A Structured Comparative Review of Digital Structural Health Monitoring Solutions

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Abstract. The rapid digitalization of transport infrastructure has led to the development of heterogeneous tools for Structural Health Monitoring (SHM), damage detection, and predictive maintenance. However, the lack of harmonized descriptors and comparative frameworks limits systematic comparison, transferability, and evidence-based decision making. This paper introduces a novel comparative framework for the structured synthesis and cross-solution analysis of existing SHM tools, based on a harmonized metadata model and similarity-based analysis. This framework is applied to thirteen representative tools, including spanning vision-based inspection, sensor-driven SHM, subsurface assessment, and commercial inspection systems. The analysis identifies dominant solution groups, maturity patterns, and recurring deployment barriers. Results show a strong concentration on monitoring and detection capabilities, limited integration of control or closed-loop interventions, and persistent gaps related to data availability, multimodal integration, and standardization. The proposed approach demonstrates how structured metadata and similarity analysis can support knowledge harmonization and inform future research and deployment strategies in infrastructure health management.

Keywords: Structural Health Monitoring (SHM), Infrastructure Health Monitoring (IHM), health monitoring, digital inspection, predictive maintenance, smart infrastructure.

1 Introduction

Transport infrastructure stability and resilience are necessary to maintain road safety, service continuity, and sustainable functionality of mobility systems [1]. Assessing road sections accurately is important in preventing hazardous conditions, mitigating risks, and allocating resources effectively [2]. Advances in sensory technology, data processing, and digital platforms have introduced multiple ways for implementing Structural Health Monitoring (SHM) [3], which has a significant role in ensuring sustainability and safety of global civil infrastructure networks [4]. These include various techniques such as vision-based damage detection, vibration-based SHM, digital twin enabled assessment, and predictive maintenance applications [3, 5–10]. Smart city initiatives and intelligent transportation systems increasingly integrate these technologies into critical assets like roads and bridges [11]. Additionally, artificial intelligence (AI) enables the use of continuous SHM to proactively identify issues before they become major problems, enabling predictive maintenance [12–14].

Although rapid advancements in technological capabilities exist, current landscape of digital SHM solutions remains highly fragmented. Each solution utilizes different sensor modalities, analytical approaches, spatial scope, maturity levels, and validation contexts [15], making meaningful comparisons difficult for researchers seeking to synthesize state of the art and practitioners searching for suitable technologies to deploy. Additional complications also exist due to the lack of consistent terminology and structured, comparative information regarding solution characteristics, evidence strength, and deployment barriers [11, 16, 17]. Energy availability and data limitations continue to hinder scale-up of Internet of Things (IoT) technologies used for continuous sensing and monitoring [11].

This study provides a structured synthesis and comparative analysis of existing digital solutions rather than assessing new monitoring technologies. The objective is to organize a representative set of SHM tools within a common framework, utilizing harmonized descriptors to highlight dominant technical patterns, functional groupings, and recurring challenges within the field [9]. This initiative aligns with European research and innovation efforts, such as the IM-SAFE action and other projects like Sustainable Bridges, LIFECON and SMARTIN which support knowledge harmonization, capacity building, and evidence-informed infrastructure management [18]. Through this structured and practitioner oriented perspective, the paper aims to clarify how current SHM solutions relate to one another, where robust evidence exists, and which gaps continue to constrain broader implementation.

2 Literature review

SHM involves continuous or periodic measurements of structural behavior, environmental conditions, and operational loads to determine its condition and predict its remaining service life [19]. Four levels are common in the SHM process. These are: Damage detection (identifies the existence of damage); Damage localization (locates where the damage exists); Damage classification (determines what kind of damage has occurred and how severe it is); and Damage prognosis (predicts when the structure will no longer be able to perform its intended function) [20, 21].

Most traditional methods used in SHM involve visual inspection, analytical models, and signal processing techniques [22]. While these have been successful in identifying some forms of damage, they have several limitations in detecting internal damage, predicting complex structural behaviors under various loading conditions, and analyzing large amounts of data generated by distributed sensor networks [23]. Recent advances in data-driven, machine learning approaches has addressed many of these limitations, enabling automated feature extraction, pattern recognition, and predictive analytics [24, 25].

Deep learning is rapidly becoming the most popular method of analyzing data generated by SHM systems. Due to the ability to recognize patterns in large datasets, deep learning has outperformed traditional machine learning approaches related to damage detection, localization, and classification [20, 26]. Cha et al. [20] provide a comprehensive review of deep learning-based SHM, encompassing non-destructive approaches, computer vision-based methods, digital twins, and vibration-based strategies. They also establish connections between traditional machine learning and deep learning methods, highlighting the evolution toward end-to-end learning systems [20].

One major advantage of unsupervised learning methods is that they do not require the availability of labeled damage data from real structures, which is a major problem in SHM [27]. As a result, vibration-based SHM has benefited greatly from unsupervised approaches. These approaches create baseline models of normal structural behavior and then use them to detect any deviation in that behavior that could indicate damage [27].

Lawal et al. [28] integrated AI into wireless smart sensor platforms for railroad bridge impact detection, implementing machine learning predictions directly on Xnode wireless sensor nodes [28]. This allows for rapid assessment and response during time-sensitive applications such as detecting impacts from over-height vehicles.

As AI becomes more prevalent in SHM, questions about model interpretability, trustworthiness, and credibility of predictions arise [29]. Mondal & Chen [29] discuss contemporary issues regarding explainable physics-informed AI in civil SHM, while outlining future research directions for innovative AI applications. Developing interpretable machine learning models that incorporate principles of structural mechanics will enhance stakeholder confidence and regulatory acceptance of AI-based SHM systems [30].

Another critical challenge is the effective integration of SHM data with existing asset management systems, maintenance planning processes, and decision-making frameworks [31]. The gap between research innovations and practical implementation in transportation agencies is explained by organizational, regulatory, and technical barriers [32]. Therefore, standardized data formats, interoperable systems, and decision support tools must be developed to realize the full potential of SHM technologies [31].

Long-term sensor reliability, data corruption, and communication failures are other significant challenges for SHM systems [33]. Wireless Sensor Networks (WSNs) limitations, particularly energy supply constraints, affect system sustainability and maintenance requirements [33]. Development of energy-autonomous sensors with energy harvesting capabilities addresses some concerns, however ensuring reliable operation over infrastructure design life times (50-100 years) remains challenging [34].

The perspective of this paper aligns closely with the ambitions of the SMARTIN project, which seeks to accelerate the digital transformation of European transport infrastructure by consolidating existing tools, promoting interoperability, and enabling data-driven asset management. SMARTIN emphasizes the integration of mature digital monitoring solutions into a coherent system of systems that utilize AI enabled analytics, data-driven innovations, and user-centric designs. By mapping current SHM tools and clarifying their functional roles, this paper contributes to SMARTIN's broader effort to build a shared knowledge base, strengthen evidence informed maintenance practices, and support the scalable uptake of digital solutions across diverse operational contexts.

3 Methodology

This study examines digital solutions for SHM, defined as methods, systems, or platforms that employ digital technologies to observe, assess, or anticipate the condition of transport infrastructure assets. The unit of analysis is the digital solution itself rather than specific deployment site or infrastructure component. A set of thirteen representative solutions is selected to reflect the diversity of current practice.

The selected solutions include different asset types, sensing technologies, and levels of maturity, allowing for comparative analysis without aim to provide exhaustive coverage of the field. An overview of the analyzed solutions and their primary characteristics is provided in **Table 1**.

Table 1. Overview of digital SHM solutions

Tool	Description
ARTeMIS Modal	A vibration-based SHM software that processes periodic weak-motion recordings and integrates easily with commercial monitoring systems.
Active sensor NDT	Ultrasonic wave-based non-destructive testing methods (Impact Echo (IE), Ultrasonic Body Wave (UBW), and Ultrasonic Surface Wave (USW)) used to measure material properties and detect internal defects in concrete and other structures.
YOLO-RD	A YOLOv8-based road-damage detector optimized for small, irregular defects using Star Operation Module (SOM), Multi-dimensional Auxiliary Fusion (MAF), and Wavelet Transform Convolution (WTC) modules for improved accuracy.
Proqio platform	A unified data-intelligence platform that centralizes, visualizes, and manages monitoring, surveying, and environmental data for infrastructure projects. It allows real-time visualization, alerts, and reporting.
GPR-NDT system	A combined Ground-Penetrating Radar (GPR) and Non-Destructive Testing (NDT) approach for surface and subsurface pavement assessment, supporting preventive maintenance and integration with GIS, Building Information Modeling (BIM), and Digital Twins for visualization and real-time monitoring.
BIM Digital twin SHM	A BIM-based digital twin system that integrates multi-sensor bridge data with 3D visualization and cloud analytics for real-time monitoring and early warnings.
Triple-threshold crack detector	An image-based pavement crack detection method using a structured forest classifier and triple-threshold processing to enhance crack continuity and reduce noise.
SHM-WIM system	A cloud-based bridge monitoring system combining structural sensors with weigh-in-motion (WIM) data for continuous condition assessment and overload detection.
Autonomous UAV-SHM	A GPS-independent Unmanned Aerial Vehicle (UAV) structural inspection system using ultrasonic beacons localization and deep convolutional neural networks (CNNs) for automated visual damage detection and geo-tagging.

Smartphone road damage detector	A CNN-based system that detects and classifies road surface defects from smartphone images captured during vehicle travel.
OMICRON Inspection	A suite of automated road-inspection solutions including multi-UAV systems, long-range UAVs, V2I/I2V road communication, and advanced sensor combinations aimed at improving safety, reducing traffic disruption, and automating inspections.
OMICRON Predictive	A predictive-maintenance platform integrating inspection data into a road digital twin and a decision support system for condition forecasting and intervention planning.
OMICRON Bridge	A modular hybrid-bridge retrofitting system paired with a BIM/GIS digital twin for lifecycle monitoring to reduce disruption and maintenance risk.

Each solution is described using a set of descriptors designed to support structured comparison across otherwise heterogeneous technologies. Specifically, the description includes:

- the types of data employed,
- the dominant analytical approaches,
- the primary functional objective of the solution,
- the spatial scale at which outputs are generated, and
- indicators of technological maturity and validation strength.

In addition, each solution reports key barriers that currently limit wider adoption or transferability.

To ensure comparability, data sources were grouped into modality categories representing common sensing and information streams in infrastructure monitoring, including visual or imaging data, embedded or field-based sensors, active remote sensing techniques, and contextual or environmental information.

Analytical approaches were similarly grouped into high-level categories, such as computer vision, signal processing, classical machine learning, and predictive or forecasting methods. Functional objectives were classified according to whether the solution primarily supports monitoring, prediction, control, or decision support. Spatial scale was defined as the dominant spatial unit at which results are produced, ranging from point or sensor level to asset, segment, corridor, or network scale. Technology Readiness Level (TRL) and evidence quality were used to represent maturity and confidence in reported performance, respectively.

Hierarchical grouping is used as an exploratory tool to illustrate similarities and differences between solutions across the selected descriptors, without imposing predefined categories or fixed classifications. Throughout the analysis, emphasis is placed on identifying similarities among solutions to reveal dominant patterns, functional groups, and recurring gaps that characterize the current state of digital SHM. By structuring heterogeneous solutions within a common descriptive and comparative framework, the methodology supports meaningful synthesis for infrastructure managers, practitioners, and researchers, while aligning with SMARTIN's broader goal of enabling knowledge harmonization, capacity building, and evidence-informed decision making.

4 Results

4.1 Data Modalities and Analytical Approaches

The thirteen SHM solutions analyzed exhibit a high degree of technological orientation. This is also true for the analytical procedures used. Computer vision methods and defect detection algorithms dominate the landscape, primarily supporting the identification of surface-level damage, cracks, and anomalies in pavements and structural elements. Signal processing and vibration-based analysis methods form a second large group. These are mostly used in SHM applications where time-series sensor data are analyzed to detect changes in dynamic or modal properties. Machine learning techniques, such as tree-based classifiers, appear across both vision-based and sensor-based solutions, while predictive and forecasting methods are mainly associated with more mature monitoring and maintenance platforms.

Overall, it appears that currently, SHM field is driven primarily by data-intensive detection and condition assessments, which emphasize perception and pattern recognition over an integrated prediction or intervention approach. The set of digital solutions included in the analysis, together with their primary characteristics, is summarized in **Table 2**.

Table 2. SHM solutions with their key characteristics

Solution	Infrastructure type	Primary data source	Main function
ARTeMIS Modal (Pro / SHM)	Bridges, civil structures	Vibration sensors	Structural monitoring
Active sensors for health monitoring	Bridges, structures	Embedded sensors	Structural monitoring
YOLO-RD	Roads, pavements	Images / video	Damage detection
proqio	Roads, urban assets	Visual data, mobile sensors	Condition assessment
GPR + NDT combined approach	Roads, bridges	GPR, NDT sensors	Subsurface inspection
BIM-based digital twin SHM	Buildings, bridges	Sensor data, BIM models	Monitoring & decision support
Triple-Threshold Pavement Crack Detection (RSF)	Roads, pavements	Images	Crack detection
SHM combined with Weigh-in-Motion (WIM)	Bridges	Vibration, WIM data	Monitoring & degradation assessment
UAV-based SHM with deep learning	Bridges, structures	UAV imagery, ultrasonic sensors	Damage detection
Smartphone-based road damage detection (DNN)	Roads	Smartphone images	Damage detection

OMICRON inspection solutions	Power & transport assets	Sensor & inspection data	Asset inspection
OMICRON predictive maintenance solutions	Power & transport assets	Sensor & operational data	Predictive maintenance
OMICRON bridge retrofitting solutions	Bridges	Inspection & structural data	Decision support

4.2 Spatial Granularity and Maturity Characteristics

Most of the sample solutions operate at the asset or segment level, focusing on individual bridges, pavement sections, or structural components. An "asset" represents a discrete, manageable unit of infrastructure whose condition can be independently monitored and maintained. This spatial focus represents the reality of how infrastructure inspections and maintenance occur, i.e., localized condition information is needed in order to plan and prioritize interventions. **Table 3** supports this observation by illustrating the application location and scale each solution was applied at. It shows also that the majority of the solutions were developed at the asset level across both emerging and matured tools.

TRL varies among all the solutions studied. Commercial inspection and predictive maintenance platforms generally possess greater levels of maturity than non-commercial solutions, as they have demonstrated their ability to perform in actual operating environments. Conversely, most research-based methods, particularly those relying on advanced computer vision or hybrid sensing approaches, demonstrate relatively low TRL. Generally, this occurs because these types of tools have either limited demonstration in the field, rely heavily on curated data sets, and/or are sensitive to site-specific conditions. These results also suggest that there remains a persistent gap between new methodologies and their successful integration into large-scale operational practices for SHM.

Table 3. Deployment sites and scales of application for each tool

Tool	Deployment	Scale	TRL
ARTeMIS Modal	Operational deployments and field tests	Asset	9
Active sensor NDT	Experimental and pilot studies	Asset	8
YOLO-RD	Dataset-based evaluation	Segment	5
Proqio platform	Pilot deployments	Asset / Segment	9
GPR-NDT system	Research case studies	Segment	5
BIM Digital twin SHM	Pilot implementation	Asset	8
Triple-threshold crack detector	Dataset-based evaluation	Segment	5
SHM-WIM system	Operational deployments	Asset	9
Autonomous UAV-SHM	Experimental testing	Asset	4
Smartphone road damage detector	Large-scale pilot deployment	Segment / Network	7
OMICRON Inspection	Operational deployment	Asset	6-7
OMICRON Predictive	Operational deployment	Asset / Network	7
OMICRON Bridge	Decision-support application	Asset	7

4.3 Grouping of SHM Solutions

The solutions show coherent grouping based upon common technical and functional features. Three groups are identified: a) Vision-based and sensor-driven monitoring tools for the purpose of detection and condition assessment, b) System-oriented SHM & predictive maintenance, and c) Specialized subsurface & intervention solutions.

Solutions within the first group share similar data modalities, analytical approaches, and functional objectives. Solutions in the second group place greater emphasis on time-series analysis, forecasting, and integration with asset management workflows, and they are generally associated with higher maturity levels and stronger evidence bases. Subsurface inspection approaches, in the third group, appear more distinct due to their specialized sensing requirements and analytical processes. **Table 4** presents the mapping of SHM solutions to their primary data modalities.

Table 4. SHM solutions and data modalities

Data modalities	Active sensor NDT	YOLO-RD	Proqio platform	Triple-threshold crack detector	Autonomous UAV-SHM	Smartphone road damage detector	ARTeMIS Modal	BIM Digital twin SHM	SHM-WIM system	OMICRON Inspection	OMICRON Predictive	GPR-NDT system	OMICRON Bridge
	Vision-based & sensor-driven monitoring						System-oriented SHM & predictive maintenance					Specialized subsurface & intervention solutions	
Active remote sensing data										✓	✓	✓	
Digital and network-based data feeds				✓	✓				✓		✓		✓
Environmental and contextual data				✓					✓			✓	
Historical and archival data												✓	
Infrastructure-embedded and field sensors			✓	✓			✓		✓			✓	✓
Positioning and motion sensors	✓		✓		✓	✓				✓	✓	✓	
Visual and imaging sensors		✓			✓	✓		✓		✓	✓	✓	✓

The tools are also grouped upon the type and availability of data on which they rely. As shown in **Table 4**, vision-based and sensor-driven monitoring tools tend to be dependent on large volumes of labeled or high-frequency data. This reinforces their similarity in both analytical approaches and functional scopes. In contrast, system-oriented and predictive solutions are mainly supported by longer-term time-series data and operational records. Therefore, they would integrate well with asset management workflows, while imposing higher data consistency and quality requirements. Specialized subsurface inspection approaches form a more distinct group due to reliance on customized or site-specific datasets.

4.4 Reported Gaps and Deployment Barriers

Building on the comparative analysis of solution groupings, this section identifies key gaps and barriers that limit the deployment, transferability, and integration of digital SHM solutions.

Vision-based and sensor-driven monitoring solutions appear to face challenges related to data availability and transferability. These tools typically rely on large volumes of labeled visual or sensor data for training and validation; however, such datasets are often scarce, heterogeneous, or context-specific. As a result, performance and reliability can vary significantly across locations, asset types, and environmental conditions. Additionally, many of these solutions remain weakly integrated with asset management or decision-support systems, limiting their ability to use detection results for improving maintenance planning.

System-oriented SHM and predictive maintenance solutions have their own unique, yet similarly enduring barriers. These solutions can be much more mature and typically well-integrated into operational workflows. However, they rely upon the existence of long-term, high-quality time-series data from multiple sources. The primary obstacle that is experienced by most users of these solutions is complexity associated with integrating various disparate data sources, particularly when combining heterogeneous sensor streams, legacy databases, and operational records. A major impediment to widespread use of these solutions are issues of interoperability, standardization, and sustaining the quality of the data. In several cases, high deployment and maintenance costs are identified as an additional obstacle to wider adoption, especially for resource-constrained infrastructure operators.

Specialized subsurface inspection and intervention solutions, such as ground-penetrating radar–based approaches and bridge retrofitting support tools, appear to have a clearer distinction in the similarity landscape, and are facing fewer but more severe challenges. The primary reasons these solutions can be difficult to scale up and apply to other sites is due to customized sensor configurations and site specific calibrations. Additionally, high complexity and operating cost, along with poor integration with broader monitoring and management frameworks, further limit their use beyond targeted inspection or interventions.

All three groups demonstrate similar gap areas related to needs for improved data standardization, better integration of heterogeneous data sources, and clearer pathways from monitoring outputs to decision-support and control mechanisms. These findings emphasize the need for knowledge-based platforms, such as those being envisioned through the SMARTIN project, that identify both technological capabilities and recurring barriers and contextual constraints. By aggregating the gap areas by solution group, the analysis provides an opportunity for future research, standardization efforts, and capacity-building actions relevant to infrastructure managers and policy makers.

To synthesize these observations and make the comparison across solution groups explicit, **Table 5** consolidates the reported gaps and deployment barriers identified in the reviewed solutions. The table aligns individual tools and platforms with recurring technical, operational, and institutional challenges, highlighting both group-specific and cross-cutting limitations. It illustrates how vision-based and sensor-driven approaches are predominantly constrained by data-related issues (e.g., labeled datasets, multimodal integration, and real-time data streams), while system-oriented SHM and predictive maintenance solutions are more frequently affected by deployment costs. At the same time, specialized subsurface and intervention-oriented solutions stand out for their site specificity, and need of data.

Table 5. Key barriers of SHM solutions

Key gaps	Active sensor NDT	YOLO-RD	Proqio platform	Triple-threshold crack detector	Autonomous UAV-SHM	Smartphone road damage detector	ARTeMIS Modal	BIM Digital twin SHM	SHM-WIM system	OMICRON Inspection	OMICRON Predictive	GPR-NDT system	OMICRON Bridge
	Vision-based & sensor-driven monitoring						System-oriented SHM & predictive maintenance					Specialized subsurface & intervention solutions	
High data processing and communication demands								✓					
Highly site- or mode-specific (difficult to generalise)									✓				✓
Insufficient real-time data streams		✓		✓	✓								
Lack of economic viability for wide deployment											✓		
Lack of high-quality labelled datasets		✓				✓						✓	
Lack of multimodal data integration (e.g. GNSS + video + IoT)	✓		✓	✓								✓	
Low TRL/SRL (immature technology or social adoption)					✓					✓	✓		
Missing guidelines or best practices for adaptation	✓										✓		
Requires labelled datasets for training				✓	✓								
Requires proprietary or costly hardware/ software	✓		✓				✓	✓	✓	✓			✓

5 Discussion

The results of this study provide a structured mapping of a sample of existing digital SHM solutions that offer insights directly relevant to ongoing efforts in knowledge harmonization and evidence-informed infrastructure management. When diverse tools are fitted into a shared explanatory framework, the interpretation can follow systematically through technological innovations and changes that may be otherwise difficult to compare and contrast because of differences in scale, development stage and terminologies.

One of the most notable conclusions is the very large concentration of solutions dedicated to monitoring and detection. Vision-based inspection systems and sensor-based SHM systems still represent the majority of existing solutions, accounting for the most recent technologies and the highest complexity levels in the field, given the maturity of data acquisition technologies. However, they are a few steps away from condition assessment functionalities towards predictive or control functionalities. Instead, this bias represents a dis-junction in the production of condition data and its application to actionable asset management processes, such as planning interventions and so on. Bridging this gap is critical to moving reactive infrastructure management paradigms forward to proactive infrastructure management paradigms.

The categorization of solutions based on sensing modalities and analytical approaches also stresses the fragmented nature of the current spectrum. While these categories may be intuitive from a technical standpoint, they also demonstrate some limitations in cross-type interoperability and integration. The three groups co-evolve primarily in parallel with little means for merging complementary data sources or analytical results across the stages of monitoring, predicting, and acting. Understand the system-level, this fragmentation limits the potentials of digital solutions in supporting full infrastructure assessments and integrated management strategies and thus calls for integrative frameworks that can connect diverse monitoring.

The examination of identified gaps and obstacles suggests that numerous challenges in digital SHM are systemic rather than pertaining to specific solutions. Some of the problems that arise are that there are not enough labeled datasets, that it is hard to combine data from different sources, and that proprietary hardware or software components make things harder. These problems show up in different types of solutions and at different stages of maturity, and they match what has been reported in the literature. Their continued existence underscores the necessity for synchronized initiatives in standardization, data-sharing protocols, and methodological clarity. The analysis organizes and groups these barriers in a way that makes it easier to decide the order of research, development, and standardization activities.

6 Conclusions

The study has undertaken a structured comparative analysis of digital solutions for SHM using a set of thirteen representative methods and tools. The organization of heterogenous digital solutions into a structured framework allows for an effective and structured comparison of tools that are generally evaluated in isolation. The analysis highlights dominant groups of technologies, differences in maturity and validation, and common barriers to wider deployment.

The findings reveal a strong concentration of current practice on monitoring and detection functions, with vision-based and sensor-driven systems dominating the field. The results also highlight a significant lack of digital solutions aimed at predictive analytics, decision support or controlling functionalities which shows a gap between condition assessments and actions taken to manage the performance of infrastructure. The grouping of solutions into three categories reveals a fragmented digital SHM ecosystem. There are limited opportunities for interoperability and poor integration of complementary data sources which prevents the development of holistic, system-wide management approaches. Therefore, there is a need for integrative frameworks that can effectively link monitoring, prediction and intervention.

The analysis of identified gaps indicates that many barriers are systemic, such as insufficient real-time data streams, problems associated with multimodal data integration, and reliance on proprietary or costly technologies. By documenting these issues in a structured format, this study provides a basis for the prioritization of future research and standardization initiatives.

Finally, the results show how comparative analysis can support decision-making by infrastructure managers, public authorities, and mobility practitioners. By clarifying relationships between solutions, identifying areas of overlap and complementarity, and highlighting persistent gaps, the analysis supports informed technology selection, benchmarking, and integration. In this way, the study contributes both to academic synthesis and to practical efforts aimed at supporting evidence-based adoption of digital solutions for SHM.

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