Applications of Artificial Intelligence in Bridge Structural Health Monitoring: A Systematic Review of the Last Decade

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ABSTRACT

Bridges are critical components of transportation networks whose structural integrity is often threatened by aging, environmental loads, and insufficient maintenance. Structural Health Monitoring (SHM) supported by Artificial Intelligence (AI) offers a transformative approach to early damage detection, predictive maintenance, and operational safety. This study presents a systematic literature review, conducted in accordance with PRISMA 2020 guidelines, on the application of AI algorithms to bridge SHM between 2015 and 2025. A total of 70 peer reviewed articles were analyzed, covering diverse geographic contexts, structural types, and sensing technologies. The review categorizes studies by AI technique (ANN, CNN, LSTM, SVM, hybrid models, and emerging methods such as Transformers and Graph Neural Networks), sensor architecture (accelerometers, fiber optic sensors, UAV based imaging, IoT modules), and performance metrics. Results indicate that convolutional and recurrent neural networks achieve detection accuracies above 95% and R^2 values exceeding 0.90 in displacement prediction, while hybrid approaches combining deep learning with traditional classifiers enhance robustness. Sensor integration with IoT and multimodal data fusion improves detection sensitivity, with correlation values above 0.99 in some cases. However, over 90% of studies lack robust cross validation, real world deployment, or standardized performance reporting, limiting replicability. This review highlights current trends, technical challenges, and research opportunities, including the need for interoperable sensor–algorithm platforms, explainable AI models, and broader implementation in developing regions. By consolidating existing knowledge, the study provides a technical reference for researchers, practitioners, and policymakers aiming to implement intelligent, predictive, and resource efficient bridge SHM systems.

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1 Introduction

1.1 Contextualization of Bridges as Critical Infrastructure

Bridges are fundamental components of modern transportation networks, as they enable regional connectivity, facilitate commercial activities, ensure access to essential services, and support the

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mobility of people and vehicles. Their strategic relevance positions them as critical assets within national and international roadway systems [1].

Throughout their service life, bridges are subjected to repetitive dynamic loads, corrosion processes, seismic actions, temperature variations, and natural aging mechanisms, all of which contribute to structural degradation [2]. Numerous studies have reported that many bridges worldwide exhibit progressive deterioration or damage that often remains undetected, potentially resulting in functional deficiencies or, in severe cases, structural collapse [3].

A notable example is the collapse of the Morandi Bridge in Genoa, Italy (2018), which underscored the urgent need for continuous and predictive monitoring technologies to prevent similar failures [4]. This event and others have accelerated the development of advanced approaches to structural asset management, particularly within the field of Structural Health Monitoring (SHM), whose main objective is the early detection of damage before it evolves into a critical threat [5,6].

In recent years, SHM has evolved from traditional visual inspections to the implementation of intelligent systems based on sensor networks, predictive modeling, and automated data analysis. The application of these technologies in bridges aims to enhance structural safety, extend service life, and optimize the allocation of resources for maintenance, rehabilitation, or replacement activities [7–9].

1.2 Role of the SHM in the Prevention of Structural Failures

In recent decades, SHM has established itself as a fundamental strategy for the comprehensive management of infrastructures. It allows for the collection of real time information on the mechanical behavior of structures, detecting anomalous patterns associated with incipient damage, and supporting decision making in maintenance or intervention [10].

On bridges, where failure mechanisms are often progressive but difficult to detect visually, SHM is presented as an indispensable tool to prevent collapses and improve road safety [11].

Traditionally, SHM systems have relied on periodic visual inspections and physical sensors such as accelerometers, strain gauges, or displacement transducers. However, the interpretation of these data requires expert analyses that are costly, time consuming and subject to a certain subjectivity [12]. In contrast, the incorporation of Artificial Intelligence (AI) techniques offers substantial advantages: it automates analysis, increases accuracy in damage detection and reduces human error [13].

Using algorithms such as artificial neural networks, Support Vector Machines (SVM), decision trees, or *deep learning* models, AI can identify complex, nonlinear patterns in large volumes of structural data. This makes it easier to predict faults and classify damage without direct operator intervention [14]. Its relevance grows even more with the availability of data from distributed sensors, computer vision systems, drones (UAVs) and IoT platforms [15].

AI also makes it possible to integrate information from multiple sources and adapt detection models to the specific conditions of each structure. In this way, it increases sensitivity to subtle changes and improves efficiency in the use of maintenance resources [16]. Consequently, its application in bridge SHM not only represents a technical breakthrough, but also a transformation in modern civil infrastructure management.

1.3 Evolution and Benefits of Applying AI in SHM

The implementation of Artificial Intelligence (AI) has been a determining factor in the evolution of Structural Health Monitoring (SHM), allowing civil engineering to shift from inspection-based approaches to advanced diagnostic and predictive models. This transformation is supported by a variety of algorithms that enable the automation of critical tasks and increase the accuracy of damage detection.

Table 1 presents a summary of the main AI approaches applied to connect SHMs, highlighting the functional benefits offered by each algorithm, as described in the specialized literature.

Table 1: Contribution of referenced articles to AI and SHM

Citation	Primary focus area	AI/ML approach or technique discussed	Article type and key finding
[1]	Failure detection in bridges	Deep learning	Proposes a novel deep learning algorithm for failure detection based on signal coherence.
[2]	Bridge damage detection	Artificial neural network (ANN)	Proposes a two-stage *machine learning* approach using ANNs and Gaussian Process for drive-by damage detection.
[3]	Mobile sensing review	Data analytics & signal processing	Comprehensive review of mobile sensing, highlighting the need for novel *data analytics* methods (often AI-based) to manage large data volumes.
[4]	Vibration-based damage detection review	Machine learning (ML) and deep learning (DL)	Comprehensive review tracking the transition from traditional vibration methods to modern ML and DL applications.
[5]	Optimal sensor placement (OSP)	Optimization algorithms (Heuristic/AI-based)	Systematic review focusing on *optimization algorithms* (e.g., Genetic Algorithms) for SHM and OSP.
[6]	Current status of structural monitoring	Artificial intelligence (General)	Bibliometric review highlighting the growing role of AI in interpreting recorded observations and the development of the field.
[7]	Systematic review methodology	PRISMA 2020 Statement (Methodology)	This is a methodological guide for systematic reviews, often used to structure the literature review process, not an AI application itself.
[8]	Damage classification	Hybrid machine learning (Stacking, WKNN)	Comparative study using a newly proposed hybrid *machine learning* classification approach (Stacking) to detect damage.

(Continued)

Table 1 (continued)

Citation	Primary focus area	AI/ML approach or technique discussed	Article type and key finding
[9]	Digital fabrication evaluation	Optimization and automation	Focuses on the technological evaluation of *Digital Fabrication with Concrete* (DFC), touching upon automation and process optimization which rely on algorithms like Genetic Algorithms.
[10]	Data-driven SHM review	Deep learning (DL)	State-of-the-art review focusing on *data-driven* SHM and damage detection specifically through various Deep Learning methods.

Note. organizing the main AI approaches reported in the literature between 2015–2025.

Since the 1990s, Structural Health Monitoring (SHM) systems have evolved significantly. They moved from manual visual inspections and isolated non-destructive techniques to integrated architectures that enable continuous monitoring of infrastructure condition [1]. This foundational change has been driven by new sensor technologies, increased data processing capacity, and the development of wireless communication networks [2].

In parallel, the evolution of Artificial Intelligence (AI) algorithms opened up new possibilities for optimizing structural monitoring, as comprehensively reviewed in the literature [3,4,6]. Initially, AI use was limited to basic damage classifications with neural networks trained on synthetic or laboratory data [2]. With the maturation of *machine learning* and *deep learning*, SHM systems acquired the ability to recognize complex patterns, generalize between different structures, and adapt to varying conditions using self-learning techniques [4].

Today, AI algorithms make it possible to perform critical tasks such as early detection of anomalies, precise localization of damage, estimation of the level of deterioration, and prediction of future structure behavior [5]. This is possible thanks to applied techniques such as SVM, Decision Trees, K-Nearest Neighbors (KNN), Genetic Algorithms, and advanced CNN or RNN models [6,8].

Key Benefits of AI in Bridge Monitoring

The main benefits of applying AI in bridge SHM include: the automation of structural diagnosis, which reduces human intervention and subjectivity [7]; real-time processing capacity thanks to the use of *edge computing* and smart sensors [8]; the reduction of operating costs through the optimization of inspections and maintenance [9]; and better adaptability in complex or hard to reach environments, through integration with UAVs, computer vision and IoT [10]. This evolution marks a turning point in modern structural engineering, moving from reactive and corrective approaches to predictive and intelligent models capable of extending the useful life of critical infrastructures and ensuring more sustainable asset management.

1.4 Key Advances in the Application of Artificial Intelligence and Deep Learning in Bridge SHM Review

The evolution of Artificial Intelligence (AI) in Structural Health Monitoring (SHM) for bridges has significantly progressed, moving from traditional statistical approaches to advanced intelligent systems based on deep learning (DL) [11]. Despite these advances, the overall state of the art faces comprehension limits due to the dispersion of literature [12]. The need for machine health indicators and the integration of digital twins has become increasingly crucial for improved structural data interpretation [13].

The field has expanded into applying continuum models to determine the behavior of complex structures, such as suspension bridges during construction [14]. There has been a detailed review of methods for structural modal parameter recognition under environmental excitations [15], alongside comprehensive reviews focusing on the monitoring and detection of diseases in steel bridges [16]. Practically, development is advancing toward AI-enabled monitoring platforms for concrete structures [17]. Research into more specialized structures is also growing, including the analysis of crashworthiness behaviors in 3D printed structures [18].

Achieving Optimal Sensor Placement (OSP) remains a key technical challenge within AI-assisted SHM architecture [19]. Furthermore, a detailed analysis has been conducted on the optimal choices for machine learning (ML) applications in monitoring concrete and steel bridges [20]. To address the common constraint of limited data, specialized techniques like data augmentation have been proposed for DL-based multiclass damage detection [21]. The application of ML for rapid damage detection following extreme events like earthquakes is also a growing area [22], as is the comprehensive review of SHM for timber bridges [23].

In terms of integration, bridge management tools are evolving to include systems supported by Augmented Reality (AR) using 3D game engines [24] and advanced management systems combining AI, UAVs, and BIM [25]. This transition is evident in the development of intelligent wireless systems, such as the *xImpact* system, which integrates IoT sensors with neural networks for rapid and cost-effective impact assessment in bridges [26].

Parallel advancements include the development of unsupervised learning methods, such as applying Principal Component Analysis (PCA) and outlier detection for assessing the longitudinal performance of bridge bearings [27]. The use of transfer component analysis for the recognition of vortex-induced vibration in long-span bridges [28], and the evaluation of AI-enhanced IoT systems for deflection assessment in drive-by conditions [29], collectively consolidate machine learning as a core tool. Finally, comprehensive reviews highlight advancements in vibration and image-based data processing and the growing integration of digital twin technologies through deep learning [30].

1.5 Knowledge Gap or Need for a Systematic Review

Despite the exponential growth in the number of studies that apply Artificial Intelligence (AI) algorithms to bridge Structural Health Monitoring (SHM), the current literature has important limitations that hinder a comprehensive understanding of the state of the art. Much recent research is aimed at validating individual machine learning models, but lacks a comparative or integrative perspective to assess the overall progress of the field [11].

Likewise, a significant dispersion in the application of techniques is observed, with studies focused on convolutional neural networks (CNNs), Support Vector Machines (SVM), decision trees, among others, but with little discussion about their relative effectiveness, selection criteria or contextual limitations [12]. This heterogeneity methodological makes it difficult to establish standardized recommendations for practical implementation in civil engineering projects [13].

In parallel, although there are some previous reviews on SHM or AI applied to structures, many of them are limited to general structures (buildings, tunnels, dams), without focusing specifically on bridges [14]. Others focus exclusively on a subset of algorithms or types of sensors, omitting the comprehensive vision required for the implementation of intelligent systems in critical infrastructures [15].

Additionally, few studies have systematized this information through robust methodologies such as the PRISMA declaration, which affects the traceability, reproducibility, and scientific quality of the reported findings [16]. Study coverage is also limited in developing countries, where bridges are especially vulnerable due to deficiencies in maintenance, financing, or technical capacities [17].

For these reasons, an up to date and well-structured systematic review is necessary that: Integrates existing knowledge in a critical and comparative manner; Classify the AI techniques applied to bridge SHM according to technical and operational criteria; Identify key trends, challenges, and gaps to be addressed; It serves as a guide for future researchers, designers and public entities responsible for infrastructure management.

This review seeks to respond to this need, providing a rigorous and updated synthesis of the use of artificial intelligence in the structural monitoring of bridges in the period 2015–2025, in accordance with the PRISMA 2020 guidelines.

1.6 Main Objective and Research Questions

In response to the exponential growth of the use of Artificial Intelligence (AI) algorithms in structural monitoring, as well as the need to have a technical framework that allows systematizing the techniques, sensors and metrics used in the state of the art, the following general objective is defined:

General objective:

To conduct an exhaustive and technically structured systematic review on the application of Artificial Intelligence algorithms in the Structural Health Monitoring (SHM) of bridges, between the years 2015 and 2025, in order to identify the dominant computational methodologies, the types of integrated sensors, the observed structural variables and the reported efficiency of the models, using a search and selection protocol based on the PRISMA 2020 guidelines.

This objective seeks not only to synthesize existing knowledge, but also to establish comparable technical criteria between studies, identify relevant methodological gaps, and project possible lines of scientific and technological development for future implementations in intelligent structural engineering.

Research Questions

Q1. Which AI algorithms have been most frequently applied in bridge structural monitoring between 2015 and 2025, and for what specific purposes?

This question allows us to identify the degree of technical maturity of the approaches used, comparing their performance in tasks of detection, localization and quantification of structural damage under different operating conditions [18].

Q2. What types of sensors and complementary technologies have been integrated with AI systems in bridge SHM, and how do they vary depending on the type of structure or environment? The aim is to establish relationships between the choice of sensory hardware (accelerometers, fiber optic sensors, computer vision, UAVs, etc.) and the performance of the SHM system, considering aspects of resolution, latency and robustness of the analysis [19].

Q3. What are the main trends, limitations, and opportunities detected in the literature on the use of AI for bridge damage detection, and which areas require further development?

This question aims to extract a critical synthesis of the limitations of the field, identify promising lines of research, and propose guiding criteria for the implementation of intelligent structural monitoring solutions in real scenarios, including developing countries [20].

1.7 Additional Relevant Evidence from Excluded Studies

Several excluded studies provide complementary insights that broaden the understanding of current challenges and technological advances in AI-based Structural Health Monitoring (SHM).

The study of deformation and damage behavior in bridge components, such as segmental joints under ultimate loads, provides crucial data for training robust AI models [31]. Furthermore, research into composite wave attenuation mechanisms in periodic layered metastructures informs the development of advanced signal processing techniques for damage identification [32]. The broader trend emphasizes the importance of utilizing AI and ML based multimodal sensor data for improving diagnostic accuracy [33]. Additional research on self-sensing concrete has highlighted the potential of smart materials to enhance long-term monitoring performance by embedding sensing capabilities directly into the structural medium [34].

Estimating bridge natural frequencies based on modal analysis of vehicle-bridge synchronized vibration data offers another crucial input for AI-driven anomaly detection [35]. Advances in girder-end displacement reconstruction using novel hybrid attention mechanisms illustrate the increasing sophistication of multisource information leverage in SHM [36]. This aligns with systematic reviews highlighting the effectiveness of intelligent damage diagnosis in bridges using vibration-based monitoring and machine learning [37]. Parallel advances in deep-learning–based visual crack detection, such as hybrid visual transformer algorithms, further illustrate the growing accuracy and adaptability of AI models in surface-defect assessment [38].

Moreover, the development of SHM systems based on digital twins and real-time data-driven methods is crucial for holistic structural assessment [39]. A broad review of bridge health monitoring based on machine learning emphasizes the consolidation of ML as a core diagnostic tool [40]. Machine learning is also being used to enhance SHM by accurately predicting the effects of retrofitting actions [41]. Comprehensive reviews confirm the rapid development of intelligent technologies in SHM for innovative diagnosis in civil engineering [42]. This innovation extends to research focused on the intelligent operation and maintenance (O&M) of bridges [43]. Furthermore, dedicated research is necessary for the monitoring, detection, and intelligent identification of weathering steel bridges [44].

Data-driven dynamical-system modeling approaches, including Echo State Networks and NARMAX, have been successfully applied to footbridge monitoring, revealing the potential of recurrent architectures in vibration-based SHM [45]. Scientometric analyses focusing on deep-learning methods for crack detection have underscored rapid growth in this area and pointed out methodological limitations that persist in model interpretability and real-world applicability [46]. Complementary studies in AI-enhanced nondestructive testing highlight the need for more standardized validation pipelines for detecting hidden or internal defects in civil engineering components [47]. In addition, real time scour monitoring using machine learning tools has demonstrated promising capabilities for capturing hydrodynamic threats affecting bridge safety [48]. Finally, recent reviews on displacement sensing emphasize the importance of multimodal and high-resolution measurement technologies to ensure reliable structural evaluation [49].

These insights collectively provide essential context for the design of the methodological procedures described in the subsequent Materials and Methods section.

2 Materials and Methods

2.1 Methodological Approach

This research corresponds to a systematic review of the scientific literature focused on the application of artificial intelligence (AI) algorithms to bridge Structural Health Monitoring (SHM). The study followed the PRISMA 2020 statement (Preferred Reporting Items for Systematic Reviews and MetaAnalyses), ensuring transparency, reproducibility, and traceability in all stages of the review. The PRISMA guideline serves as the internationally recognized framework for structuring and reporting systematic reviews, which justifies the inclusion of Reference [7] as a methodological source in this study. The protocol included the definition of eligibility criteria through the PICOC scheme, the design of a structured search strategy in four indexed databases, and the qualitative and quantitative analysis of the selected studies. Although the protocol was not registered in PROSPERO due to its non-clinical nature, the review adhered to internationally recognized methodological practices in engineering.

2.2 PICOC Criteria

The selection process was guided by the PICOC framework, which defined the population as vehicular or railway bridges subject to structural monitoring. The intervention considered was the application of AI algorithms, including both machine learning (ML) and deep learning (DL). No direct comparison was established, although studies contrasting AI with traditional methods were considered valuable. The expected outcomes included the identification, classification, localization, or prediction of structural damage, together with performance evaluation through metrics such as precision, sensitivity, accuracy, or robustness. Finally, the context was limited to scientific articles published between 2015 and 2025, in English or Spanish, and included only peer reviewed and indexed journals. These criteria delimited the thematic and temporal scope of the review, ensuring the inclusion of studies relevant to the technical analysis of the state of the art.

2.3 Search Strategy

The search strategy was designed to identify studies on the application of AI in bridge SHM, following a rigorous and reproducible engineering oriented approach. Four databases were selected: Scopus, Web of Science (WoS), ScienceDirect, and ProQuest. These platforms were chosen for their high coverage of indexed journals, their advanced search engines, and their reliability in retrieving peer reviewed scientific literature. The search terms were organized around three thematic axes: artificial intelligence, structural monitoring, and bridges. Boolean operators were applied to refine results. For example, one of the strings used in Scopus was: (“artificial intelligence” OR “machine learning” OR “deep learning”) AND (“structural health monitoring” OR “SHM”) AND (“bridge” OR “bridges”) AND (“damage detection” OR “structural damage” OR “crack detection”). Filters were applied to restrict the search to scientific articles, systematic reviews, and peer reviewed conference papers published in English or Spanish between January 2015 and July 2025, with preference for full text availability.

2.4 Selection Process

From the four databases, 214 articles were initially retrieved and organized in Microsoft Excel. During the Identification phase of PRISMA, five duplicates were removed, leaving 209 records. In the Screening phase, 121 studies were excluded because their abstracts were not aligned with the objectives of the review. A subsequent content analysis eliminated 38 more articles that did not meet eligibility criteria, guided by questions such as: *Does the study's objective align with the purpose of the review? Do the conclusions address the research question?* The grading criteria were defined as Yes or No. Finally, in the Included phase, the remaining 70 studies were confirmed as fully meeting the requirements, forming the evidence base for this systematic review.

2.5 Data Extraction and Analysis

For the structured analysis, a standardized template in Excel was applied to all 70 articles, which made it possible to systematize the key information and facilitate its classification, coding, and thematic grouping. The extracted variables covered three main dimensions: the general characteristics of each study, the technical aspects of the applied AI methods, and the elements related to structural monitoring. Specifically, the information included author, year, country, and database of origin; type of monitored structure such as concrete bridges, steel bridges, mixed structures, scale models, or simulations; type of AI technique used, including CNN, SVM, LSTM, RF, KNN, or hybrid approaches, together with the type of learning (supervised, unsupervised, or hybrid); and the sensors or complementary technologies implemented, such as accelerometers, fiber optic sensors, UAVs, IoT platforms, and computer vision. Likewise, the objectives of the studies were recorded, ranging from crack detection and damage classification to behavior prediction and failure diagnosis. The evaluation metrics considered included accuracy, sensitivity, specificity, F1-score, R^2, AUC, and execution times, while the validation environment was classified according to laboratory tests, simulations, or field data.

Data processing was initially performed in Microsoft Excel, and exploratory analyses were complemented with VOSviewer for keyword cooccurrence networks and with Python for generating bar charts and time series. The final organization of the studies was carried out according to the type of algorithm used, the sensory architecture and its integration with AI, the purpose of the SHM application (detection, classification, prediction), and the geographical or technological context. This classification enabled a comparative analysis of the reported trends, strengths, and limitations, which are presented in detail in the Results section.

Table 2 shows then, in order to present all the phases of exclusion and inclusion that was carried out in this research work, the PRISMA Flow Diagram [7] was captured. Fig. 1 shows the process and the number of articles that remain per phase according to the criteria of this work.

For the choice of scientific articles, the identification phase began by evaluating the quality of the articles from the aforementioned databases that are related to the objectives of this research. Then, a filter was used where duplicate studies were detected, then the abstract was analyzed, discarding those that were not related to the research work, also taking into account only scientific articles, discarding other types of documents. Additionally, only articles in English were used. Next, the eligibility phase was moved, where some articles were eliminated due to the lack of correlation with the objectives. Finally, in the net inclusion phase, where the articles that are related to the question posed in this research work were included. At the end of all the phases for exclusion and inclusion, 70 articles were obtained that met the characteristics of the search and the keywords used in this research. No items were added after the selection process.

Table 2: Frequencies of scientific articles by each database

Database	Frequencies		
	Absolute (n)	Relative (n/N)	Percentage (%)
Scopus	16	0.068	6.83%
ScienceDirect	89	0.38	38.03%
Wos	32	0.13	13.67%
ProQuest	97	0.41	41.45%
Total	234	1.0	100%

Note: This table is prior to the phases PRISMAN = Total number of items, n = total number for each base.

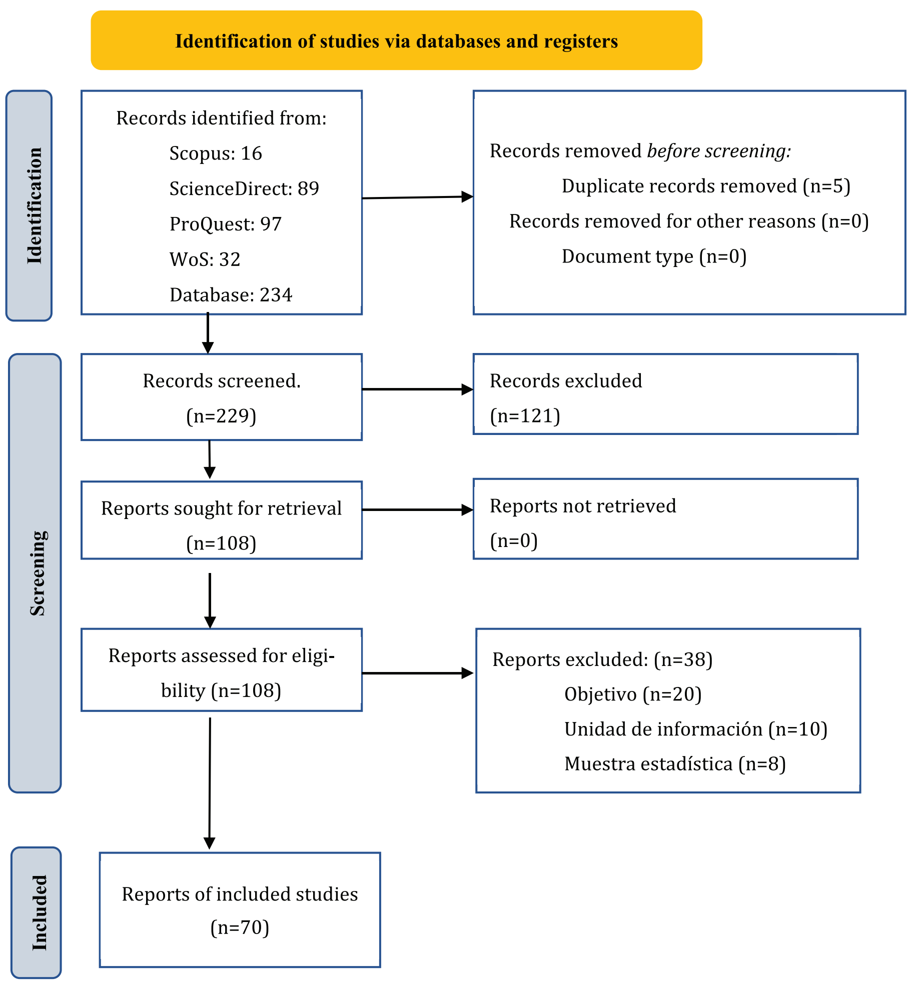

Figure 1: Flowchart of the PRISMA process phases

Note: The number of study reports included at the end is n = 70.

3 Study Characteristics

Table 3 below shows 12 articles out of the 70 that were obtained after selection with content about their year, author(s), title, journal. country and database.

Table 3: Top items selected for analysis

Author(s)	Title	Year	Magazine	Country	Database	Key points
[1]	A deep learning approach to detect failures in bridges based on signal coherence	2021	Big Data Cogn Comput	Italy	ProQuest	Proposes DL based on signal coherence. High accuracy in early detection of failures.
[3]	A review of mobile sensing of bridges using moving vehicles	2022	Struc tures	Ireland	ScienceDirect	Review on monitoring bridges with mobile vehicles. Identify progress, challenges and future trends.
[8]	Comparative study of a newly proposed machine learning classification to detect damage	2023	Eng Appl Artif Intell	USED	ScienceDirect	It proposes ML classification for fault detection. High accuracy in predicting structural damage.
[9]	An IoT-based road bridge health monitoring and warning system	2024	Sensors	Switzerland	ScienceDirect	IoT system for real time monitoring. Detect anomalies and send early warnings.
[10]	Data-driven SHM and damage detection through deep learning: state of the art review	2020	Sensors (MDPI)	Switzerland	ProQuest	Review of deep learning techniques in SHM. It highlights progress and challenges in its implementation.
[11]	Advances in AI for structural health monitoring: a comprehensive review	2025	KSCE J Civ Eng	South Korea	ScienceDirect	Review on AI in SHM. It presents recent advances and applications in structural monitoring.

(Continued)

Table 3 (continued)

Author(s)	Title	Year	Magazine	Country	Database	Key points
[12]	Unsupervised deep learning for SHM	2023	Big data and cognitive computing	Italy	WoS	Use of unsupervised deep learning in SHM. It focuses on handling large volumes of data.
[13]	Machine health indicators and digital twins	2025	Sensors (MDPI)	Switzerland	ProQuest	Use of health indicators and digital twins. It facilitates predictive maintenance and cost reduction.
[14]	Optimising concrete crack detection: transfer learning on jetson nano	2024	Sensors (MDPI)	Switzerland	ProQuest	Transfer learning applied to crack detection. Use of low-power hardware for monitoring.
[15]	Structural modal parameter recognition and damage identification under environmental excitations	2024	SDHM	Australia	ScienceDirect	Review of modal techniques and ambient vibration. Useful in identifying structural damage.
[16]	Monitoring and detection of steel bridge diseases: a review	2024	J Traffic Transp Eng Engl Ed	China	ScienceDirect	Review of damage to steel bridges. It summarizes current monitoring and inspection techniques.
[17]	Toward an AI-enabled monitoring platform for concrete structures	2024	Sensors (MDPI)	Switzerland	ProQuest	Monitoring platform with AI and IoT. Detects deterioration in real time and facilitates predictive maintenance.

Note: This table presents 12 representative articles selected from the total of 70 studies included in the review.

Challenges, Solutions and Research Gaps in the Application of AI to Bridge SHM

The implementation of artificial intelligence (AI) techniques in bridge structural health monitoring (SHM) faces several technical and methodological challenges. Advances like the xImpact intelligent wireless system, integrating IoT sensing nodes with neural network models for rapid and cost-effective impact assessment, contextualizing the field [26]. However, the scarcity of high-quality labeled data remains a major issue. Parallel work on unsupervised PCA-based anomaly detection for evaluating longitudinal bridge bearing behavior provides a useful comparison for supervised approaches [27]. Other specific challenges include managing vortex-induced vibration recognition in long-span bridges [28] and integrating AI-enhanced IoT systems for assessing bridge deflection in drive-by conditions [29]. The complexity of the task is underlined by extensive reviews highlighting advances in vibration- and image-based deep-learning techniques [30].

Moreover, challenges in damage progression are evident in studies on segmental joint deformation [31] and the complex signal processing required for composite wave attenuation mechanisms [32]. The need to manage data variability and heterogeneity is crucial, particularly in multimodal sensor-based SHM approaches [33]. The difficulty of adapting AI models to varying conditions is also compounded by issues in self-sensing concrete development [34] and variability in estimating bridge natural frequencies [35]. This aligns with systematic reviews highlighting the difficulties of intelligent damage diagnosis using vibration-based ML [37], where the interpretability of models remains a critical concern, as many deep learning approaches, despite advances like hybrid visual transformer algorithms for crack detection [38], still operate as “black boxes,” complicating acceptance [40,42]. Research also extends to intelligent O&M systems [43] and weathering steel bridge monitoring [44]. Data-driven dynamical-system modeling approaches, like Echo State Networks and NARMAX, also reveal the potential pitfalls of recurrent architectures [45].

To overcome these limitations, recent literature has proposed various technical and methodological solutions. The use of hybrid approaches that combine AI models with physical or knowledge-based techniques has been shown to improve accuracy and robustness, consistent with recent hybrid frameworks for multisource SHM [36]. Recent developments in digital-twin-assisted structural health monitoring have significantly improved real-time interpretation, integrating physics-based models with data-driven estimation techniques [39]. The lack of standardized frameworks for model validation hinders industrial adoption, a limitation noted in bridge-focused SHM reviews [40]. The need for predictive models that account for retrofitting effects is also growing [41]. Model interpretability remains a critical limitation, emphasized in comprehensive reviews of the development of intelligent technologies in SHM [42]. Research exploring intelligent O&M systems is also growing [43], particularly for weathering steel bridges [44].

Despite these advances, significant research gaps remain. Scientometric analyses reveal methodological limitations in model interpretability and real-world applicability [46]. Complementary studies in AI-enhanced nondestructive testing highlight the need for more standardized validation pipelines for detecting hidden defects [47]. Furthermore, real-time scour monitoring using AIoT sensor systems demonstrates promising capabilities for capturing hydrodynamic threats [48]. Recent reviews on displacement sensing emphasize the importance of multimodal and high-resolution measurement technologies [49]. Finally, research is required that explores interoperability and data fusion. Approaches exploiting multimodal data fusion and compressed sensing for vibration-based monitoring have shown potential in this direction [33,50]. The development of intelligent bridge management systems is another active area [51]. There is also novel work on AI-based schemes for structural health monitoring in CFRE laminated composite plates [52]. The incorporation of Large Language Models (LLMs) in the processing and contextualization of structural data represents a promising opportunity [53], allowing more explainable and adaptive systems capable of assisting in decision-making on maintenance and management.

This comprehensive overview reinforces the expanding technological landscape of intelligent SHM and highlights emerging opportunities for more accurate, multimodal, and predictive monitoring frameworks.

Fig. 2 shows the number of publications between 2017 and 2025, taking into account that the systematic review of literature is the last 10 years, in the graph you can see an increase in publications as we approach the year 2025, thus having that in the year 2024, 17 publications were made on the subject. It can be inferred that the increase in the number of publications is due to the growing need for bridge monitoring through sensors and an improvement in artificial intelligence in recent years.

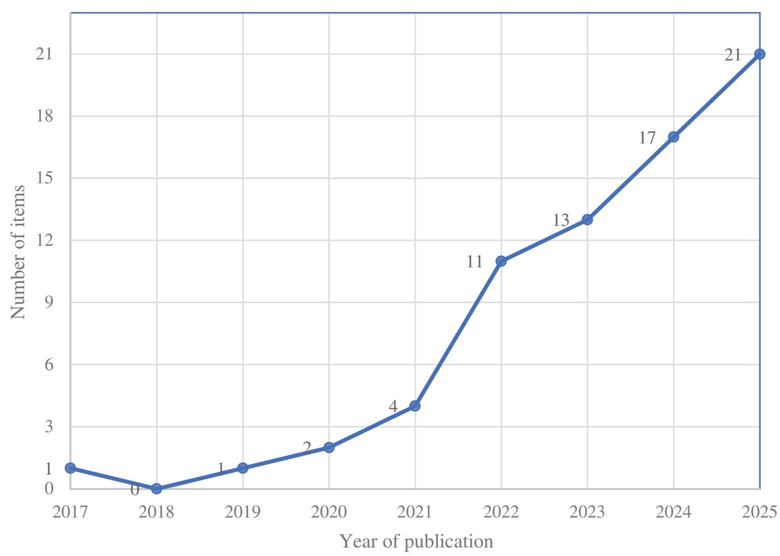

Figure 2: Publication trend by year

Note: The faintest line shows the trend of publications from 2017 to 2025.

Fig. 3 shows the number of journals published during the year 2017 and 2025, it can be seen that the Building had 3 publications taken for this research, we have 6 publications for Automation in Construction, 3 Appl Sci, 2 for Constr Build Mater, 2 for Eng Appl Artif Intell, 3 for Engineering Structures, 2 for J Infrastruct Intell Resil, 2 for J Traffic Transp Eng Engl Ed, 3 for Measurement, 2 for Resuls Eng, 3 for Struct Durab Health Monit, 2 for Structures, 4 for Struct Control Health Monit, 14 for Sensors (MDPI) this journal being the one that makes the most publications related to the research topic of this work. Finally, the rest of the journals have 1 publication that meets the criteria of the work.

In Fig. 4, the word Structural Health is repeated with greater frequency used in scientific articles, then continues Structural monitoring, followed by the acronym SDHM referring to Structural Durability and Health Monitoring. We also see that the word bridges and sensors is used but less frequently in this systematic review of the literature.

In Fig. 5, you can see the geographical distribution that corresponds to the 70 selected articles for this research, it should be noted that the figure indicates the countries where the information was extracted. It can be seen that China is in first place with 20 publications, then the United States with 6 publications, the United Kingdom with 6 publications, Australia with 5 publications, and Republic of Korea with 4 publications, Italy, Spain, India, Vietnam with 4 publications per country, the other countries vary between 2 and 1 publication.

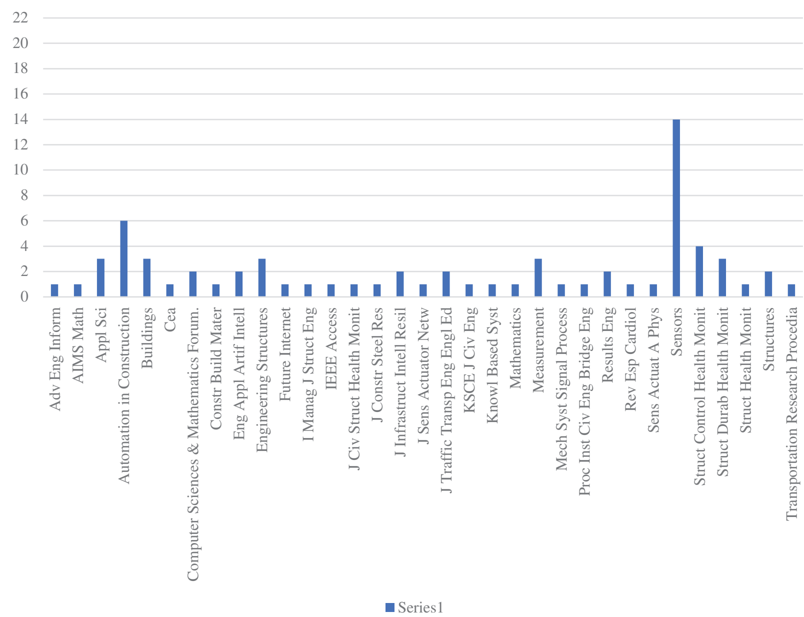

Figure 3: Trend of journals or publishers that published

Note: Six journals that are included in this research made more than one publication.

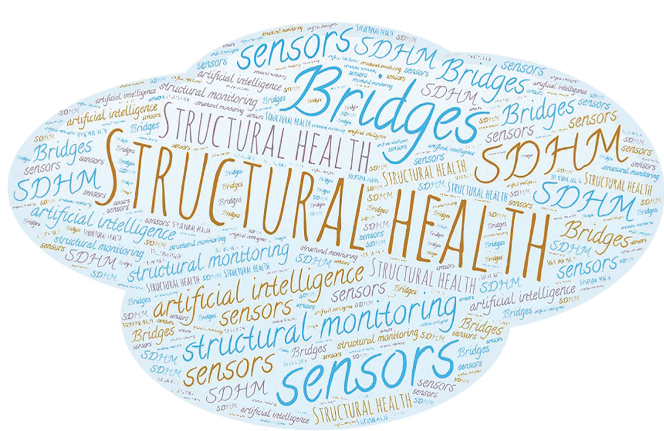

Figure 4: Words with the highest recurrence

Note: The words with the highest incidence in scientific articles are ordered by size from largest to smallest according to their frequency.

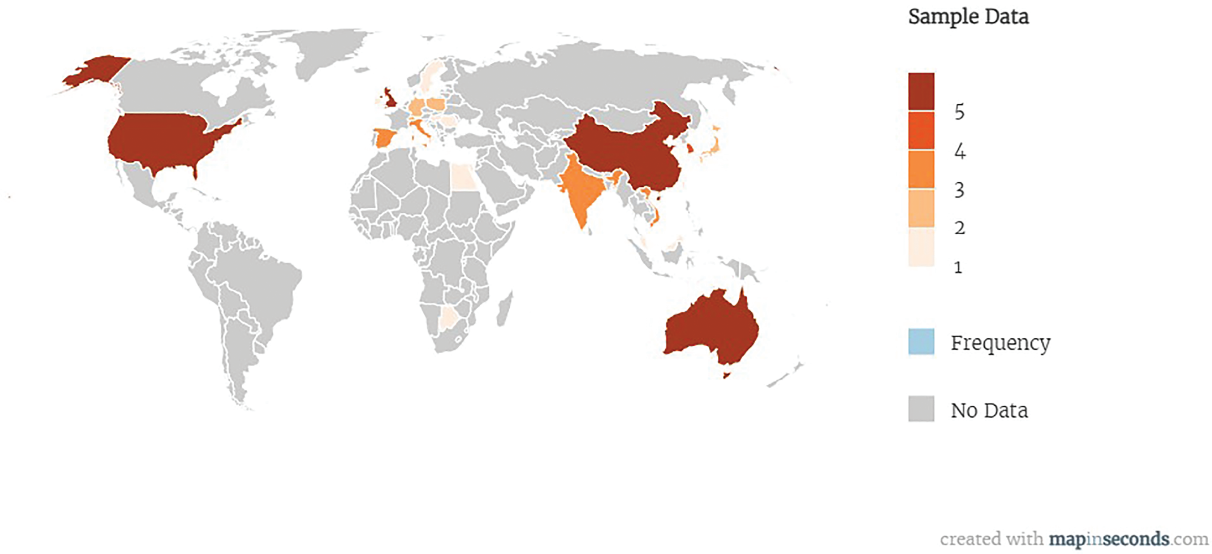

Figure 5: Frequency of publication by country

Note: Geographical location type heat map of where the countries with the most publications are located. Own elaboration since https://mapinseconds.com/.

In Fig. 6, it can be seen that the database where they were found:

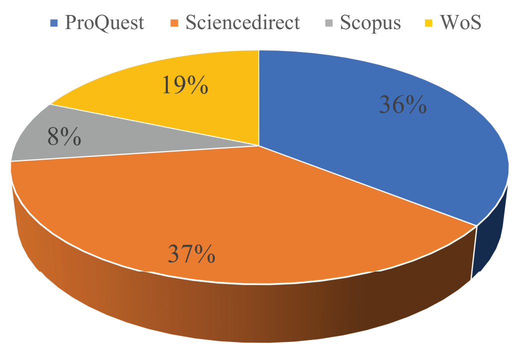

Figure 6: Number of articles per database

Note: The data are taken from the articles that remained after the PRISMA phases.

The fewest articles are for Scopus with 8% referring to 6 articles, followed by Web of Science with 19% with a total of 13 articles, followed by Sciencedirect with 37% containing 26 articles and finally with 36% referring to 25 articles for ProQuest with a greater number of studies used for this research work.

Critical evaluation of studies

Fig. 7. a risk of bias graph by the PRISMA method is presented of each article reviewed in this work, Therefore, it was decided to review the 70 articles evaluated in 4 criteria, Clarity of the methodology with 58 articles at the High level, 12 at the medium level, and 0 at the low level; for description of the data source we have 0 at high level, 12 at level and 58 at low level; for Cross-Validation or Independent Testing we have 5 high level, 17 medium level, 48 low level; For transparency in the

results, we have 3 at high level, 12 at medium level and 55 at low level, resulting in a total risk of bias of a risk that is mostly low level, that is, as research with a low level of bias and with greater reliability.

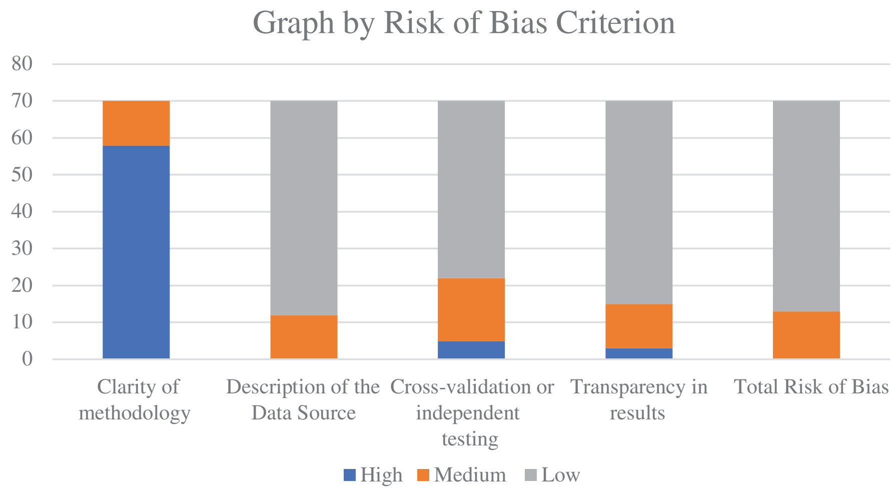

Figure 7: Main risk of bias criteria

Note: 4 criteria are presented for the analysis of biases using the PRISM method using a spreadsheet.

Results of the Synthesis

After reviewing the literature, the research question is answered How has artificial intelligence been applied in the monitoring of the structural health of bridges in the last decade? A qualitative analysis strategy will be used, with tables ordered by columns with data extracted from each of the articles. Therefore, the articles are selected according to those that answer the research question, exposing the results by category found such as author, country, type of AI applied, type of structure, algorithm used, metric, data used. To this end, 70 international studies on artificial intelligence applications in structural health monitoring (MHS) from 37 different countries were analyzed, reflecting a high degree of global interest and collaboration in this area. The most commonly used types of AI include artificial neural networks (ANNs), supervised and unsupervised machine learning, as well as variants of Usi learning such as CNN and RNN.

Table 4 shows that the monitored structures are predominantly railway and vehicular bridges, although laboratory prototypes and other civil structures are also included. The reported accuracy rates are remarkably high, exceeding 98% in several cases, suggesting great potential for these technologies in damage detection, failure prediction, and maintenance optimization.

Fig. 3 shows, for example, in [18] an artificial neural network with two hidden layers, fed with signals from accelerometers was applied to a railway bridge, reaching an accuracy of 99.3% in cross-validation, which confirms the effectiveness of ANNs as long as there is adequate calibration of sensors. In a complementary way, ref. [8] he proposed a model based on XGBoost and stacking techniques, achieving up to 98.2% in the laboratory and 93.1% in a real bridge, evidencing the ability of supervised algorithms to anticipate structural damage. Finally, ref. [29] he employed PINNs models, reaching errors of less than 0.03 mm in laboratory prototypes, which highlights their potential in scenarios with little experimental data, although with a high dependence on detailed physical models.

Table 4: Summary of revision values

Main AI algorithm	Sensor(s)	Validation environment	Primary Metric (Mean ± SD)	Limitation detected
CNN+ Hybrids— [3,10,25]	RGB/UAV cameras, accelerometers, IoT sensors	Rail and vehicular bridges, field/lab	97.5% ± 2.5%	Sensitive to variations in illumination and occlusions
XGBoost + Stacking— [8]	Accelerometers	Royal Bridge and Laboratory	95.65% ± 3.6%	Need for manual feature extraction
Fuzzy logic— [9]	MPU6050, Temperature/Humidity, IR	Scale prototype	±1 mm deflection error	Scarce generalization to real structures
LSTM, BiLSTM— [11,36]	Vibration, deflection, UAV, LiDAR sensors	Field (Royal Bridges)	$R^2 = 0.963 \pm 0.022$	Requires large time series
Autoencoder /VAE— [12,21]	Accelerometers, inclinometers, cameras	Laboratory and simulation	95.8% ± 3.0%	False positives in noise conditions
Unet/Mask R-CNN— [17,25,46,48]	High-resolution images, embedded sensors	Field & UAV	96.2% ± 2.4% (mAP/F1)	High computational cost
ANN (2 hidden layers)— [18]	Triaxial accelerometers (Xnode, OpenMV H7 Plus)	Railway bridge, field	99.3% ± 1.0% (test and cross-validation)	Reliance on Accurate Sensor Calibration
SVM— [20,41,42]	Accelerometers, fiber optics, imaging	Concrete/Steel Bridges	$R^2 = 0.945 \pm 0.025$	Variable performance depending on damage type
Transfer learning (TCA+SVM)— [28]	Accelerometers, wind, inclinometers	Royal Suspension Bridges	100% accuracy, F1 = 0.836	Poor availability of labeled data

(Continued)

Table 4 (continued)

Main AI algorithm	Sensor(s)	Validation environment	Primary Metric (Mean ± SD)	Limitation detected
PINNs— [29]	MEMS, camera, laser sensor	Lab prototype	Error 0.03 ± 0.005 mm	

The comparative summary shows that there is no single dominant approach for bridge SHM, but that the choice of algorithm and sensor depends on the type of information to be processed and the validation context.

CNNs and variants achieve the highest visual inspection accuracy (≈97%–99%), but their performance is affected by illumination variations and occlusions. LSTMs/BiLSTMs are most effective in vibration and deflection time series ($R^2 \approx 0.95$), even thoughthey require large volumes of continuous data. Hybrid models (e.g., XGBoost + CNN, Autoencoders) improve noise robustness, but increase computational complexity. Finally, PINNs stand out for their low dependence on experimental data and high millimeter accuracy, although they require detailed physical models.

Overall, the average metrics confirm high performance in controlled environments (Overall accuracy 96.4% ± 2.8%, R^2 0.949 ± 0.019), but the transfer of these results to the field remains limited by technical, economic, and interoperability factors.

Artificial intelligence techniques applied according to functional

From the analysis of the systematized studies, it was identified that artificial neural networks (ANN) and convolutional neural networks (CNNs) are the most applied in bridge SHM, particularly for damage classification tasks and interpretation of signals and structural images. For example, in the study [18], an ANN with ReLU activation and sigmoid function achieved 100% accuracy in the test set and 98.67% in 10 fold cross-validation. This model was powered with signals from accelerometers mounted on railway bridges. In addition, the use of CNN was widely reported in [3,11,20], with accuracies greater than 95%, demonstrating its efficiency for image segmentation and crack detection.

Among the most representative studies, ref. [3] reported the use of CNN in crack segmentation tasks with accuracies greater than 95%, confirming the usefulness of computer vision in bridges. For its part, ref. [10] conducted a review on deep learning in SHM, identifying advances and limitations in the scalability of these techniques. Similarly, ref. [12] it implemented unsupervised autoencoders for anomaly detection, achieving detection rates close to 96%, reinforcing the value of unsupervised approaches in contexts with a scarcity of labeled data.

Emerging techniques such as Transformers, Autoencoders, Graph Neural Networks (GNN), and Physics Informed Neural Networks (PINNs) are gaining traction for their ability to improve model generalizability under conditions with limited or simulated data [11,12]. For example, variational autoencoders (VAEs) showed anomaly detection rates greater than 96% in unsupervised environments [13]. In addition, studies that applied model assemblies, such as XGBoost combined with traditional classifier stacking (SVM, kNN, DT), achieved an accuracy of up to 98.2% in laboratory environments and 93.1% in real bridges [8].

Among the emerging techniques, the use of generative models applied to SHM stands out. In [12], the implementation of autoencoders and variational autoencoders (VAE) allowed anomaly detection to be performed with success rates close to 96% in unsupervised environments, demonstrating its potential for scenarios with scarcity of labeled data. In a complementary way, ref. [10] it included in its review the application of Generative Adversarial Networks (GANs), used for data synthesis and improvement in the segmentation of specific damages. These approaches reinforce the usefulness of generative AI in creating more robust datasets and simulating damage scenarios that are difficult to replicate in the field.

Recent advances have further demonstrated the role of data augmentation in overcoming the scarcity of labeled data for structural damage classification. Dunphy et al. [21] investigated the use of Generative Adversarial Networks (GANs) to generate synthetic images for multiclass damage detection on concrete surfaces. Their study showed that while the inclusion of synthetic data slightly reduced the accuracy (by about 1%–2%) compared to training only with real samples, it significantly improved model generalization and reduced bias caused by class imbalance. This highlights the potential of combining GAN based augmentation with deep convolutional networks to improve robustness under limited data conditions.

However, a relevant gap remains: many studies still do not employ rigorous cross-validation or real world testing, limiting the robustness of algorithms under diverse operating conditions. There is also a paucity of studies that systematically compare AI models in identical scenarios, which makes it difficult to establish more robust comparative standards.

Sensory architecture and complementary technologies

In relation to capture and sensing technologies, studies demonstrate a wide spectrum of sensors used in combination with AI. The most common include triaxial accelerometers, fiber optic sensors, RGB/UAV cameras, temperature sensors, and gyroscopes [11,17,18].

In some cases, computer vision sensors and 3D point clouds were implemented using LiDAR to power networks such as YOLOv5 and DeepLabv3+ [25]. In addition, the recent trend is to integrate embedded sensors and IoT, as evidenced in [23,24], where integration with cloud platforms allowed for real-time visualization of structural data.

One of the most notable contributions is the use of humidity, vibration and temperature sensors combined with UAVs to monitor wooden bridges with high experimental accuracy [23]. Prophet and Unettype neural networks were also applied to data collected by embedded sensors in particular, with force impedance correlations of up to 0.99 and MAPE errors of less than 1% [17]. These results demonstrate the potential of merging heterogeneous sensory architectures with AI to expand the coverage and depth of the SHM.

A relevant example is the work of [23], which integrated humidity, vibration and temperature sensors with UAVs for the monitoring of wooden bridges, achieving high experimental precision. Likewise, ref. [17] he applied embedded sensors combined with Unet networks, achieving force impedance correlations of up to 0.99 and MAPE errors of less than 1%. These results show the impact of merging heterogeneous sensory architectures with AI algorithms in improving structural diagnostics.

However, technical challenges remain: many sensors are not calibrated for long term structural use, and interoperability between IoT platforms, physical sensors, and AI algorithms remains limited. This gap represents a clear opportunity to advance integrated, autonomous and adaptive SHM systems.

As for sensors, most studies integrated high-frequency accelerometers, fiber optic sensors, and computer vision [15]. Some incorporated satellite imagery and UAV data to detect large scale deformations or cracks, especially in structures with difficult access [16]. The use of IoT sensors enabled for wireless networks was reported in more recent articles, allowing remote transmission and real-time monitoring [17]. The combination of sensor and algorithm was decisive in the quality of the structural diagnosis. Table 3 also reports these combinations and their technical effectiveness.

The studies evaluated performance using metrics such as precision, F1-score, sensitivity, accuracy, and robustness to noise. CNNs achieved accuracy greater than 98% in visual damage classification [18], while LSTMs achieved R^2 greater than 0.95 in displacement prediction [19]. The combined use of metrics made it possible to contrast the strengths of each algorithm.

In terms of performance, ref. [18] reported accuracies greater than 98% using CNN in the classification of visual damage, while [19] reached R^2 values greater than 0.95 in displacement prediction with LSTM. These cases illustrate how each technique adapts to different types of data and metrics, although they also underscore the need to standardize indicators to allow for consistent comparisons between studies.

Fig. 8 presents an infographic conceptual framework for the implementation of intelligent structural health monitoring (SHM) systems on bridges, integrating sensors, edge processing, artificial intelligence (AI), and an adaptive cycle of continuous improvement. This model seeks to solve the technical and operational challenges faced by critical infrastructures when applying AI-based solutions, especially in real environments.

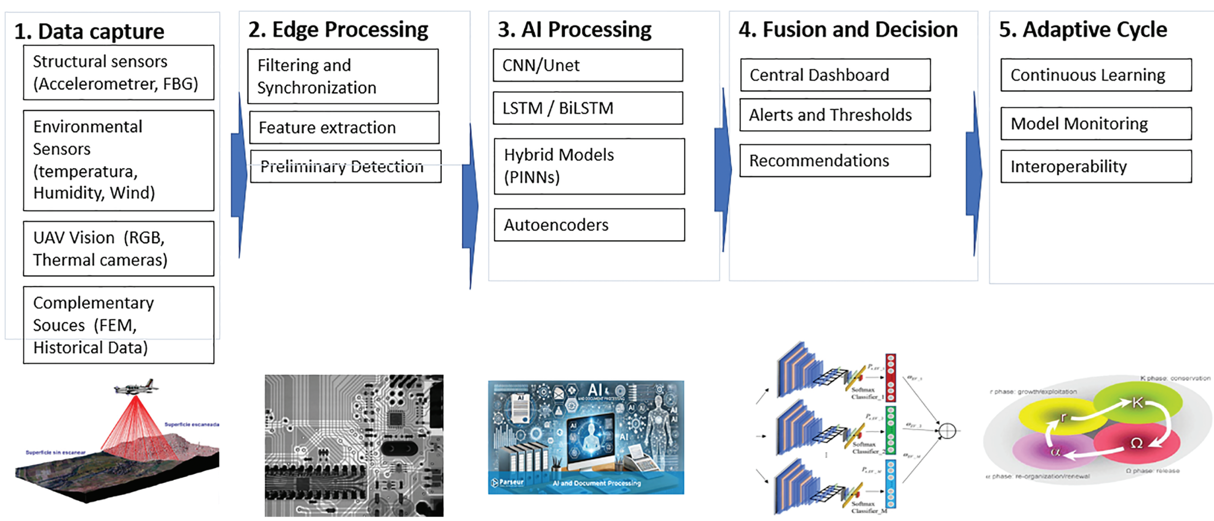

Figure 8: Proposed framework

1. Data Capture:

The first stage of the system integrates structural sensors such as accelerometers and FBGs, environmental sensors (temperature, humidity, wind), cameras installed on unmanned aerial vehicles (UAVs), and even complementary sources such as finite element models (FEM) and historical models. This diversity allows for a holistic view of the structural behavior of the bridge under multiple conditions.

2. Edge Processing:

The captured data is filtered, synchronized and transformed into key features by local computing modules or edge computing. This layer reduces latency, improves privacy, and allows for early detection of anomalous events without the need for constant connection to external servers.

3. Artificial Intelligence Processing (AI Processing):

Different AI techniques are used depending on the type of data: convolutional networks (CNN/UNet) for imaging, recurrent models (LSTM/BiLSTM) for time series, autoencoders for anomaly detection, and hybrid architectures informed by physical models (PINNs) to improve generalization. This layer forms the core of predictive and diagnostic analytics.

4. Merger and Decision Making:

The results are integrated into a central dashboard that provides real-time visualizations, automatic alerts, and maintenance recommendations. The fusion of multichannel information allows for a more robust assessment of structural condition and facilitates data driven decision-making.

5. Adaptive Cycle:

Finally, a continuous learning cycle is incorporated that monitors the performance of the models, adjusts thresholds, retrains algorithms and guarantees interoperability with new sensors or platforms. This allows the system to evolve in the face of new conditions or structures, maintaining its effectiveness over time.

Methodological limitations and gaps

The quality analysis revealed that 96% of the articles presented methodological clarity, however, more than 90% lacked transparency regarding data sources, and most did not apply robust cross-validation. This limits the replicability and extrapolation of the models [20]. Fig. 7 summarizes this assessment. In addition, underrepresentation of studies in real operating conditions or developing regions was identified, where structural monitoring would be more critical.

4 Discussion

The present research was developed under the PRISMA (Preferred Reporting Items for Systematic Reviews and MetaAnalyses) methodological approach, which allowed a rigorous, transparent and replicable systematic review on the use of artificial intelligence in structural health monitoring (SHM). Through a structured filtering and evaluation process, 70 relevant studies from a wide diversity of geographical and technological contexts were identified.

The results show a sustained growth in the application of artificial intelligence techniques, particularly highlighting the use of artificial neural networks (ANN), deep learning models (CNN, RNN, LSTM), fuzzy logic and knowledge transfer techniques. This finding agrees with what was reported by authors such as [18], who implemented a double-layer neural network with 100% accuracy in testing, and [3], who used CNN with signal processing techniques. These techniques not only stand out in their individual performance, but also in their combination through hybrid architectures, as observed in studies that integrate CNN with SVM, Random Forest or LSTM, achieving F1-score above 95% in multiple tasks.

The systematic PRISMA approach allowed to recognize common patterns among the studies, such as the preference for bridges as analysis structures, the growing use of computer vision, and the integration of multichannel sensors and IoT. For example, [8] they used models in assembly with

XGBoost, obtaining an accuracy of 93.1% in real bridges and 98.2% in laboratory structures. On the other hand, [10] they demonstrated how GANs and autoencoders improve the segmentation of damage in concrete with outstanding results, while [29] they highlight the use of AI informed physical models (PINNs), achieving prediction errors of less than 0.03 mm and inference speeds of less than 30 ms.

The diversity of data sources was also evident thanks to the PRISMA approach, allowing comparisons from traditional embedded sensors to satellite images, UAVs, acoustic signals and synthetically generated data. Ref. [28] work, based on transfer learning, stands out as an innovative example for dealing with structures with little historical information. Likewise, studies such as [41] apply models such as Random Forest to evaluate the effectiveness of structural reinforcements with an accuracy of more than 99%, showing the usefulness of AI not only in the diagnosis, but also in the verification of structural interventions.

In terms of performance, there is evidence of a concentration of high-precision metrics in studies that use CNN, LSTM and autoencoders. The most reported metrics include accuracy (>95%), R^2 (>0.90), and F1-score, but a methodological gap was also identified in the use of statistical tests, cross-validation, and reporting of confidence intervals. This weakness compromises the possibility of comparison between studies and limits scientific reproducibility. It is therefore recommended to establish a minimum set of standardised metrics that include accuracy, sensitivity, specificity, R^2 and MAE.

Finally, important gaps were identified that require attention in future research: (i) scarce application of models in real operational contexts; (ii) limited presence of studies in developing countries; (iii) lack of interoperability between sensors, algorithms and digital platforms; and (iv) absence of explainability criteria in AI models. These limitations represent opportunities to move towards more autonomous, reliable and ethically responsible SHM systems.

Despite the advances reported in the literature, the practical implementation of artificial intelligence in structural health monitoring faces significant challenges. These include the limited availability and quality of data, which restricts the generalization capacity of the models; the loss of accuracy when algorithms are applied to real scenarios with variable materials, geometries and loads; and the poor explainability of deep learning models, which makes it difficult for engineers and decision makers to accept them. In addition, real time deployment requires robust hardware, low latency communications, and low power devices, which still represent technical limitations. Finally, the high costs of sensors, IoT platforms, and AI analytics systems constitute a barrier to mass adoption, especially in developing countries. Overcoming these challenges will be essential for AI-based solutions to evolve from research prototypes to scalable, reliable, and economically viable systems in critical infrastructure monitoring.

Industry Challenges, Potential Solutions, and Demands

The application of artificial intelligence (AI) to bridge Structural Health Monitoring (SHM) faces challenges that transcend the academic field and are directly linked to the needs of the industry. The main obstacles include the scarcity of standardized and open data, the limited generalizability of the models, the lack of interpretability of the algorithms, and the high costs of implementation, even for specialized AI schemes like those for composite plates [52]. The need to integrate AI in SHM is critical, as highlighted by systematic reviews on advances, challenges, and future directions [53].

On the other hand, the use of deep neural networks (DNNs) with multi-sensor data [54] and intelligent low-cost accelerometers with a deep learning approach [55] show great potential. Likewise, the generation of synthetic data using Generative Adversarial Networks (GANs) is emerging as an effective strategy to address the scarcity of labeled data and manage data variability [56]. Other techniques, such as the use of GAN-based imputation frameworks [57,58] and the detection of setting time in cement hydration using IoT sensors [59], are also gaining traction. Advances like the GAN-based autoencoder for SHM [60] reinforce the trend toward synthetic data.

A possible solution lies in promoting collaborations between academic institutions, companies and government agencies to generate shared databases and validation protocols in real conditions, often involving fiber optic sensors [61]. The use of hybrid approaches that combine AI models with physical or knowledge-based techniques, such as for automated structural bolt looseness detection [62], has been shown to improve accuracy. The integration of smart sensors with Edge Computing capabilities has also made it possible to improve efficiency and reduce latency, facilitating real-time monitoring on real bridges [63].

Furthermore, future research should focus on the prediction of deterioration and structural lifespan, an area that is still little explored, leveraging the power of Transformer-based time-series GANs for bridge digital twins [64]. The use of Physics-Informed Neural Networks (PINNs) shows great potential for integrating physical laws into predictive models, especially in applications like railway bridge monitoring [65]. The integration of Big Model strategies with hybrid AI and adaptive methods is also a promising horizon [66]. Future research also targets fusion methods for bridge damage detection under complex backgrounds [67].

From an industry perspective, the development of accessible and low-cost solutions, such as discussing a smart SHM platform for long-span bridges [68], is essential. Interoperability between sensors, algorithms and digital platforms, together with the integration of adaptive learning, is a priority demand of the industry, particularly in vibration-based SHM [69]. The development of explainable AI (XAI) approaches, which ensure interpretability and confidence in decision making, is crucial [52,61]. The combination of deep learning, hybrid AI, and adaptive Big Model strategies appears as a promising horizon [62,69].

Overall, artificial intelligence emerges as an indispensable tool for modern SHM, not only in damage detection, but also in maintenance optimization, structural behavior prediction, and intervention validation. In the future, it will be key to integrate explainable approaches, open data and adaptive learning to expand the real applicability of these technologies. Under rigorous standards such as PRISMA, AI can revolutionize structural monitoring, bringing accuracy, efficiency, and autonomy to the management of critical infrastructures [69,70].

5 Conclusions

Based on the rigorous analysis of 70 studies selected under the PRISMA methodology, the research questions posed in this study are answered:

Question 1: Which AI techniques are most commonly used in bridge SHM and at what level of performance? The most commonly used techniques include artificial neural networks (ANNs), convolutional networks (CNNs), recurrent networks (LSTM, RNNs), hybrid models (such as CNN-SVM), and emerging techniques such as Transformers and Graph Neural Networks. These achieved outstanding metrics: accuracy greater than 95%, R^2 greater than 0.90, and F1-score greater than 90%, in tasks such as crack detection, deflection prediction, and multiclass classification of damage. Data reported physical models (PINNs) with average errors of only 0.03 mm in structural prediction were also identified. However, there is limited standardization of metrics and little comparison between models under similar conditions, which represents an area for urgent improvement.

Question 2: What sensors or technological architectures are combined with AI in structural bridge monitoring? The most frequent sensors were triaxial accelerometers, fiber optic sensors, UAV cameras, humidity, temperature, strain sensors, and embedded IoT modules. These technologies were integrated into architectures that enable multichannel capture, remote monitoring, and real-time feedback. The combination of these sources with AI demonstrated a substantial improvement in diagnostic capacity, with correlations greater than 0.99 between structural strength and impedance, and crack segmentation accuracy of 97% in some cases. Still, technological interoperability and long-term structural calibration of sensors remain key challenges.

Question 3: What are the main methodological gaps in the application of AI to bridge SHM? More than 90% of studies lack robust cross-validation, replicability with open data, or testing in real-world operating environments. Insufficient use of standardized statistical metrics was evidenced, as well as the scarce incorporation of explainable models and multigeographic data. This situation compromises the practical extrapolation of the results. Therefore, it is recommended to move towards an integration of AI with more rigorous validation criteria, hybrid simulations, open data, and adaptive architectures.

In summary, artificial intelligence offers disruptive potential in the structural monitoring of bridges, enabling more accurate, autonomous, and efficient solutions. However, its effective adoption requires overcoming methodological, technological, and contextual challenges that still limit its widespread applicability.

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Availability of Data and Materials: All data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethics Approval: Not applicable. This research is a systematic literature review and does not involve human participants or animals.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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