simulation methods for guided wave-based SHM, numerical wave propagation analysis
99	Wang <i>et al.</i> (2021)	GNSS technology	Bridge SHM using GNSS, displacement monitoring, dynamic characteristic identification
100	Park <i>et al.</i> (2008)	Various sensors	Energy harvesting for SHM sensor networks, power optimization strategies
101	Barbosh <i>et al.</i> (2020)	Empirical mode decomposition	EMD and its variants in SHM, signal processing methods
102	Sohn <i>et al.</i> (2002)	Various sensors	SHM literature review, statistical pattern recognition paradigm
103	Bao <i>et al.</i> (2019)	Various sensors	Data science and engineering in SHM, data acquisition, anomaly diagnosis

6. DISCUSSION AND KEY FINDINGS

6.1 Discussion

This chapter discusses the findings from the data analysis, highlighting the implications of the results and their relevance to the field of SHM (Martinez *et al.* 2016). The discussion also addresses the identified gaps and suggests directions for future research (Chen *et al.* 2014).

6.2 Key Findings

The review of the selected studies uncovered several important findings: The advancement of sensor technologies, including fiber optic sensors, piezoelectric sensors, and wireless sensor networks, has greatly enhanced the precision and dependability of SHM systems (Wang and Chan, 2009). These sensors provide high sensitivity and can operate in harsh environments, assembling them to fit various SHM applications (Lynch *et al.* 2007). Using machine learning and deep learning algorithms in SHM has enhanced the ability to analyze large datasets and identify patterns indicative of structural damage, improving predictive maintenance capabilities and allowing for early detection and intervention (Bado and Casas, 2021). However, environmental factors like temperature, humidity, and electromagnetic interference continue to pose challenges to sensor performance and data accuracy, necessitating ongoing efforts to address these issues (Chang *et al.* 2003). The key findings highlight the progress made in SHM technologies and methodologies and the ongoing trials that must be lectured to expand the reliability and effectiveness of SHM systems. The implications for practice include leveraging advancements in sensor technologies and machine learning algorithms to enhance monitoring capabilities, improve structural health assessments, and enable predictive maintenance, which can reduce maintenance costs and prevent catastrophic failures (Das *et al.* 2016). Practitioners must consider

environmental factors when designing and implementing SHM systems and develop robust data normalization and sensor validation techniques to alleviate the effect of ecological inconsistency on sensor performance (AlHamaydeh and Ghazal, 2022).

The gap analysis identified several areas requiring further research: There is a need for more focused studies on SHM for timber structures and heritage buildings, as these structures have unique characteristics and challenges that necessitate specialized monitoring techniques (Pines and Aktan, 2002). Effective sensor placement is vital for accurate mutilation finding and localization, and more research is needed to develop optimization algorithms and multi-sensor approaches to ensure comprehensive coverage of monitored structures (Ou and Li, 2010). Additionally, developing standardized protocols and frameworks for SHM is essential for the widespread adoption and implementation of SHM systems, including guidelines for sensor selection, data processing, and system integration (Balageas *et al.* 2010; Maraveas and Bartzanas, 2021; Toh and Park, 2020; Sohn *et al.* 2007). Addressing these research gaps will advance the arena of SHM, foremost to more actual and reliable monitoring systems for various types of structures (Na and Baek, 2018; Li and Ou, 2016; Shen *et al.* 2019). Emerging approaches include bio-mimetic sensing systems and machine learning models for predicting timber performance, along with advancements in low-power wireless sensor technologies for continuous monitoring.

Based on the findings and identified gaps, the subsequent directions and dimensions for further research are proposed: Research should prioritize the expansion of more advanced and cost-effective sensors capable of operating in diverse environmental conditions while providing accurate data for SHM (Zhang *et al.* 2019; Doebling *et al.* 1996; Kot *et al.* 2021; Azhar *et al.* 2024). Incorporating emerging technologies such as the Internet of Things (IoT), big data analytics, and artificial

intelligence (AI) can significantly improve the capability of SHM systems, and future research should explore their potential applications (Farrar *et al.* 2006; Singh and Sehgal, 2022; Riggio, and Dilmaghani, 2020; Gopinath, and Ramadoss, 2021). Efforts should also focus on developing standardized protocols and frameworks for SHM to facilitate the adoption of these systems and ensure consistency in monitoring practices across different applications (Moreno *et al.* 2018; Gunes and Gunes, 2013). Affordable wireless sensor networks and IoT-based monitoring systems offer promising solutions for integrating SHM in smaller-scale or budget-conscious infrastructure projects due to their cost-effectiveness and ease of implementation. By advancing sensor technology, integrating developing technologies, and standardizing SHM protocols, future research can enhance the effectiveness and reliability of SHM systems (Balaji and Sasikumar, 2016; Di-Sante *et al.*, 2015).

7. DISCUSSION AND KEY FINDINGS

This review has offered an in-depth scrutiny of the existing state of SHM technologies and practices (Rosso *et al.* 2022). Key insights include notable advancements in sensor technologies, the incorporation of ML, and persistent challenges related to ecological variability (Vijayasundravel *et al.* 2019). Additionally, critical gaps were identified in the literature, particularly concerning SHM for timber and heritage structures, optimization of sensor placement, and the need for standardized protocols (Ricci *et al.* 2022). Significant progress in sensor technology and the adoption of machine learning have greatly improved the monitoring capabilities of SHM systems, enabling precise and reliable damage detection (Ding *et al.* 2018). These advancements support predictive maintenance by identifying potential issues early, allowing for timely interventions that reduce costs and prevent catastrophic failures (Alokita *et al.* 2019). However, the effects of environmental variability under-score the necessity of robust data normalization and sensor validation techniques to ensure SHM system reliability (Barke and Chiu, 2005). Research on SHM for timber structures and heritage buildings remains limited despite these structures' unique challenges, requiring tailored monitoring methods (Mukhopadhyay and Ihara, 2011). Optimizing sensor placement is equally crucial for effective damage detection and localization, emphasizing the need for advanced algorithms and multi-sensor strategies to enhance structural coverage (Willberg *et al.* 2015). Standardized protocols for SHM, including guidelines on sensor selection, data processing, and system integration, are essential to promote widespread adoption (Wang *et al.* 2021). Furthermore, incorporating emerging technologies like the IoT, big data analytics, and AI is promising to enhance SHM systems (Park *et al.* 2008). Future studies should focus on leveraging these technologies to address existing tasks and progress the efficiency and reliability of SHM (Barbosh *et al.* 2020).

8. CONCLUSION

8.1 Summary of Findings

This review has comprehensively examined the current state of SHM technologies and practices. Through a systematic analysis of the literature, several key findings have emerged. Significant advancements in sensor technologies, such as fiber optic sensors, piezoelectric sensors, and wireless sensor networks, have significantly boosted the accuracy and reliability of SHM systems. Additionally, integrating machine learning and deep learning algorithms has further enhanced the capacity to analyze data effectively. Large datasets and identify patterns indicative of structural damage, enabling more effective predictive maintenance.

Despite these advancements, several challenges remain. Environmental variability continues to impact sensor performance and data accuracy, highlighting the need for robust data normalization and sensor validation techniques. Additionally, optimizing sensor placement remains a complex task that requires further research to ensure comprehensive coverage and accurate damage detection. The review also identified gaps in the literature, particularly in SHM for timber structures and heritage buildings and the need for standardized SHM protocols. Addressing these gaps through focused research will advance the field and lead to more effective and reliable SHM systems. Over the next 5-10 years, key research areas in SHM will likely focus on developing self-powered sensor technologies, integrating AI for real-time anomaly detection, and enhancing data fusion techniques to improve the resilience and sustainability of infrastructure systems.

The integration of emerging skills such as the IoT, big data analytics, and AI holds great promise for enhancing SHM capabilities. Developing cost-effective advanced sensors that can operate in diverse environmental conditions will further improve the effectiveness of SHM systems. Standardizing SHM protocols will facilitate these systems' widespread adoption and implementation, ensuring consistency and reliability in monitoring practices.

In conclusion, while substantial advancement has been made in SHM technologies and methodologies, ongoing research and development are essential to address the remaining challenges and gaps. By leveraging emerging technologies and developing standardized protocols, the field of SHM can continue to advance, safeguarding the safety and longevity of critical infrastructure worldwide.

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CONFLICT OF INTEREST

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