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Review article

Edge-to-cloud computing and intelligence for IoT-based Structural Health Monitoring: A comprehensive review

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ABSTRACT

Structural Health Monitoring (SHM) is experiencing a paradigm shift from reactive, human-dependent systems toward proactive, autonomous entities empowered by ubiquitous computing and intelligence, embedding computational capabilities seamlessly from edge sensors to cloud platforms and enabling continuous monitoring, adaptive learning, and intelligent decision-making. This review systematically examines IoT-based SHM for generic structures through the unified lens of ubiquitous computing and intelligence, transcending the fragmented treatment of IoT systems, AI methods, and SHM applications in previous reviews. Employing a novel three-perspective analytical framework that integrates architectural paradigms, computational intelligence algorithms, and application domains, this work establishes ubiquitous computing and intelligence as the central organizing principle, revealing how components mutually enable and constrain each other across the SHM ecosystem. The review demonstrates that ubiquitous computing and intelligence hold tremendous potential for enhancing SHM performance across multiple dimensions, with systems undergoing profound transformation from centralized to distributed paradigms. However, critical challenges persist, including resource–performance trade-offs, data quality issues, privacy-data sharing tensions, and real-time reliability requirements. Future research directions center on distributed intelligence paradigms harmonizing edge–cloud computing, hybrid AI frameworks, and emerging technologies, pointing toward SHM systems evolving into proactive, self-adapting intelligent partners seamlessly integrated with infrastructure.

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1. Introduction

SHM is entering a new phase that emphasizes distributed or ubiquitous computing and intelligence, representing a fundamental shift from reactive, human-dependent systems to proactive, autonomous entities capable of pervasive sensing and intelligent decision-making [1,2]. This transformation has been accelerated by the convergence of key technologies including IoT, AI, Digital Twin, and edge computing [3–7], with IoT serving as the foundational infrastructure enabling continuous data flow and seamless connectivity across diverse environments [2,8]. Ubiquitous computing [9], as a fundamental paradigm, refers to the seamless integration of computational capabilities throughout the physical environment, where computing resources are embedded, distributed, and accessible anywhere and anytime. In the spatial dimension, this pervasive nature encompasses the full spectrum of computational resources from edge devices to cloud platforms, representing comprehensive coverage of diverse computing paradigms across the entire system architecture. This comprehensive view requires attention to both traditional centralized, cloud-based computing paradigms with resource-rich capabilities and distributed, edge-device-based computing paradigms with resource-constrained characteristics. Similarly, from the algorithmic perspective, this review examines not only traditional signal processing methods and classical AI approaches, but also emerging AI technologies and their integration with edge devices, which enable intelligent computation at the network periphery. In the context of IoT-based SHM, this paradigm manifests as a pervasive computational infrastructure spanning from edge sensors to cloud platforms, enabling continuous monitoring, real-time analysis, and intelligent decision-making across all system layers. This review addresses three key research questions: (1) How can computing principles systematically unify the entire IoT-based SHM ecosystem from edge to cloud? (2) What are the key architectural, algorithmic, and application perspectives that enable intelligent and autonomous SHM systems? (3) What are the critical challenges and future research directions for advancing computing and intelligence in SHM?

This comprehensive review systematically examines the literature on IoT-based SHM systems published from 2016 to 2025, focusing on peer-reviewed journal articles involving computing paradigms, intelligent algorithms, and their applications in structural monitoring. To provide a quantitative foundation, we conducted bibliometric analysis of 7326 publications retrieved from 19 selected core SHM-related journals through the OpenAlex API, using a comprehensive two-step search approach with 13 domain-specific keywords to identify relevant papers in titles, abstracts, and keywords. The 13 search keywords are: "structural health monitoring", "shm", "health monitoring", "structural monitoring", "condition monitoring", "damage detection", "damage identification", "fault detection", "anomaly detection", "system identification", "structural assessment", "structural integrity", and "damage assessment". The selected journals, as illustrated in Fig. 1(a), span multiple disciplines including civil engineering, materials science, signal processing, and sensor technology, reflecting the interdisciplinary nature of IoT-based SHM research. The temporal analysis of publication trends, shown in Fig. 1(b), demonstrates significant growth with volume accelerating after 2018. Notably, the proportion of publications employing AI/ML methods has increased from 2.4% in 2016 to 50.5% in 2025, with AI adoption reaching 33.4% of all publications in the analyzed dataset, reflecting the field's evolution toward mature, deployable intelligent systems. The keyword co-occurrence analysis, visualized in Fig. 2, reveals important concepts in the field and the strength of their interconnections, with keywords extracted exclusively from paper titles to ensure focused representation of research themes. Fig. 3 presents the distribution of various ML/AI methods among data-driven publications identified in our bibliometric analysis, revealing the relative adoption rates of different algorithmic approaches. A notable trend is that emerging methods in recent years still have substantial room for growth in their adoption rates, indicating opportunities for further exploration and application of advanced AI techniques in IoT-based SHM systems.

Fig. 4 provides readers with a panoramic view and coordinate system that helps them understand the position of each topic within the entire IoT-based SHM ecosystem, serving as a navigational framework for the comprehensive review. To provide a comprehensive understanding of computing in IoT-based SHM, this review first examines the underlying infrastructure and data workflows that form the foundation for computational capabilities, as illustrated in Fig. 4. The IoT system serves as the foundational layer, providing the physical and computational backbone for continuous structural monitoring through a complex ecosystem of sensing devices, communication networks, and processing units. Central to this infrastructure is the data pipeline, which captures the temporal logic of SHM operations through two main phases: data collection (acquiring accurate and reliable information) and data consumption (transforming data into actionable insights). Understanding this infrastructure is essential before examining how distributed computing transforms these processes toward greater automation and intelligence.

Existing reviews in IoT-based SHM have made valuable contributions by examining various aspects of the field, including centralized and cloud computing architectures [10], knowledge-driven and data-driven computational methods [11,12], and application domains such

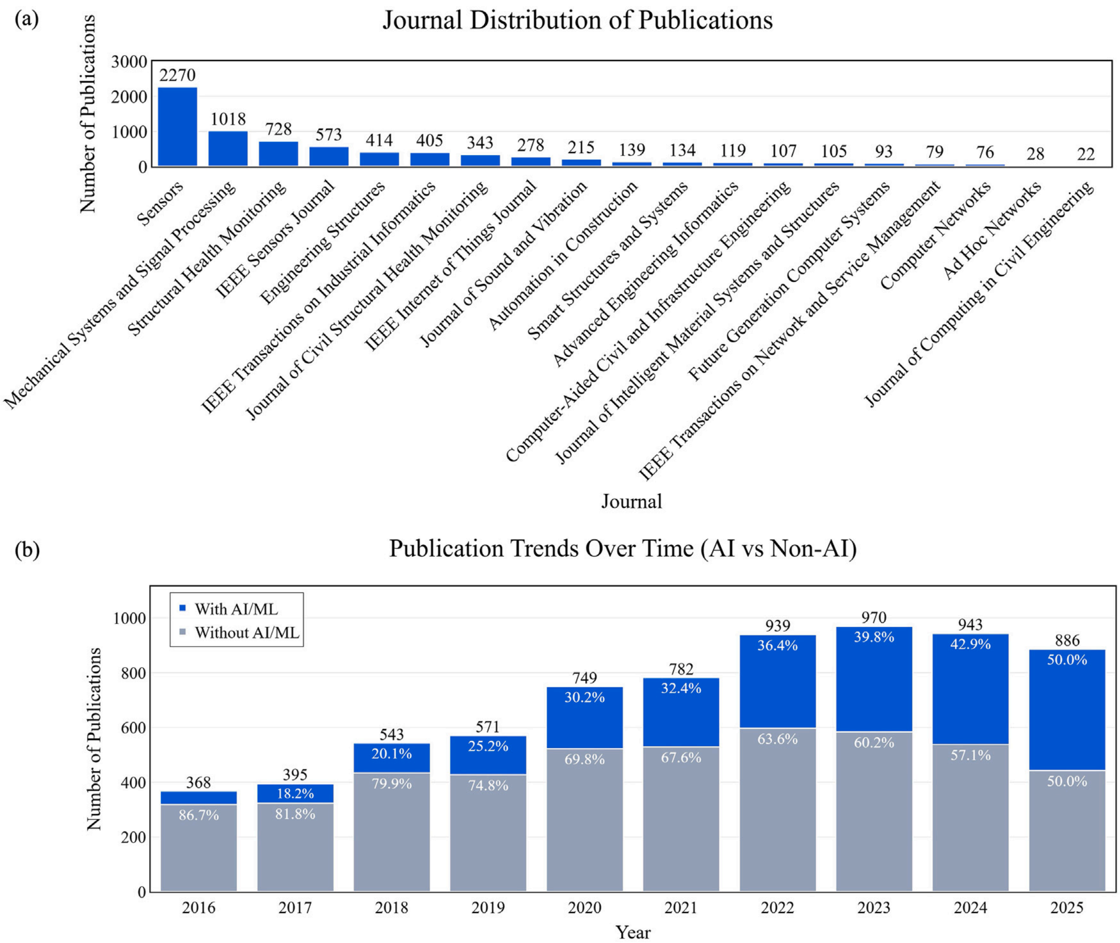

Fig. 1. Bibliometric analysis of IoT-based SHM literature: (a) distribution of publications across selected SHM-related journals and (b) publication trends over time (2016–2025).

as measurement, system identification, and damage assessment [13, 14]. However, these reviews typically examine IoT systems, AI methods, or SHM applications as separate domains, resulting in fragmented coverage. Most existing reviews approach the field from a civil engineering perspective, with limited exploration of IoT system perspectives that reveal how computational paradigms reshape monitoring capabilities. Even when reviews address IoT system aspects, they predominantly concentrate on traditional centralized computing and cloud-based architectures [10,13], with limited systematic exploration of edge computing and distributed intelligence paradigms. From the computational methods perspective, existing reviews have provided comprehensive coverage of knowledge-based approaches and traditional AI-based methods [11,12,15,16], but have not yet incorporated the latest developments in AI technologies, particularly large language models (LLMs), agentic AI, and other emerging AI paradigms. From the application perspective, numerous reviews have discussed SHM applications but have not systematically integrated them with computing paradigms, architectural considerations, and emerging AI methods. Collectively, these limitations point to a fundamental gap: the absence of a comprehensive review that systematically examines IoT-based SHM through the unified lens of ubiquitous computing and intelligence. In contrast to these previous reviews, this work addresses these gaps by establishing ubiquitous computing and intelligence as the central organizing principle that unifies architectural, algorithmic, and application dimensions through a novel three-perspective analytical framework.

Given the broad and interdisciplinary nature of this field, an effective strategy for conducting a comprehensive review is to organize the discussion around key perspectives that bridge diverse concepts and technologies. This paper introduces a three-perspective analytical framework that establishes ubiquitous computing and intelligence as the central organizing principle, systematically integrating architectural, algorithmic, and application dimensions within a unified structure. As illustrated in Fig. 4, the framework encompasses: (1) computing paradigms and architectures, examining how computational resources are organized across edge, fog, and cloud layers; (2) intelligent algorithms, distinguishing between knowledge-based and AI-driven approaches; and (3) SHM applications, covering core tasks including measurement, system identification, and damage assessment. This unified perspective enables systematic examination of how computational capabilities are embedded, distributed, and coordinated throughout the monitoring environment, from edge sensors to cloud platforms.

Unlike previous reviews that predominantly focused on cloud computing and traditional AI methods, this review places particular emphasis on edge computing and emerging AI techniques, systematically examining how these technologies advance intelligent monitoring in SHM. This review makes three key contributions: (1) it provides the first comprehensive review that systematically integrates edge-to-cloud computing paradigms within a unified framework, addressing the fragmentation in existing literature; (2) it introduces a three-perspective analytical framework that treats computing and intelligence as the unifying force connecting the entire SHM ecosystem, enabling holistic understanding of how computational capabilities transform structural monitoring; and (3) it provides comprehensive coverage of edge computing capabilities and emerging AI methods (including intelligent agents, embodied intelligence, federated learning, and LLMs), examining how these technologies advance intelligent monitoring in SHM

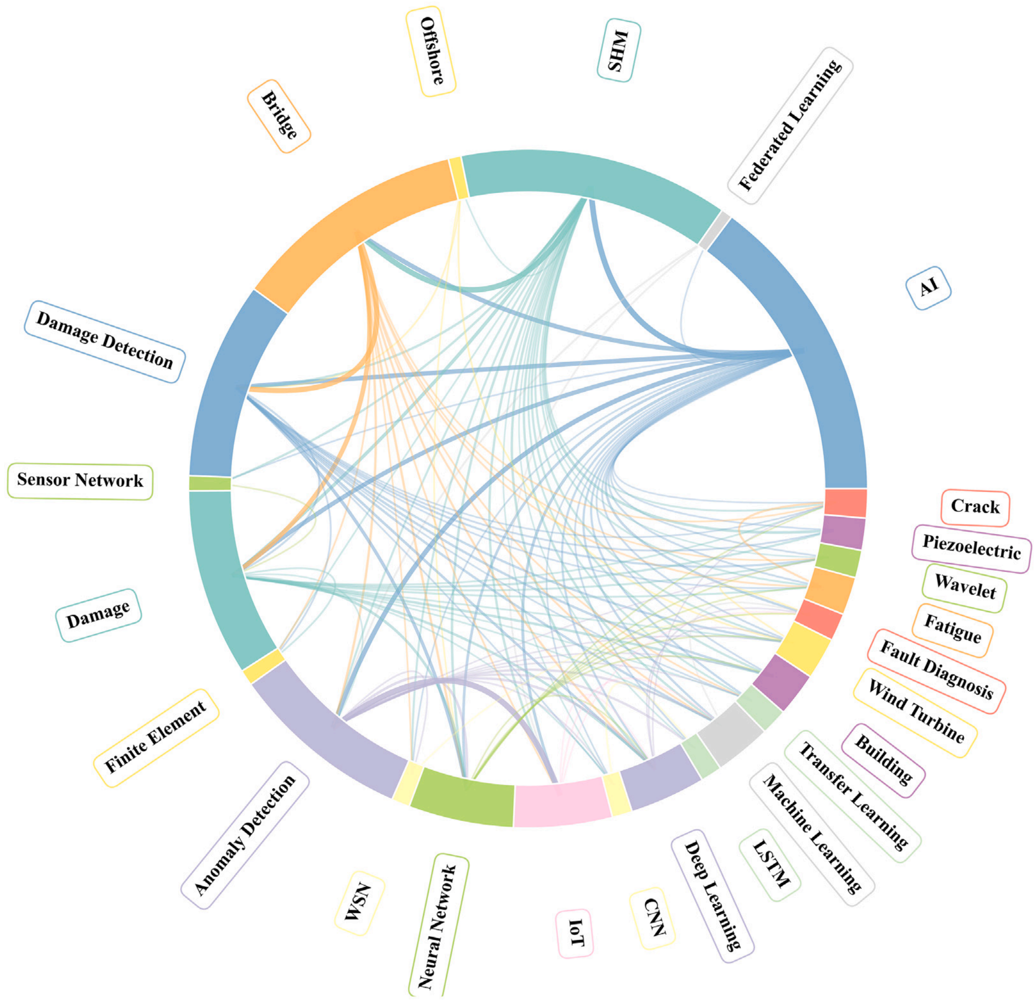

Fig. 2. Network analysis of keyword co-occurrence in SHM research from selected core journals (2016–2025).

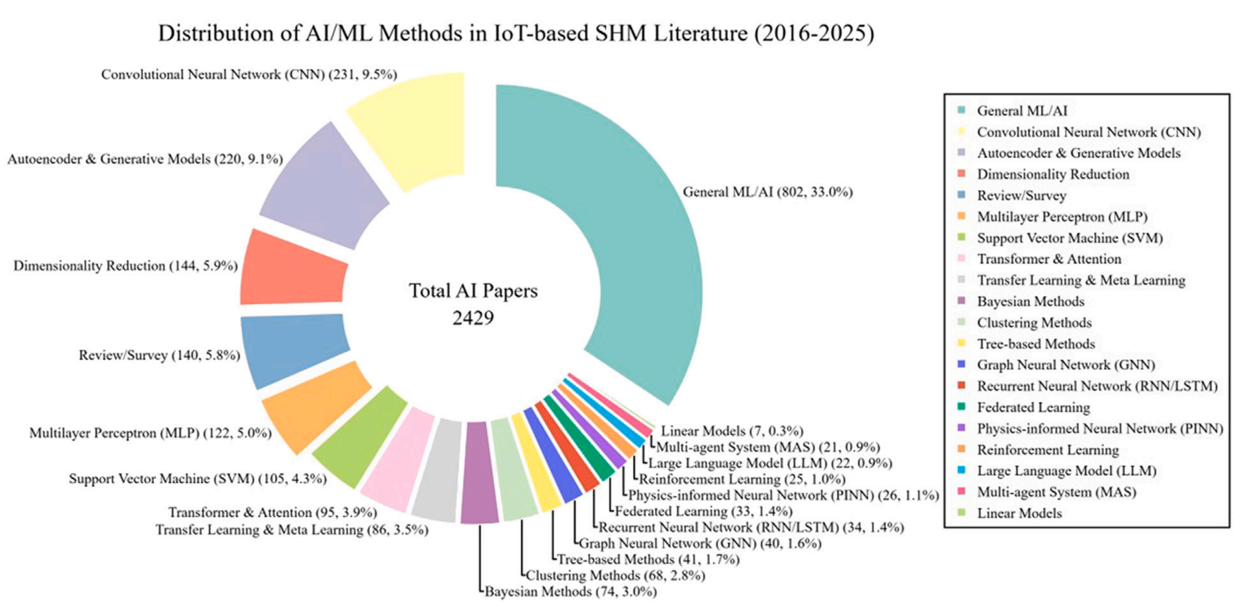

Fig. 3. Distribution of AI methods among AI/ML-enabled publications from the bibliometric analysis (2016–2025).

applications, while analyzing over 20 representative case studies to validate the framework and reveal practical implementation challenges. Together, these contributions position this review as both a timely synthesis of current state-of-the-art and a forward-looking roadmap

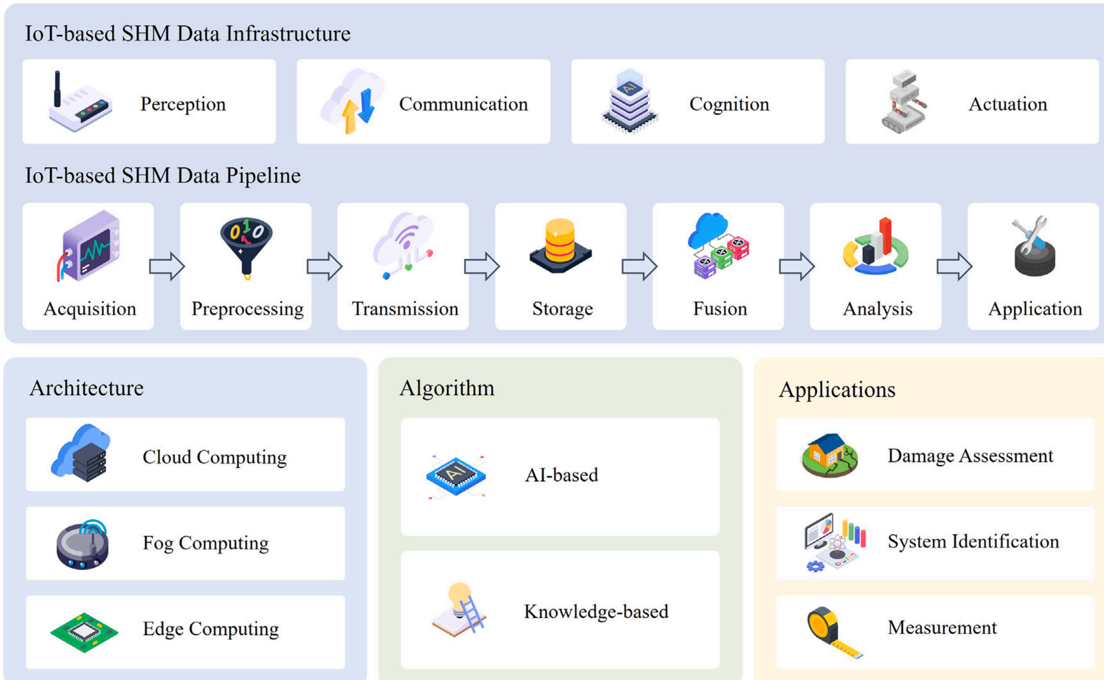

Fig. 4. Schematic illustration of the review framework for IoT-based SHM: IoT data infrastructure and data pipeline, organized through a three-perspective analytical framework (computing paradigms and architectures, intelligent algorithms, and SHM applications).

that establishes ubiquitous computing as the fundamental paradigm for next-generation autonomous and intelligent SHM systems.

The remainder of the paper is organized as follows: Section 2 reviews the data infrastructure and end-to-end workflows of IoT-based SHM systems; Section 3 presents an architectural perspective on computing, emphasizing edge–fog–cloud hierarchies and comparing centralized and distributed paradigms; Section 4 discusses computing algorithms, including knowledge-driven and AI-based approaches; Section 5 explores applications, covering measurement, system identification, and damage assessment (including detection, localization, and quantification); Section 6 analyzes a set of representative IoT-based SHM systems reported in recent years, using the proposed framework to validate the review's key arguments and to demonstrate its practical relevance to real-world implementations; Section 7 synthesizes key challenges, enabling technologies, and engineering considerations with practical insights for real-world deployment; and Section 8 concludes the review.

2. Data infrastructure and workflow in IoT-based SHM

As shown in Fig. 5, which corresponds to the data infrastructure component in Fig. 4, IoT system architectures can be viewed from two complementary perspectives: as functional blocks (perception, actuation, communication, and cognition) and as hierarchical layers (device, network, and application). The IoT infrastructure enables continuous sensing, transmission, and organization of structural data, forming the foundation for SHM systems. The data pipeline describes how information flows through the system, spanning from acquisition to application. As illustrated in Fig. 4, this pipeline consists of seven stages: acquisition, preprocessing, transmission, storage, fusion, analysis, and application, which are grouped into three functional categories: (1) acquisition and preprocessing, (2) transmission, storage, and fusion, and (3) analysis and application. These categories map onto different architectural layers: acquisition and preprocessing at the device layer, transmission and fusion across layers, and analysis and application at the application layer. The IoT infrastructure and data processing workflow introduced in this section are essential for understanding SHM's digital transformation, while the transition toward automation and intelligence depends on computational paradigms and methods examined in the sections that follow.

2.1. Perception and actuation

As fundamental components of the IoT-based SHM data infrastructure, perception and actuation constitute two fundamental pillars at the device layer, i.e., sensing the structural state and interacting with the environment. Together, they form the essential interface bridging the physical and digital worlds, as depicted in Fig. 5.

Perception. Sensors are responsible for converting physical stimuli into digital signals, typically through piezoelectric, capacitive, optical, magnetic, or thermal effects [4,8,17]. SHM applications adopt diverse sensing modalities to capture physical or chemical phenomena, including vibration, strain, geometry, motion, vision/audio, environmental, and electromagnetic data [18–34]. Synchronized IoT-based SHM systems enable coordinated data acquisition across distributed sensor networks [35]. MEMS sensors are increasingly favored for their compactness, low power consumption, wireless connectivity, and on-board processing, enabling scalable and efficient deployments [2,19]. However, balancing performance, durability, and cost remains a significant challenge, especially under harsh or remote conditions [36]. Adaptive sensor calibration and compensation techniques can mitigate environmental effects and improve measurement accuracy [37,38]. Sensor data quality is critical for reliable SHM outcomes [39]. Noise in sensor measurements arises from hardware-level sources including electronic noise, quantization errors, environmental interference (e.g., electromagnetic interference, temperature fluctuations), mechanical vibrations, and sensor aging or drift [39]. Hardware-level noise mitigation strategies include selecting sensors with appropriate signal-to-noise ratios, implementing proper sensor mounting and isolation, using shielded cables and proper grounding, selecting sensors with built-in filtering capabilities, and regular sensor calibration [38,39]. Optimal sensor placement and orientation also minimize environmental disturbances and maximize signal fidelity. SHM data encompasses various forms: (1) time-series data (e.g., vibrations, stresses), (2) spatial

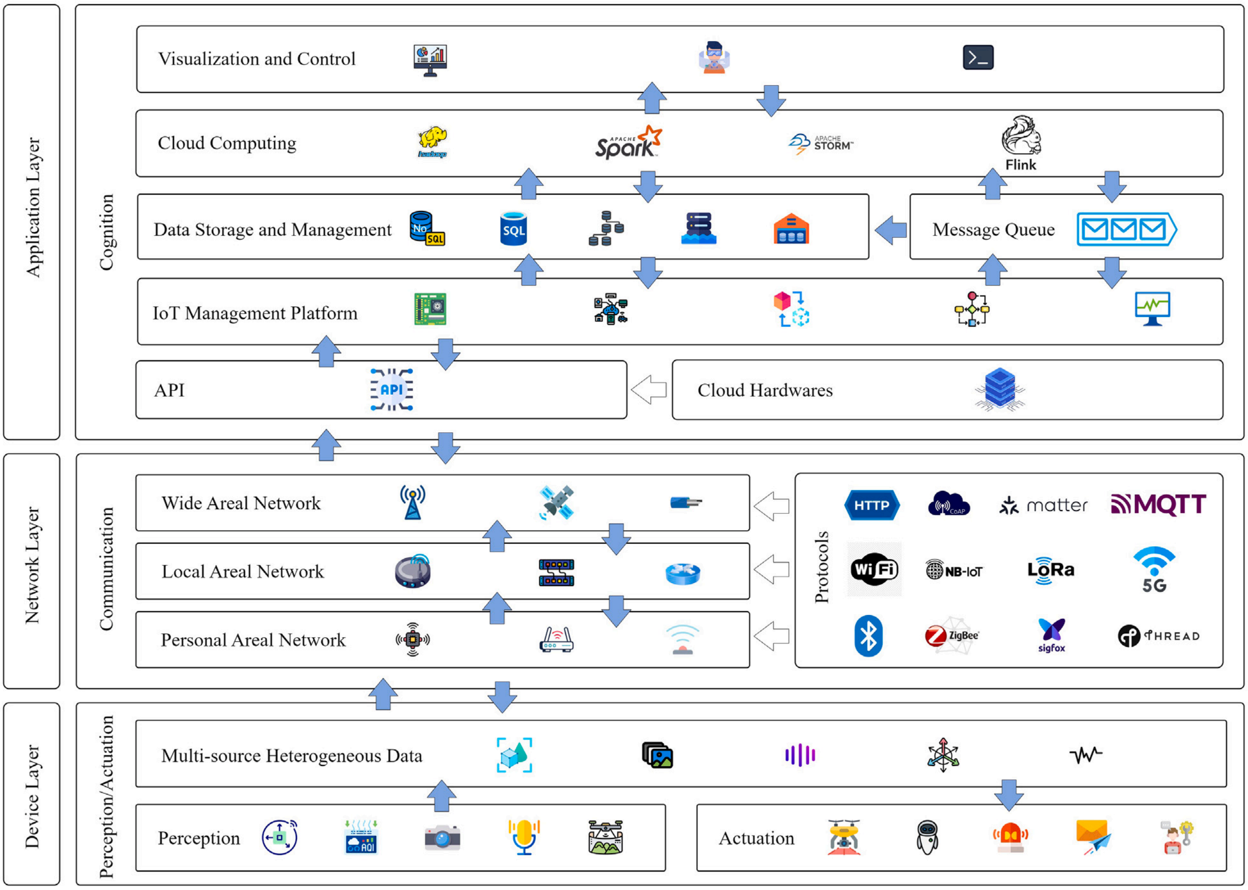

Fig. 5. Data infrastructure and associated data flow in IoT-based SHM.

data (e.g., point clouds, images/videos), (3) audio data for event detection [40], and (4) textual data for semantic or compliance analysis [41, 42]. These structured and unstructured datasets support downstream modeling and decision-making. In large-scale SHM projects, multiple sensor types and diverse data modalities are typically integrated, as exemplified by the monitoring system of the Hong Kong–Zhuhai–Macao Bridge [18].

Actuation. In contrast to sensing, actuation enables SHM systems to respond and adapt to structural conditions. It plays a critical role in tasks such as control, inspection, repair, and structural adaptation [43–45]. Traditional actuators, including hydraulic, pneumatic, and piezoelectric types, have been joined by intelligent systems like robotic arms, drones, and adaptive dampers [46,47], allowing SHM systems not only to observe but also to intervene. Computationally, SHM-oriented actuation involves path planning, navigation, and manipulation, requiring adaptability to complex environments [48]. Despite recent progress, many actuation processes still depend on manual operation due to reliability, cost, and environmental constraints. Emerging embodied AI technologies promise to enhance autonomy and intelligence in actuation, paving the way for more adaptive and context-aware SHM interventions [49]. A representative example is the four-wheel robotic vehicle system for bridge frequency identification [50].

2.2. Network and communication

As a critical component of the IoT-based SHM data infrastructure, network and communication form the backbone of IoT-based SHM systems, linking the device and application layers by enabling connectivity among sensors, users, computational nodes, and actuators. To understand their role in system design and performance, this section examines the IoT network from three complementary aspects: structural organization, topological layout, and communication protocols.

Network structure. The IoT network can be categorized from various perspectives: spatially into edge, fog, and cloud layers (Fig. 5); by scale into Personal Area Network (PAN), Local Area Network (LAN), and Wide Area Network (WAN) (Fig. 6); and functionally by the 7-layer OSI model, from the physical to the application layer (Fig. 7) [4,14,51]. Fault-tolerant architectures based on software-defined networks enhance system reliability and resilience [52].

Topology. Network topology directly affects system performance, influencing reliability, scalability, and cost. As shown in Fig. 8, common topologies include bus (simple but fragile), star (centralized and manageable), and mesh (robust but complex). The choice of topology should match the SHM deployment's communication range, energy constraints, and fault tolerance requirements [4,53]. A typical example is De Masi et al.'s review of network topology impacts on IoT performance, highlighting how topology selection affects reliability and costs in SHM [53].

Protocols. Communication protocols vary across layers and use cases (Figs. 5, 7). At the physical and data link layers, Ethernet and USB support wired connections, while NFC and RFID enable short-range wireless communication. Wi-Fi, Bluetooth, Zigbee, and LoRa are used for mid-range transmission, and cellular technologies such as 2G, 3G, 4G, 5G, and NB-IoT support long-range data transfer [51]. Fig. 9 presents a comparison of common wireless protocols in terms of key performance parameters. At higher layers, protocols such as IP, TCP, UDP, HTTP, MQTT, CoAP, XMPP, AMQP, and DDS are used to manage routing, ensure reliable data transport, and support scalable telemetry across constrained and heterogeneous SHM environments [4, 54,55]. Table 1 provides scenario-based protocol selection guidance for different structure types in urban and rural areas. For example,

Table 1
Scenario-based protocol selection guidance for different structure types in urban and rural areas.

Structure	Location	Physical/Data link	Application	Notes
Residential	Urban	Wi-Fi, Ethernet, 4G/5G	MQTT, HTTP	Dense WiFi; 4G/5G backup; Ethernet reliable
Residential	Rural	LoRa, NB-IoT, 4G/5G, Zigbee	CoAP, MQTT, HTTP	Limited WiFi; LoRa/NB-IoT long-range
Commercial	Urban	Wi-Fi, Ethernet, 4G/5G	MQTT, HTTP, AMQP	High data rate; Wi-Fi flexible; 5G high bandwidth
Industrial	Urban	Wi-Fi, Ethernet, 4G/5G	MQTT, HTTP, AMQP	High reliability; Ethernet critical; 5G high bandwidth
Industrial	Rural	4G/5G, Ethernet, LoRa, NB-IoT	MQTT, HTTP, CoAP	Wired preferred; 5G remote; LoRa/NB-IoT wide coverage
Tunnels	Urban	Wi-Fi, Ethernet, 4G/5G	MQTT, HTTP	Indoor; Wi-Fi flexible; cellular backup
Tunnels	Rural	LoRa, NB-IoT, 4G/5G, Zigbee	CoAP, MQTT, HTTP	Limited infrastructure; LoRa long-range
Bridges	Urban	Wi-Fi, Ethernet, 4G/5G	MQTT, HTTP	Outdoor; Wi-Fi flexible; 5G high bandwidth
Bridges	Rural	LoRa, NB-IoT, 4G/5G	CoAP, MQTT, HTTP	LoRa/NB-IoT long-range low-power; 4G/5G connectivity

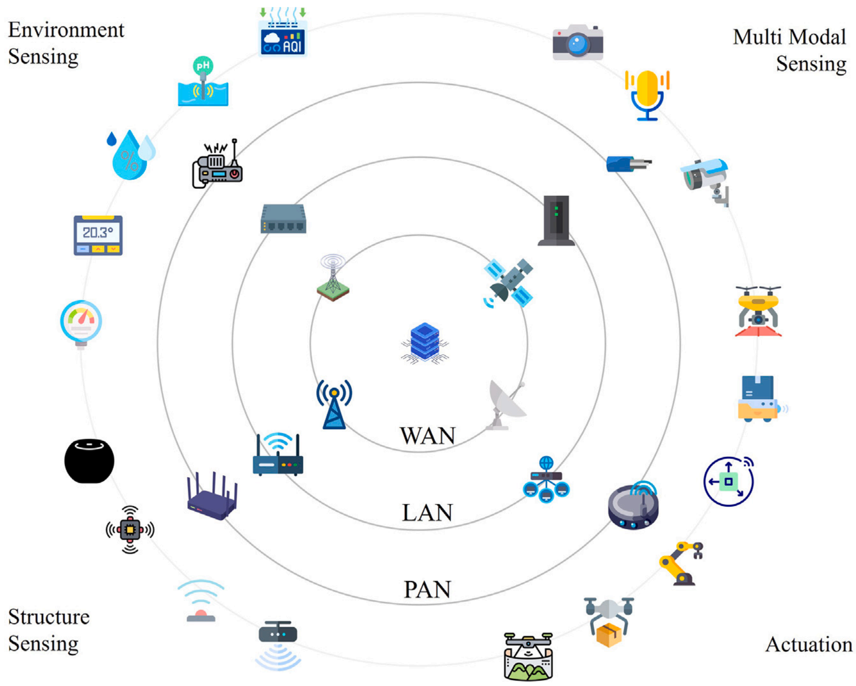

Fig. 6. Illustration of IoT-based SHM network structure.

Al-Masri et al. compared MQTT, CoAP, and HTTP protocols for IoT applications, providing practical guidance for protocol selection in SHM systems [51].

2.3. Cognition

As the cognitive layer of the IoT-based SHM data infrastructure, cognition refers to the system's essential capability to interpret sensed data, extract knowledge, and support intelligent decision-making. Functionally, it bridges perception and actuation, enabling a shift from passive monitoring to proactive structural insight. While edge and fog layers increasingly support latency-sensitive cognition, cloud computing remains the primary platform for system-wide analytics, offering the scalability and flexibility required to address the 5Vs of big data: volume, velocity, variety, veracity, and value [10]. Ontology-based approaches provide structured knowledge representation for SHM systems [56]. The realization of cognition in IoT-based SHM relies on three interrelated infrastructural pillars: first, elastic and scalable computing resources that provide the physical backbone for cloud-based processing; second, robust data storage and management mechanisms that ensure continuous access to high-quality information; and third, service interfaces, often in the form of APIs, that modularize computing capabilities and enable seamless integration across sensing, analytics, and actuation layers. These three aspects together constitute the operational foundation that supports cognitive intelligence in SHM. Fig. 10 illustrates the key components of cloud computing and big data technologies, which are essential for realizing the cognitive capabilities of IoT-based SHM systems.

Cloud hardware, services, and APIs. At the core of cognitive infrastructure lies elastic computing capacity provided by commercial cloud platforms such as AWS, Azure, and GCP. These platforms deliver services through Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) models [4], enabling SHM systems to access computing resources as needed without maintaining physical servers. Modular APIs facilitate seamless integration between sensing, analysis, and actuation components, while abstracting underlying system complexity. One representative example is Gigli et al.'s edge–cloud continuum architecture, demonstrating seamless integration of edge processing with cloud analytics for SHM [57].

Data storage and management. Effective cognition depends on the continuous availability, consistency, and reliability of data. Device management platforms such as ThingsBoard [58] and AWS IoT coordinate the acquisition and integration of heterogeneous sensing devices. Middleware tools like Kafka and RabbitMQ decouple data collection from downstream processing through scalable message queuing (Fig. 10) [59]. For persistent storage, hybrid database systems are commonly employed, including relational databases, NoSQL databases, and time-series databases. These are often used in conjunction with data lakes and warehouses to handle both structured and unstructured data at scale [60,61]. Supporting mechanisms such as indexing, encryption, and automated backup are essential to ensure data integrity, security, and recoverability [62,63]. Exemplified by Yang et al.'s review of

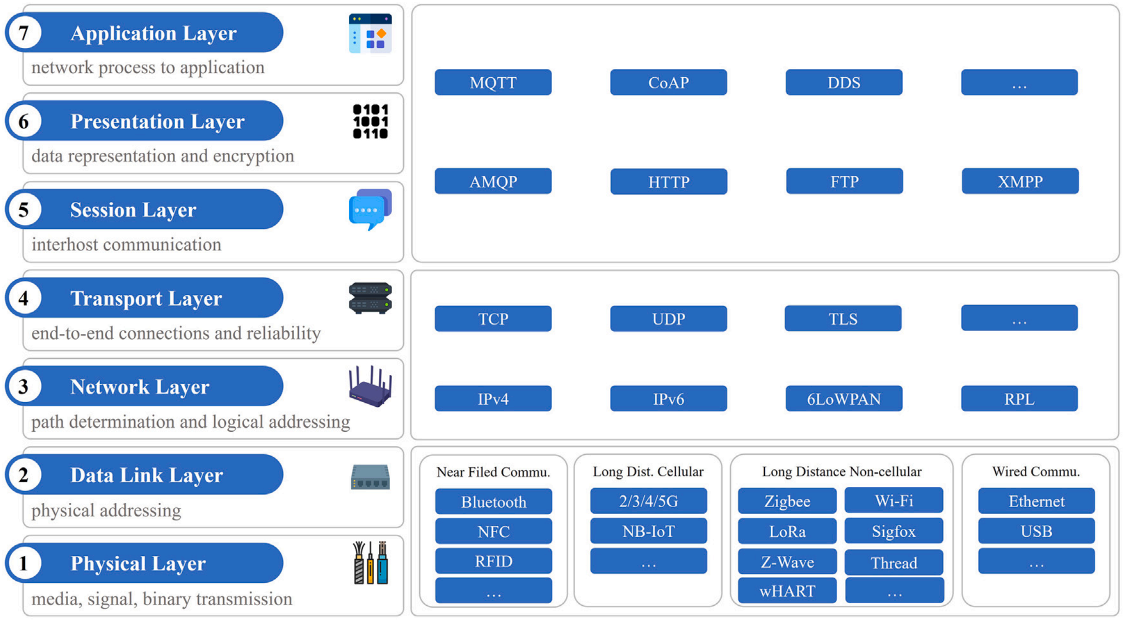

Fig. 7. Illustration of OSI model and related protocols.

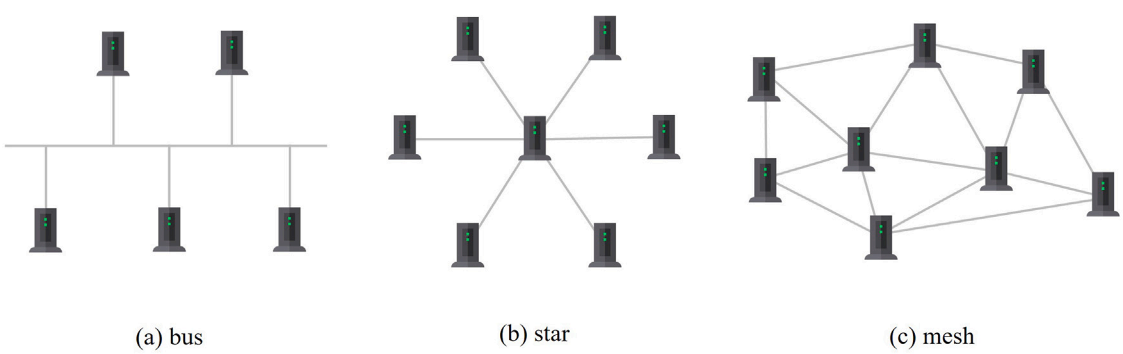

Fig. 8. Illustration of network topologies: (a) bus topology, (b) star topology, (c) mesh topology.

big data technologies, which provides insights into scalable storage architectures for large-scale SHM datasets [60].

Cloud computing, analyses, and user interfaces. Built upon the computing and data layers, cognitive functions are executed through a combination of stream and batch processing frameworks. Tools such as Apache Flink and Storm support real-time analytics, while Hadoop and Spark handle retrospective, large-scale computation [60,64]. Analytical workflows often utilize platforms like Python and MATLAB for modeling, signal analysis, and inference. To support interpretation and human interaction, results can be visualized through business intelligence tools (e.g., Tableau, Power BI) or immersive 3D environments built using Unity, Unreal Engine, or WebGL (e.g., Three.js). APIs serve as the bridge between cloud-based analytics and real-world systems, enabling computed insights to be converted into actionable commands, thus closing the loop from data to response. A typical example of cloud computing integration is Hassan et al.'s optimization of SHM systems through integrated fog and cloud computing within an IoT framework [65]. For 3D visualization, Lu et al. reviewed image-based 3D reconstruction methods for civil infrastructure projects, demonstrating how immersive 3D environments enhance structural monitoring and visualization [21].

2.4. Data acquisition and preprocessing

This subsection marks the beginning of the SHM data workflow, shifting focus from the structural composition of data infrastructure to the temporal organization of SHM workflows, following the chronological progression from acquisition to application. For each stage, only the most common and essential computational procedures are summarized to highlight their roles in shaping a representative SHM data pipeline. As illustrated in Fig. 11, which corresponds to the data pipeline component in Fig. 4, the end-to-end information flow in IoT-based SHM systems is categorized into three functional groups: (1) data acquisition and preprocessing, (2) data transmission, storage, and fusion, and (3) data analysis and application. Each stage is further aligned with corresponding spatial layers in the IoT architecture, including edge, fog, and cloud domains. More broadly, this flow reflects a transition from physical-level data collection to higher-level data consumption through analysis, decision-making, and interaction, embodying the essence of ubiquitous computing and intelligence throughout the monitoring ecosystem.

Stage I — data acquisition. Data acquisition marks the entry point of the SHM data pipeline, interfacing the physical structure with the digital system. Located at the device layer, sensing nodes capture physical quantities like acceleration, strain, temperature, or acoustic signals, converting them into digital data for computation. The fidelity and interpretability of downstream analysis depend heavily on this stage [66]. Key requirements include real-time responsiveness, low power consumption, and stable operation under constraints [67]. Common tasks include signal sampling, analog-to-digital conversion (ADC), triggering, timestamping, and power management [68–70]. Sampling

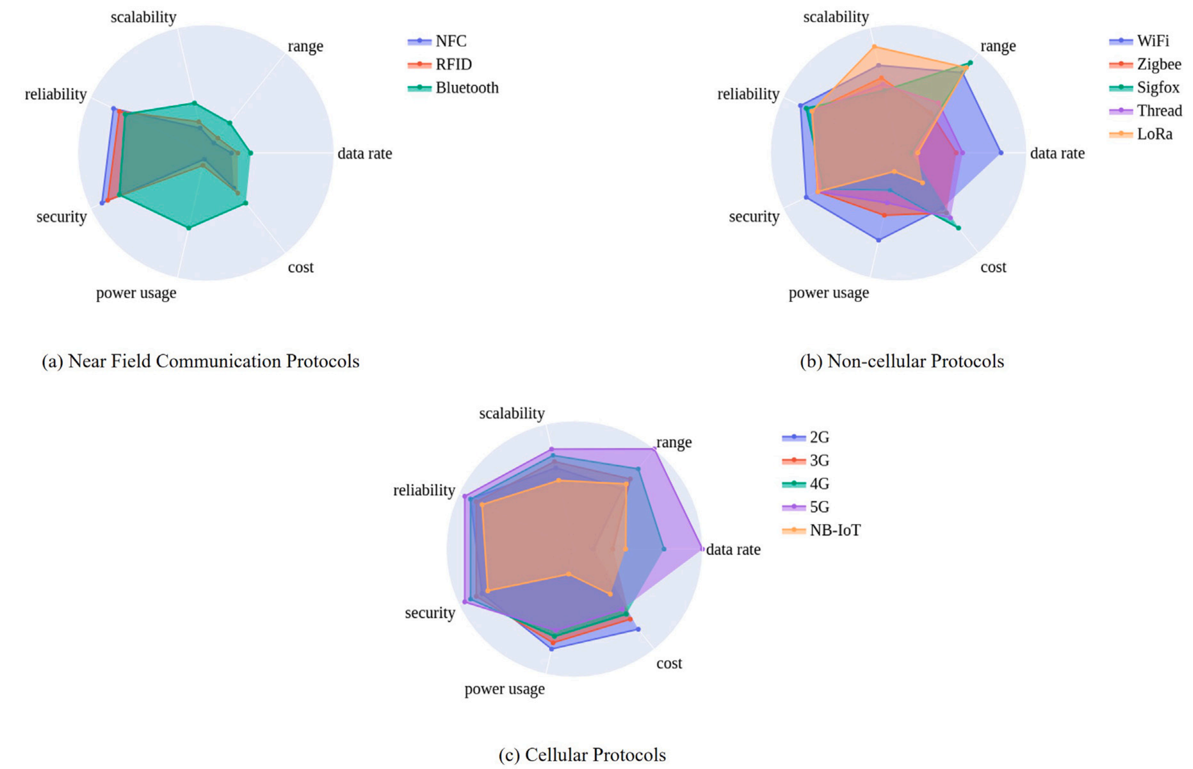

Fig. 9. Comparison of common wireless protocols: (a) near-field communication, (b) non-cellular communication, (c) cellular communication.

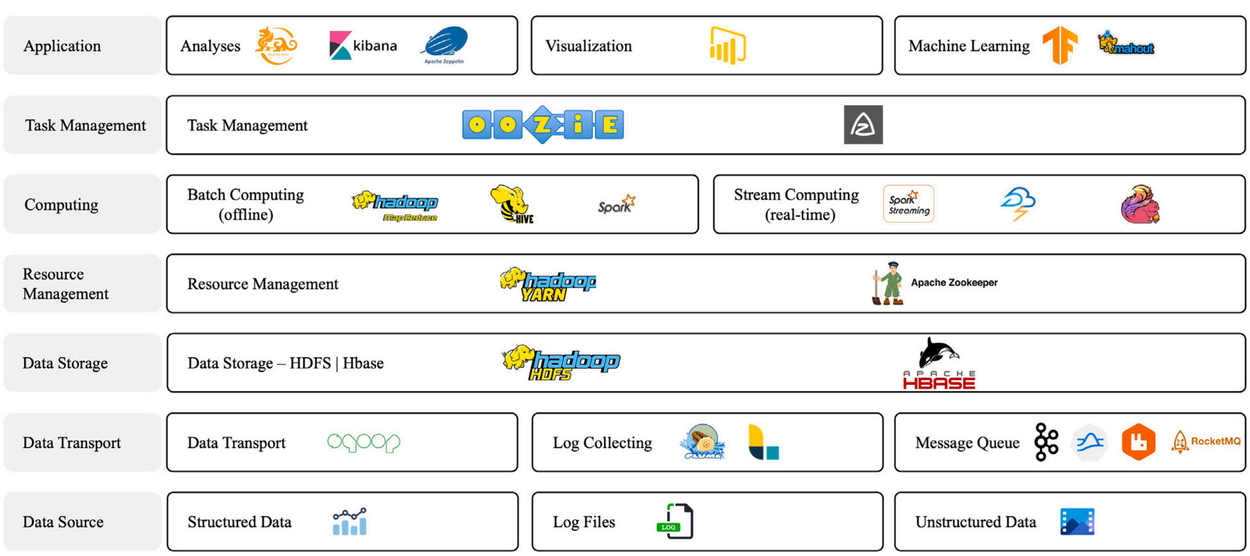

Fig. 10. Illustration of big data technology stack and common tools ranging from data sources to applications.

rates are defined by monitoring objectives and Nyquist criteria [71], while ADC digitizes analog input. To ensure signal quality during this conversion process, anti-aliasing filters are essential to prevent frequency folding and ensure accurate signal reconstruction, while sensor dynamic range determines the ability to capture both small and large amplitude signals without saturation or loss of resolution. Beyond signal acquisition, triggering mechanisms (e.g., amplitude-based or motion-based) reduce unnecessary data flow [36,72]. Timestamping ensures temporal alignment, and power scheduling manages duty cycles to extend device lifetime. Sensor placement, while primarily a design optimization problem, critically affects data value and often involves computational algorithms for optimal positioning [73]. These combined operations lay the groundwork for reliable SHM data workflows. For instance, Fu et al. developed a high-fidelity data acquisition system demonstrating advanced sampling and triggering mechanisms for reliable structural monitoring [74].

Stage II — preprocessing. Preprocessing enhances raw data quality and consistency before transmission or analysis [4]. It operates across both the device and network layers. Basic tasks, such as filtering and normalization, are typically performed at the sensor level, whereas more complex operations, including alignment and imputation, are often handled by gateways or fog nodes. The main objectives of preprocessing are to suppress noise, correct sensor errors, unify data formats, and reduce redundancy. To address noise suppression, software-level noise handling encompasses digital filtering (e.g., FIR,

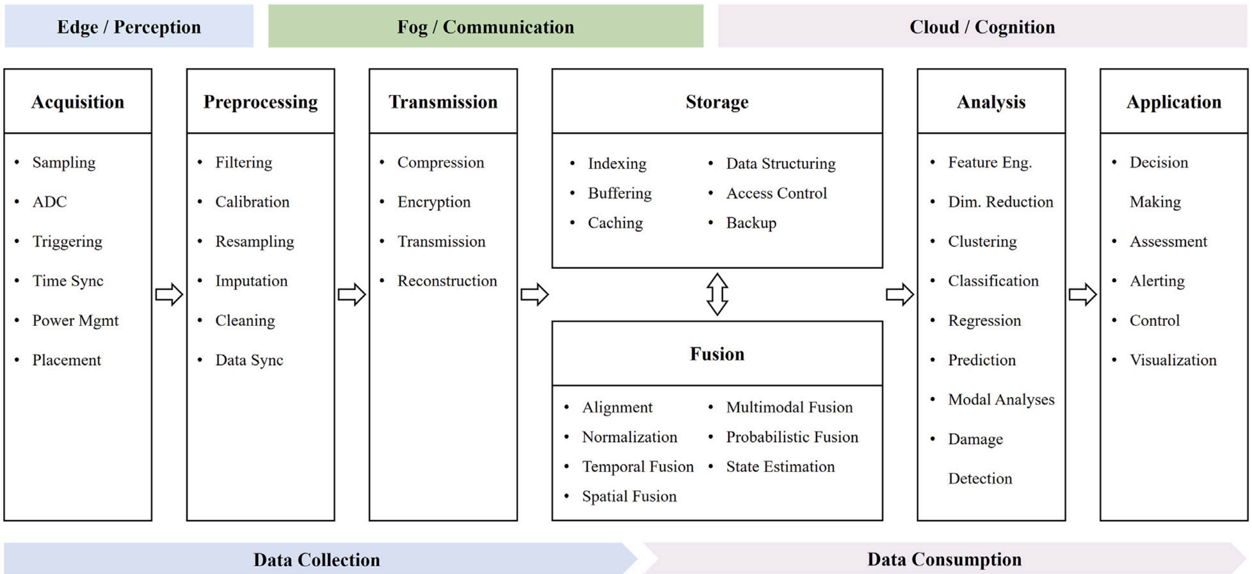

Fig. 11. Computation-oriented data flow in IoT-based SHM.

IIR, and wavelet-based filters), adaptive filtering, and denoising algorithms (e.g., wavelet denoising, empirical mode decomposition). Regularization strategies (L1/L2 and Tikhonov regularization) handle noisy measurements and boundary condition uncertainty, enabling robust parameter estimation and system identification. Environmental normalization compensates for temperature and humidity variations that cause structural response changes (e.g., frequency shifts, strain variations) potentially misinterpreted as damage, using regression-based methods, principal component analysis, or machine learning models to extract and remove environmental effects from measured signals. Common procedures include digital filtering (e.g., FIR, IIR, and wavelet-based methods), sensor calibration using correction coefficients, resampling and interpolation for rate harmonization, imputation for missing values, anomaly removal, and signal synchronization [8,74]. Collectively, these steps transform raw signals into clean, structured data ready for downstream processing. An illustrative case is Fu et al.'s preprocessing pipeline, which transforms raw sensor data into high-quality inputs through filtering, calibration, and synchronization [74].

2.5. Data transmission, storage, and fusion

As the middle stage of the SHM data workflow, this phase focuses on how sensor data are transmitted, organized, and integrated to support downstream analysis, spanning the device, network, and application layers. It consists of three key stages: transmission, storage, and fusion, which collectively ensure efficient delivery, reliable retention, and meaningful combination of information across the IoT architecture. These interconnected processes form the backbone of ubiquitous computing infrastructure, enabling distributed intelligence and seamless data orchestration throughout the monitoring ecosystem.

Stage III — data transmission. Data transmission serves as the conduit between local data processing and cloud-based computation, enabling timely and secure data flow throughout the IoT architecture. Spanning both the device and network layers, this stage addresses practical constraints at the edge, including limited bandwidth, latency sensitivity, and energy efficiency. Core operations encompass data compression, encryption, scheduling, and packet reconstruction [4,75–78]. Battery lifespan enhancement strategies are crucial for long-term IoT deployments, particularly in wireless sensor networks [79,80]. Compression, whether lossless (e.g., Huffman coding) or lossy (e.g., Discrete Wavelet Transform, DWT), reduces data volume for efficient transmission. Sensor-agnostic compression approaches provide flexible solutions for diverse IoT deployments [81]. Data deduplication techniques further optimize storage and transmission efficiency [82]. Recent frameworks provide comprehensive solutions for IoT-based SHM system development [83]. Time–space dynamic incentives can optimize data transmission strategies [84]. Encryption protects data integrity during wireless transfer, while scheduling mechanisms regulate flow control to prevent congestion. Packet reconstruction ensures that fragmented or lost data segments are reassembled correctly at the receiving end. For example, Ukil et al. developed sensor-agnostic compression approaches that reduce data volume while maintaining signal fidelity in resource-constrained SHM networks [81].

Stage IV — data storage. Data storage serves as a foundational component for retaining information over time and throughout the layered architecture of SHM systems. At the network layer, edge and fog nodes provide temporary buffering to accommodate transmission delays and support local processing. At the application layer, cloud platforms offer long-term storage for historical analysis, model development, and decision support. Storage and fusion processes may be configured in sequence or in parallel, depending on system needs. Typical storage tasks include buffering to handle intermittent data flows, caching for accelerated access to frequently requested data, indexing to enable fast query operations, and database management for structured and unstructured data. Storage systems often integrate relational databases (e.g., SQL), time-series databases (e.g., InfluxDB), and distributed platforms (e.g., HDFS, S3) [85,86]. To ensure data resilience, systems implement replication, versioning, and automated failover strategies that protect against data loss and system failure [87]. A typical example is Nambiar et al.'s comparison of relational, NoSQL, and time-series databases for large-scale SHM deployments [85].

Stage V — data fusion. Data fusion synthesizes information from multiple sensors, whether homogeneous or heterogeneous, to construct a unified representation of structural behavior [88,89]. By aggregating complementary data sources, fusion improves the reliability, robustness, and interpretability of SHM outcomes, particularly under noisy or uncertain conditions. It can be applied at various points within the data pipeline, enabling both real-time responsiveness and retrospective analysis. At the network level, fusion involves operations such as temporal alignment, local aggregation, and signal merging among neighboring nodes. At the application level, it incorporates advanced techniques for multimodal data integration and probabilistic reasoning. Common approaches include Kalman filtering for recursive state estimation [90], particle filtering for nonlinear and non-Gaussian systems [91], and Bayesian networks for capturing conditional dependencies [92,93]. These techniques enable coherent interpretation across diverse data modalities such as acceleration, strain, and acoustic signals. Explicitly quantifying and propagating uncertainties through the fusion process is crucial for trustworthy monitoring outcomes, as sensor data inherently contains uncertainties arising from noise, calibration errors, environmental variations, and communication failures. Bayesian methods provide a principled framework for uncertainty-aware fusion, explicitly modeling and propagating uncertainty distributions while adaptively weighting sensor contributions based on their confidence levels [89,94–96]. This approach becomes particularly crucial in IoT-based SHM systems where heterogeneous sensor data quality, safety-critical decisions, and multimodal data fusion require explicit uncertainty management. Exemplified by Wu and Jahanshahi's review of data fusion approaches, which overviews typical data fusion methods for multi-sensor integration in SHM [89].

2.6. Data analysis and application

As the final stage of the SHM data workflow, this phase transforms processed data into insights and actions through two stages: analysis and application, embodying the core intelligence capabilities of ubiquitous computing systems that enable autonomous decision-making and adaptive responses across the entire monitoring ecosystem.

Stage VI — data analysis. Data analysis serves as the computational core of SHM intelligence, converting raw or fused data into insights about structural condition, behavior, and performance [97]. Operating primarily at the application layer, it draws on tools from signal processing, statistical modeling, machine learning, and physics-informed approaches to extract meaningful features, detect anomalies, and forecast system states. SHM systems can be broadly categorized into model-driven and data-driven approaches [12], where model-driven methods rely on physical principles and domain knowledge to establish analytical or numerical models, while data-driven methods leverage statistical learning and pattern recognition to extract insights directly from sensor data. Feature engineering includes both time-domain techniques and transformed-domain methods such as Empirical Mode Decomposition (EMD), Fourier transforms, and wavelet analysis [71,98–100]. Analytical tasks span dimensionality reduction (e.g., PCA), clustering for pattern discovery, classification for state recognition, and regression for continuous output prediction [101,102]. From a control perspective, analysis also encompasses system identification, structural simulation, and control strategies [45,103]. Collectively, these methods enable intelligent, data-driven interpretation of structural dynamics and lay the foundation for informed decision-making. One representative example is Bao et al.'s review of recent advances, demonstrating how signal processing and machine learning enable intelligent structural condition analysis [97].

Stage VII — data application. The final stage of the SHM pipeline translates analytical insights into actions that enhance structural safety and operational performance [2,4]. Acting as the interface between digital analysis and physical intervention, it involves visualization, alert generation, decision support, and actuation. Tools such as Power BI, Unity, and WebGL present results in intuitive formats, while alerts are triggered by anomalies or threshold breaches. Decision support systems combine analysis with domain knowledge to guide maintenance and emergency responses. Through APIs, insights are delivered to actuators for automated actions such as sensor adjustment, robotic inspection, or structural control. This stage completes the feedback loop, enabling SHM systems to move from monitoring to intelligent response. A representative example is Wang et al.'s monitoring system for the Hong Kong–Zhuhai–Macao Bridge, which features a large-scale dynamic visualization dashboard at the bridge management center serving as an information and control hub, enabling effective user interaction and management of the monitoring system [18].

3. Paradigms and architectures

The preceding section reviewed IoT-based SHM systems through infrastructure-centric and dataflow-centric perspectives, outlining the key components across the device, network, and application layers, and detailing how data is acquired, transmitted, processed, and utilized. These perspectives primarily address the "what" and "how" of system operation: what technical elements constitute the system, and how they interact across the SHM data pipeline. However, they do not yet reveal the deeper rationale that governs the placement, distribution, and coordination of computational tasks within the system. These insights are crucial for understanding how SHM can evolve beyond digitalization toward ubiquitous computing and intelligence. To advance toward greater levels of automation and intelligence, it is necessary to move beyond the functional structure and examine the architectural principles that drive system design choices. This section therefore adopts an architectural viewpoint to investigate the motivations and logic that shape the spatial and temporal organization of computation, addressing the fundamental "why" questions that underlie computational architecture decisions, with particular attention to how performance, latency, scalability, and resilience are influenced by decisions about where and when computation is performed. Distinguishing this section from other reviews, we provide comprehensive and in-depth coverage of distributed computing paradigms and edge computing, which have received limited attention in existing SHM literature.

This section analyzes computing architecture in IoT-based SHM systems through five interconnected aspects. It begins by examining two fundamental paradigms of computation, namely centralized and distributed computing, which represent contrasting yet complementary strategies for organizing computational workloads. As illustrated in Fig. 12, these paradigms differ fundamentally in their computational workload distribution and communicational overhead across cloud, fog, and edge layers. These paradigms are then explored in their physical realizations through cloud, fog, and edge computing, each offering distinct advantages and responsibilities within the SHM hierarchy. Together, these layers form a continuum of computational capabilities that can be dynamically orchestrated to address diverse monitoring objectives and operational conditions. The remainder of this section elaborates on each component, clarifying their roles, technical characteristics, and integration in scalable, low-latency, and resilient SHM systems.

3.1. Centralized computing paradigm

Centralized computing rests on a long-standing computational tradition in which system-wide optimization is achieved through unified control and authority [75,104]. This paradigm emphasizes the consolidation of computational logic, data repositories, and decision-making within centralized infrastructures, typically large-scale cloud platforms or institutionally managed data centers. In SHM, centralized computing provides a stable foundation for managing complex structural data across diverse assets and geographic regions, enabling consistent enforcement of analytical models, governance protocols, and operational standards across multiple monitoring sites.

Centralized SHM systems are structured around cloud-based or private data centers that provide elastic computing and scalable storage. These platforms abstract hardware complexity through service models such as IaaS and PaaS, orchestrating workflows through unified interfaces and centralized APIs [4,10]. A key architectural advantage is the ability to maintain semantic consistency and centralized metadata governance, which enhances interoperability and supports long-term system sustainability.

This paradigm is especially effective for SHM tasks requiring high computational power and long-term temporal or spatial scope, including machine learning model training using historical data, structural simulation, long-term trend detection, and anomaly correlation across infrastructure networks [60]. Centralized dashboards allow engineers

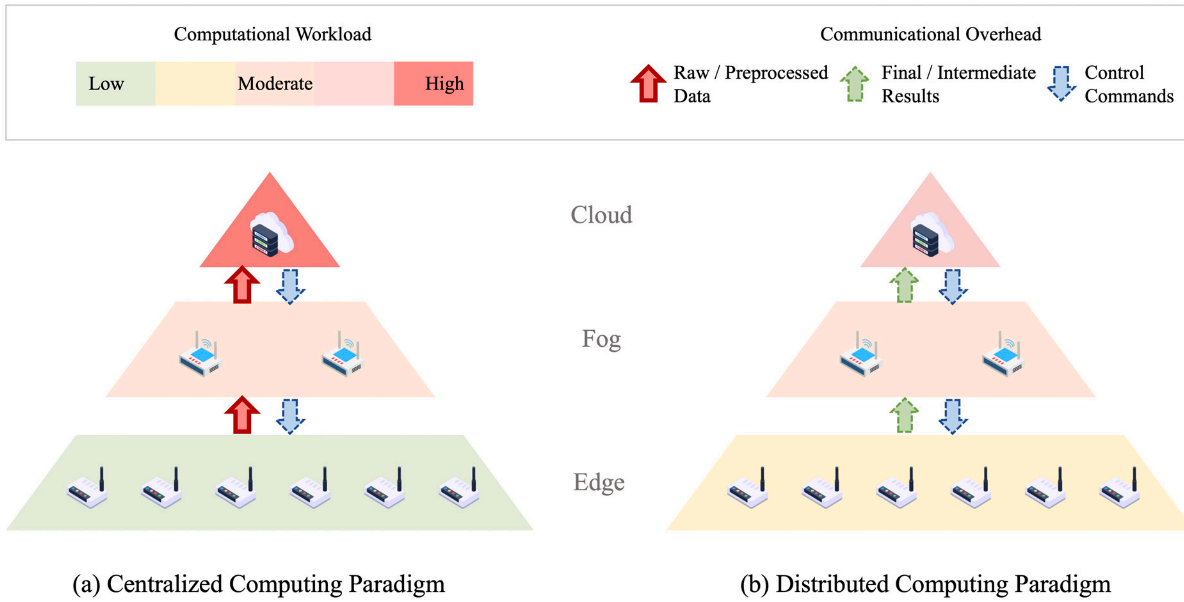

Fig. 12. Comparison of centralized and distributed computing paradigms in IoT-based SHM systems, illustrating computational workload distribution and communicational overhead across cloud, fog, and edge layers.

to synthesize information from various sites and perform holistic diagnostics. Processing engines such as Apache Spark and Google Cloud Dataflow support both retrospective and real-time analytics, while metadata registries and cloud storage systems ensure traceability and auditability [62]. A representative example is the long-term structural performance monitoring system for the Shanghai Tower, which employs a centralized architecture to manage comprehensive sensor data from the supertall building (632 m), enabling integrated analysis, long-term trend tracking, and holistic structural health assessment through a unified cloud-based platform [105].

However, this approach faces challenges in real-time responsiveness and communication efficiency [106]. As illustrated in Fig. 12, centralized architectures concentrate computational workloads at cloud data centers, creating bottlenecks and increasing computational burden on central servers. Transmitting high-frequency structural data from edge devices to remote servers introduces significant network latency and bandwidth burdens, particularly problematic in wireless or battery-powered deployments. Additionally, centralized systems exhibit reduced resilience, as failures at the central server or network disruptions can compromise the entire monitoring system. Centralized storage of sensitive structural or locational data also raises privacy, cyber risk, and compliance concerns [4]. These limitations reduce the practicality of centralized-only architectures in scenarios where connectivity is unreliable or rapid response is needed.

To overcome these drawbacks, SHM systems are increasingly adopting hybrid architectures that combine centralized coordination with distributed intelligence [7,107]. In such systems, edge and fog nodes manage real-time or localized processing tasks, while the cloud supports strategic oversight and system-wide model management, enabling reduced network load, improved resilience, and balanced global stability with local agility. Table 2 provides a comparison of centralized and distributed computing in SHM environments.

3.2. Distributed computing paradigm

Distributed computing promotes a philosophy of decentralization, autonomy, and responsiveness [4,75]. It disperses computational intelligence across edge, fog, and cloud layers rather than concentrating it at a central point. As illustrated in Fig. 12, in contrast to centralized architectures that concentrate workloads at cloud data centers, distributed computing distributes computational tasks across edge and fog layers, reducing computational burden on central servers, minimizing network latency through local processing, and enhancing system resilience by avoiding single points of failure. This paradigm emphasizes processing near the data source to reduce latency, enhance contextual awareness, and support system resilience. In SHM, distributed architectures are particularly effective in remote, bandwidth-constrained, or latency-sensitive environments. Conceptually, it represents a transition from centralized authority to collaborative autonomy [106].

Distributed SHM systems typically adopt a layered architecture with edge devices co-located with sensors handling real-time preprocessing, event detection, and signal transformation; fog nodes serving as intermediate aggregators that buffer data, synchronize multiple sources, and perform mid-level inference; and the cloud layer supporting long-term coordination and historical analysis, with its role shifting from sole executor to supervisor and orchestrator [107]. Task allocation across layers is dynamic, depending on network health, application urgency, and available resources. Spencer et al. discussed distributed computing strategies for multi-scale monitoring systems, highlighting how distributed architectures enable scalable and efficient monitoring across diverse infrastructure scales [70]. Distributed computing supports a wide range of SHM functions such as vibration-triggered sensing [72], real-time fault detection [66,108], and local decision-making [7,109]. These tasks are executed on resource-constrained platforms using lightweight inference models enabled by techniques like quantization [110], pruning [111], and knowledge distillation [112] for efficient edge deployment of neural networks. Fog nodes support spatial fusion, temporal buffering, and alert coordination, reducing upstream transmission and enabling faster, localized decisions. A representative example is the IoT monitoring system for the Hong Kong–Zhuhai–Macao Bridge, which exemplifies distributed edge computing and AI-enabled IoT SHM monitoring through edge-based anomaly detection, intelligent data processing, and distributed intelligence across the massive bridge infrastructure [18].

Several emerging technologies empower distributed SHM architectures. Federated learning enables collaborative model training across devices without transferring raw data, preserving privacy while enhancing generalizability [113]. Multi-agent systems and reinforcement learning support adaptive decision-making, load balancing, and failure recovery [114,115]. Game-theoretic frameworks offer coordination

Table 2
Comparison of centralized and distributed computing paradigms.

Aspect	Centralized computing	Distributed computing
Computing philosophy	Global control, unified logic	Local autonomy, collaborative execution
Processing location	Primarily in cloud data centers	Primarily at edge or fog nodes
System strength	High power, holistic analytics	Low latency, adaptive response
Data flow	Raw data sent to cloud	Data preprocessed locally
Fault tolerance	Sensitive to central failure	Resilient with local fallback
Privacy handling	Central storage poses risk	Local processing improves privacy
Typical use cases	Trend analysis, cross-site diagnosis	Event-triggered sensing, local detection

mechanisms under resource constraints, improving task allocation and communication fairness [116]. Together, these technologies enable decentralized intelligence that is both robust and scalable. New computing paradigms typically emerge first in computer science, electronics, or communications domains before migrating to application scenarios like SHM. Methods such as federated learning and multi-agent systems are currently being actively explored for SHM applications.

A notable trend in distributed SHM systems is the evolution from coordinated computing to cooperative computing paradigms. In coordinated computing, individual nodes operate under centralized orchestration, following predetermined protocols and responding to external commands. In contrast, cooperative computing represents a paradigm shift where distributed entities become increasingly autonomous and proactive, engaging in peer-to-peer collaboration, self-organizing behavior, and collective intelligence. This transition reflects a fundamental change from passive, reactive systems to active, adaptive entities that can negotiate, learn from each other, and collectively optimize system-wide objectives without requiring constant central oversight.

Despite its advantages, distributed computing is not a universal substitute for centralization. Resource limitations, synchronization challenges, and a lack of standardization across platforms remain persistent barriers. Nevertheless, when integrated effectively with centralized systems, distributed computing offers a powerful complement. Edge and fog nodes extend the reach of cloud-based intelligence, providing rapid response, local context, and operational continuity. The convergence of both paradigms supports the evolution of SHM systems toward architectures that are intelligent, agile, and resilient in complex real-world conditions.

3.3. Cloud computing

Cloud computing remains the foundation of centralized intelligence in SHM systems, offering scalable resources, elastic service models, and global coordination [104]. Its architecture centralizes computation and data management in remote servers, making it well suited for long-term model maintenance, historical integration, and cross-site structural analysis. As shown in Table 3, the cloud provides the highest capacity in computation and storage, supporting system-wide reasoning and strategic planning across infrastructure portfolios, enabling comprehensive trend analysis and stakeholder coordination.

Major cloud platforms such as AWS, Azure, and Google Cloud offer IaaS, PaaS, and SaaS models that abstract hardware complexity and streamline service access, enabling SHM practitioners to deploy scalable solutions without direct infrastructure management. SHM workflows benefit from containerized deployments, serverless backends, and orchestration services that host AI training, simulation, and visualization pipelines. Metadata governance mechanisms ensure semantic consistency across projects, facilitating interoperability and institutional knowledge retention [4,10], while CI/CD workflows and infrastructure version control enable automated testing and maintainable system evolution.

Cloud computing supports compute-intensive SHM tasks, including large-scale simulations, deep learning model training, and multi-site health condition aggregation [60,117], leveraging parallel processing and elastic scaling capabilities. Engineers access centralized dashboards to compare signals, monitor trends, and support network-level decision-making. Cloud-based analytics platforms such as Apache Spark and Google Cloud Dataflow enable high-throughput data processing, while time-series databases and object storage systems maintain long-term archives of sensor streams and diagnostic logs [62]. Cloud-native APIs integrate visualization tools and reporting services that enhance decision support workflows. A typical example is the over 25-year monitoring system of the Tsing Ma Suspension Bridge in Hong Kong, demonstrating long-term cloud-based data management and analysis for large-scale infrastructure [118].

However, cloud-centric architectures face limitations in latency-sensitive or bandwidth-constrained SHM scenarios. Transmitting high-frequency signals introduces delay, energy overhead, and potential packet loss, especially in remote or mobile deployments. Reliance on stable connectivity creates single points of failure that compromise system resilience, while privacy concerns arise when sensitive structural or geolocation data are aggregated in centralized repositories [75,106]. These challenges highlight the need to reduce reliance on continuous upstream transmission.

Cloud platforms are increasingly evolving into orchestration hubs rather than sole computational engines, managing coordination, model fusion, and learning updates across fog and edge tiers. In hybrid SHM architectures, the cloud supports global model training, anomaly pattern correlation across sites, and lifecycle management of deployed edge analytics. This evolution reflects a broader architectural transition in SHM toward hybrid paradigms that prioritize distributed responsiveness while retaining centralized oversight [7,107]. Future developments may see cloud systems act as intelligent control centers that selectively trigger edge-side updates or respond to multi-node alerts, enabling a more dynamic and adaptive SHM ecosystem.

3.4. Fog computing

Fog computing provides an intermediate layer that bridges the cloud's centralized intelligence and the edge's immediate reactivity [75], emerging as a strategic response to the growing demand for latency-sensitive analytics, bandwidth reduction, and context-aware coordination. By operating closer to the sensing source than the cloud, yet with more capacity than the edge, fog computing enables situational awareness and distributed decision-making at the regional level. As indicated in Table 3, fog nodes occupy a functional midpoint, delivering timely processing while reducing upstream communication load.

Fog systems are typically deployed on gateway devices, local servers, or base stations situated near sensor clusters, possessing greater computational and storage resources than embedded edge devices to support intermediate-level analytics, event buffering, and multi-device orchestration [75]. Architecturally, fog nodes operate as both aggregators and decision-making units, performing real-time inference, data filtering, regional coordination across edge sensor networks, and data compression and prioritization for efficient cloud transmission [4].

In SHM applications, fog computing plays a pivotal role in enabling spatial–temporal fusion of sensor streams, local anomaly scoring, and preliminary damage evaluation. By collecting and synthesizing signals from multiple edge devices, fog nodes identify patterns that may not be discernible at the local node level, supporting regional alerting

Table 3
Comparison of cloud, fog, and edge computing in SHM systems.

Aspect	Cloud computing	Fog computing	Edge computing
Location	Remote data centers	Gateways or local servers	On-site with sensors
Latency	High	Medium	Low
Responsiveness	Strategic or batch	Near real-time	Real-time
Compute power	High	Moderate	Limited
Storage capacity	Large-scale	Moderate	Constrained
Network dependency	Constant, high bandwidth	Intermittent tolerance	Autonomous when offline
Fault tolerance	Low under disconnection	Moderate fallback	High with local decision
Privacy	Centralized risk	Balanced control	High (local data stay local)
Power efficiency	Low	Moderate	High
Upgradability	Remote and flexible	Regional updates	Complex, device-specific
Typical use cases	Model training, cross-site analytics	Data fusion, buffering, coordination	Triggered sensing, filtering, anomaly detection

and early warning mechanisms particularly important in bridge or tunnel monitoring where fast, localized decisions are required [107]. When cloud access is limited due to connectivity issues or regulatory constraints, fog nodes provide continuity of operation by retaining inference capacity at the edge of the network [7]. An Edge/Fog/Cloud architecture for facilitating structural health monitoring and management in civil infrastructures demonstrates how the three-layer hierarchy enables effective coordination and distributed intelligence [119].

Despite these advantages, fog computing remains hindered by the lack of standardization in both hardware and software ecosystems. The heterogeneity of fog deployments introduces integration difficulties and increases system management burden. In contrast to mature cloud infrastructure, fog systems lack uniform orchestration tools, well-supported development platforms, and scalable lifecycle management solutions, requiring deliberate system design and robust coordination protocols to maintain synchronization across fog layers and ensure compatibility with upstream and downstream systems.

Looking ahead, fog computing is expected to play an increasingly important role alongside edge computing in the shift toward decentralized intelligence. As SHM systems expand in scale and complexity, fog and edge nodes together provide a distributed backbone for real-time responsiveness, local processing, and hierarchical coordination. With the adoption of frameworks such as federated learning, fog nodes can support regional model refinement and serve as intermediaries that reduce communication overhead with the cloud. Developments in lightweight AI deployment and event-driven scheduling are enabling edge and fog layers to jointly deliver scalable, adaptive, and context-aware monitoring. Rather than replacing centralized infrastructure, this collaborative architecture enhances modularity and resilience, allowing SHM systems to operate effectively under diverse and dynamic field conditions.

3.5. Edge computing

Edge computing embodies the principle of embedded autonomy, enabling SHM systems to perform real-time analytics directly at or near sensing nodes [4,106,110]. As summarized in Table 3, the edge layer forms the first line of interaction with structural environments, offering ultra-low-latency processing, reduced energy consumption, and robustness to connectivity loss. In contrast to centralized systems, it reduces dependence on continuous cloud access, which is essential for remote or delay-sensitive deployments [4,107].

Edge devices are commonly based on embedded platforms such as microcontroller units (MCUs), microprocessor units (MPUs), field-programmable gate arrays (FPGAs), or neural processing units (NPUs). These platforms are characterized by limited memory, restricted processing power, and tight energy budgets. To overcome these constraints, recent SHM implementations have increasingly adopted embedded deep learning and signal processing workflows optimized for real-time execution [120–126]. Low-power wireless sensing platforms enable energy-efficient edge-based SHM deployments [127]. Popular toolchains such as TensorFlow Lite [128] and Edge Impulse [129] support the deployment of compressed AI models and lightweight inference engines on these devices. Standard embedded libraries such as CMSIS provide optimized DSP and neural network functions for ARM-based microcontrollers [130–132]. Optimizations such as quantization reduce the precision of numerical operations to enable fixed-point execution [110], while pruning techniques remove unnecessary parameters to lower memory and computation requirements [111]. Knowledge distillation further enables the transfer of performance-critical information from large cloud-trained models to compact versions suitable for edge deployment. Some studies have also introduced neural architecture search (NAS) [112] to automate the design of efficient networks tailored for embedded SHM tasks. Despite these advancements, it is worth emphasizing that SHM remains underserved by standard embedded libraries [7]: unlike general-purpose AI or DSP applications, SHM requires domain-specific functions such as modal parameter estimation, frequency-domain integration, and time–frequency transforms, most of which are not readily supported by existing embedded frameworks [133]. The lack of a unified and modular SHM computation library for edge deployment remains a pressing challenge that limits algorithm portability, cross-project reusability, and engineering scalability [133].

Currently, edge computing development in the SHM domain is primarily project-oriented. Although standardized tool support is lacking, the field is experiencing rapid growth due to its tremendous potential. Edge computing has demonstrated its capability to enable a broad range of SHM functions, including vibration-triggered data acquisition, on-board damage assessment, and local anomaly screening. By conducting signal preprocessing and feature extraction at the sensing node, edge systems reduce raw data volume and prioritize high-value content for transmission. A representative example demonstrating the advantages of edge computing over cloud-based approaches is the adaptive edge intelligence system for rapid structural condition assessment [7]. In displacement estimation tasks, this system achieves a 64-fold reduction in total processing time (from 4.51 s to 0.07 s), with computing time reduced from 0.63 s to 0.03 s and transmission time dramatically reduced from 3.88 s to 0.04 s, illustrating how edge processing eliminates the network latency bottleneck inherent in cloud-based architectures. The power consumption advantages are equally striking: computing power decreases from 8.5 mAh for server-based processing to 0.019 mAh for edge-based processing, while transmission power is reduced from 0.74 mAh to 0.26 mAh, resulting in an overall power reduction of approximately 33-fold. This example clearly demonstrates how edge computing transforms SHM systems from latency-bound, energy-intensive cloud-dependent architectures to responsive, energy-efficient autonomous monitoring platforms [7,18,107]. These improvements are achieved through local processing and intelligent data reduction strategies [110,127]. This enhances bandwidth efficiency, lowers energy consumption, and supports continuous monitoring under power-constrained or duty-cycled conditions. A low-cost, low-power edge computing system for SHM in an IoT framework demonstrates practical implementation of resource-efficient edge processing for structural monitoring [134]. Techniques such as real-time wavelet filtering, fast Fourier transform

(FFT), or statistical feature generation can be implemented using optimized DSP routines. Additionally, edge-based AI models can classify damage states or detect abnormal signal patterns with high responsiveness, making them particularly suitable for applications involving impact monitoring, fatigue analysis, or rapid response diagnostics [7]. Two particularly important directions in edge computing for SHM are worth highlighting. First, data and information fusion has become critical, as SHM often involves multiple sensors generating heterogeneous signals that must be aligned and interpreted in real time. This creates challenges in timing coordination, synchronization, and multi-source integration under computation constraints. Second, accurate and efficient computation under resource-limited conditions demands not only model optimization, but also intelligent multi-task scheduling and high-efficiency memory management strategies that can flexibly allocate resources across concurrent sensing, processing, and transmission tasks [106,110]. For instance, Fu et al. developed a neural network micro memory control strategy for mechanical fault edge recognition, demonstrating how intelligent memory management can enable efficient neural network inference on resource-constrained edge devices [110].

Despite its advantages, edge computing also brings technical limitations. Hardware resource constraints impose strict limits on model complexity and algorithmic diversity. Many high-level SHM techniques, such as system identification, Bayesian inference, or structural model updating, are difficult to scale down for edge execution without significant simplification. Furthermore, embedded development ecosystems are fragmented, and few toolchains offer support for SHM-specific tasks. Firmware updates, remote debugging, and performance profiling are more challenging than in centralized environments. Coordinating edge nodes within a distributed system also requires time synchronization, secure model updates, and efficient peer-to-peer or hierarchical communication protocols [110]. These gaps further underscore the need for dedicated edge-side SHM computing libraries that abstract low-level complexity while exposing reusable, interpretable, and extensible structural monitoring primitives.

As embedded hardware and embedded-AI toolchains continue to advance, edge computing is expected to evolve from simple data filtering toward decentralized intelligence. Emerging techniques such as federated learning [113,135] will enable distributed model training while preserving privacy and reducing bandwidth use. Recent advances in edge-based SHM systems demonstrate the potential for lightweight and efficient monitoring solutions [136]. Integration with digital twins allows edge nodes to simulate local structural behavior in parallel with physical observation, enabling predictive diagnostics and model updating [137–139]. Multi-agent control and reinforcement learning are also beginning to appear in SHM prototypes, supporting adaptive sampling and collaborative inference under dynamic environmental conditions [114,115,140]. In the era of artificial intelligence, edge computing must further embrace AI advancements through the development of standardized toolchains and modular interfaces that support the deployment and orchestration of large models and intelligent agents [141]. Cooperative offloading strategies in UAV-enabled mobile edge computing systems optimize resource allocation and energy efficiency [142]. These frameworks will be essential for enabling scalable cognition at the edge, allowing SHM systems to move beyond signal processing into real-time understanding and autonomous decision-making. Taken together, these trends suggest that edge computing is poised to become not merely a sensor interface, but a proactive reasoning layer capable of supporting the autonomy, adaptability, and intelligence required in next-generation SHM frameworks.

4. Computational intelligence algorithms

While the previous section examined the deployment of computing in IoT-based SHM systems from an architectural perspective, contrasting centralized and distributed paradigms to understand the structural organization of computational resources, this section shifts focus to the underlying forces that drive the computation itself. Specifically, it distinguishes between knowledge-based and AI-based approaches, which represent two fundamentally different paradigms for deriving computational intelligence in ubiquitous computing environments. Knowledge-based methods are grounded in structured domain expertise, physical modeling, and rule-based logic, offering reliable and interpretable solutions for well-understood structural behaviors. In contrast, AI-based methods rely on data-driven learning, statistical inference, and adaptive generalization, enabling systems to autonomously identify patterns, adapt to changing environments, and make informed decisions. These capabilities are essential for advancing SHM toward higher degrees of automation and intelligence. The integration of these algorithmic approaches across edge, fog, and cloud layers embodies the essence of ubiquitous intelligence, where computational capabilities are seamlessly embedded and distributed throughout the monitoring ecosystem. Given the vast and rapidly evolving landscape of SHM algorithms, this section does not aim for exhaustive coverage but instead selectively discusses representative and widely adopted methods that exemplify key ideas within each paradigm. A clear understanding of these algorithmic foundations is critical for designing SHM systems that not only deploy computation effectively, but also perform the right kind of computation to support autonomous operation and intelligent inference across ubiquitous computing infrastructures.

4.1. Knowledge-based approaches

Knowledge-based approaches are grounded in well-established domain knowledge and logical reasoning frameworks. These methods do not require large volumes of training data, instead relying on structured expert insight to guide tasks such as signal processing, modal identification, simulation, and fault reasoning. They are particularly useful in early-stage SHM deployments and safety-critical environments where the cost of erroneous decisions is high and interpretability is essential.

Rule-based engines. Rule-based systems automate decision-making using explicitly defined if-then rules, enabling the encoding of human expertise in interpretable form. In SHM, they are often employed for threshold-triggered alerts, filtering noisy sensor readings, and flagging deviations from expected behavior. Their transparent logic structure allows for straightforward validation and auditing, which is valuable in regulated or safety-sensitive contexts [143]. However, their rigidity limits adaptability to changing system dynamics or unseen fault patterns.

Expert systems. Expert systems extend rule-based logic by combining heuristic rules with inference mechanisms such as forward or backward chaining, allowing them to emulate decision-making processes typically performed by human engineers. In SHM, they are suited for autonomous diagnostics and fault classification, especially in under-instrumented sites where human intervention is limited [144]. The quality of such systems strongly depends on the accuracy and comprehensiveness of the encoded knowledge base, and updating them to accommodate new fault scenarios can be labor-intensive.

Ontologies. Ontologies define shared vocabularies and hierarchical relationships among domain-specific entities such as sensor types, structural components, and failure modes through formal logic representations. In SHM, ontologies enhance semantic interoperability across heterogeneous devices and platforms, supporting consistent data labeling, structured querying, and automated reasoning. They are particularly useful in complex systems with layered data integration needs [145].

Knowledge graphs. Knowledge graphs provide a flexible and extensible means of representing interconnected SHM concepts through graph structures. They are capable of integrating live sensor data with symbolic relationships, supporting tasks such as semantic search, structural state tracking, and context-aware fault reasoning [146]. By embedding evolving observations into structured knowledge spaces, they facilitate adaptive system updates and integrative analytics.

Model-based reasoning. Model-based reasoning (MBR) applies explicit mathematical or physical models such as finite element formulations or analytical dynamic models to predict system behavior, simulate structural responses, or estimate internal parameters based on observable outputs [147]. It emphasizes deductive reasoning based on generalizable physical laws, offering rigorous simulation capabilities in scenarios where sensor data may be sparse but structural understanding is strong. A central application of MBR in SHM is structural model updating, which involves adjusting model parameters (e.g., stiffness, mass, damping) to minimize discrepancies between predicted and observed structural behavior. Model updating combines experimental data from static or dynamic tests with numerical models, enabling the identification of hidden structural resistance and improved representation of actual structural conditions [148]. MBR is particularly effective for simulating damage scenarios under varying loading, solving inverse problems, and validating observed anomalies. However, it typically requires detailed system modeling and high-fidelity parameterization, which can be challenging in large-scale or ill-defined systems.

Case-based reasoning. Case-based reasoning (CBR) solves new problems by retrieving and adapting solutions from previously encountered situations [149,150]. In SHM, CBR leverages databases of historical structural damage, environmental loading, or sensor response cases to inform the assessment of current conditions. It is grounded in inductive reasoning, offering flexibility in complex, data-rich environments where explicit modeling is difficult. Its adaptability improves over time as the case library grows. While CBR lacks the strict physical underpinnings of MBR, it can be more robust when models are incomplete or system heterogeneity is high. The two approaches are complementary: CBR can assist MBR in selecting appropriate models or tuning parameters, while MBR can validate CBR predictions by simulating boundary conditions or failure scenarios.

In summary, knowledge-based approaches provide a transparent and logically grounded foundation for SHM system intelligence. Their strengths in interpretability and domain alignment make them indispensable for traceable engineering decisions, particularly in settings with limited data availability or high reliability requirements. However, their limitations in adaptability and generalization capacity motivate the integration of AI-based methods, especially in data-rich, dynamic environments. The complementary nature of these two paradigms is increasingly leveraged through hybrid architectures that combine symbolic reasoning with learning-based adaptability.

4.2. AI-based approaches

AI-based methods leverage statistical learning and adaptive generalization to tackle SHM tasks such as classification, regression, and anomaly detection. These techniques are particularly effective in environments with large-scale sensing, uncertain inputs, and nonlinear behavior. Compared to knowledge-based systems, they offer superior flexibility, scalability, and pattern recognition capability. While traditional AI learns purely from data, recent advances incorporate domain knowledge to enhance interpretability and robustness [151]. Hybrid approaches, including physics-informed neural networks and Bayesian inference, embed physical principles or prior information into learning pipelines, which is especially valuable when data is limited or physical fidelity is critical. In parallel, the distributed nature of IoT-based SHM has fueled the rise of collaborative AI, such as federated learning and multi-agent systems. These methods support decentralized training and cooperative decision-making [142,152,153] across spatially distributed nodes, showing strong potential for scalable, privacy-preserving, and adaptive SHM implementations.

Physics-informed neural networks. The mathematical essence of PINNs lies in embedding physical laws (e.g., elasticity or wave equations) as additional terms in the neural network loss function [154]. The total loss combines data fidelity loss with a physics-based residual term that penalizes deviation from governing equations evaluated at collocation points, typically using automatic differentiation to compute spatial or temporal derivatives. This formulation enables the network to learn solutions consistent with known structural behavior while respecting physical constraints. In SHM, PINNs have been successfully applied to inverse problems and parameter estimation [155], damage localization tasks [156], and structural health monitoring applications [157]. The primary advantage of PINNs is their improved generalizability and physical interpretability compared to purely data-driven models, making them particularly valuable in data-sparse or noisy settings where physical understanding is strong. However, PINNs face several limitations, including sensitivity to hyperparameter selection, challenges in optimizing high-dimensional latent spaces while maintaining long-term dependencies imposed by PDE constraints, lack of generalization across different structural configurations, computational complexity for large-scale systems, and difficulties when boundary conditions are uncertain [158]. Potential SHM applications include real-time structural response prediction, model updating under sparse sensor configurations, and damage quantification in complex structures. Opportunities exist in combining PINNs with advanced deep learning architectures such as graph neural networks, transformers, and neural operators to enhance SHM performance, integrating PINNs with digital twins for enhanced predictive capabilities, and deploying PINNs to edge devices for real-time inference [158]. While numerous precedents exist for applying PINNs to SHM, research on deploying PINNs to edge devices, particularly resource-constrained microcontrollers, remains scarce and represents a promising future direction. PINNs can help improve data observation, structural state inference, and state transition computation, enabling reconstruction of real-world physical behavior with errors as low as 0.1% [155].

Bayesian inference. The mathematical foundation of Bayesian inference lies in Bayes' theorem, which combines prior knowledge (encoded as prior distributions) with observational data to obtain posterior distributions that quantify both parameter estimates and their uncertainties [159]. The framework naturally accommodates hierarchical modeling, where uncertainty at multiple levels, spanning from sensor noise to model parameters to structural state, can be jointly estimated and propagated through the entire inference pipeline [95]. In SHM, Bayesian methods are widely used for damage assessment and parameter estimation [94], as well as residual life prediction under uncertainty [109]. The fundamental strength of Bayesian methods is their ability to explicitly model and propagate uncertainty from sensor measurements to final diagnostic decisions, enabling risk-informed decision-making in safety-critical applications. This uncertainty quantification is particularly critical in SHM, where decisions have safety implications and data may be sparse, noisy, or incomplete. However, Bayesian methods can be computationally intensive, especially for high-dimensional problems, and require careful specification of prior distributions. Recent developments such as Bayesian neural networks and deep Gaussian processes integrate these principles into modern learning architectures, combining the flexibility of deep learning with principled uncertainty handling. Potential SHM applications include adaptive sensor scheduling under uncertainty, multi-sensor fusion with reliability weighting, and probabilistic damage prognosis. The main challenges involve computational scalability and prior specification, while opportunities exist in developing efficient approximate inference methods and integrating Bayesian principles with edge computing for real-time uncertainty-aware monitoring. A representative example is the adaptive edge intelligence system that employs Gaussian process regression and stochastic process control methods from Bayesian inference to construct a purely data-driven anomaly detection and rapid structural condition assessment model, deployed on resource-constrained Xnode devices [7]. This Bayesian-based edge system achieves a 64-fold reduction in total processing time and an approximately 33-fold reduction in overall power consumption compared to cloud-based approaches, demonstrating the practical benefits of deploying Bayesian inference methods on edge devices for real-time uncertainty-aware monitoring. Another example demonstrates the effectiveness of Bayesian optimization in trigger sensing applications, where the integration of closed-loop feedback control, Bayesian optimization, edge computing, and digital twins achieves a 30% improvement in the F-β performance metric, while reducing computational load by two to three orders of magnitude compared to exhaustive search methods at a given search granularity [72].

Graph neural networks. The mathematical essence of GNNs lies in learning node representations through iterative message passing, where each node's representation is updated based on information aggregated from its neighbors [101]. This process respects the graph structure through an inductive bias that naturally captures structural connectivity and spatial relationships. The graph structure can encode various types of relationships: physical connectivity (e.g., structural members), functional relationships (e.g., load paths), or similarity relationships (e.g., sensors with similar characteristics). In SHM, GNNs have been used for damage localization, anomaly detection, and load path analysis, leveraging topology-aware reasoning to improve robustness under sensor loss, noise, or incomplete data [160]. The primary advantages of GNNs include their ability to encode structural priors directly into the learning architecture, generalize to graphs of different sizes and structures, and capture complex dependencies that traditional methods might miss. This makes them particularly suitable for spatially distributed systems such as bridges, trusses, or sensor grids. However, GNNs can be sensitive to graph structure quality and may require careful design of message passing schemes. GNNs can model both spatial correlations and temporal evolution by extending to dynamic graphs or integrating with recurrent layers. A representative example is the population-based modal identification framework that integrates GNNs with transformers and physics-informed loss functions, which reconstructs full-field mode shapes from sparse sensor data and outperforms traditional methods (e.g., EFDD, SSI) and standard deep learning models (e.g., MLPs, LSTMs) in identifying modal properties under non-stationary and data-sparse conditions [161]. Potential SHM applications include distributed damage localization in large-scale infrastructure, adaptive sensor network reconfiguration, and multi-scale structural health assessment. The main challenges involve designing appropriate graph structures and handling dynamic graphs, while opportunities exist in developing attention mechanisms for adaptive relationship weighting, integrating GNNs with physics-informed constraints for enhanced interpretability, and combining GNNs with edge computing to enable direct GNN execution on wireless sensor networks (WSNs) rather than centralized computers.

Transfer learning. The mathematical principle of transfer learning involves reusing learned feature representations from a source domain and adapting them to a target domain through fine-tuning with limited target data [101]. This is typically achieved by freezing early layers that capture general features and fine-tuning later layers on target-specific data. In SHM, transfer learning has been successfully applied to adapt models trained on simulated data, laboratory structures, or well-instrumented sites to new assets with minimal retraining [162]. Recent advances demonstrate its effectiveness in domain adaptation for population-based monitoring, particularly in bridge applications where models trained on one structure can be adapted to similar structures with minimal labeled data [163]. Common applications include adapting damage classifiers across bridge spans, transferring modal identification knowledge between buildings, and using source-trained embeddings for downstream anomaly detection. The primary advantages are accelerated deployment, reduced data requirements, and enhanced generalization across different structural types or environmental conditions. However, transfer learning effectiveness depends on domain similarity, and negative transfer can occur when source and target domains are too dissimilar. Multi-fidelity training extends transfer learning by combining data from different fidelity levels, leveraging abundant low-fidelity simulation data to learn robust features while using limited high-fidelity experimental data to refine predictions. Potential SHM applications include rapid deployment of monitoring systems for new infrastructure, cross-structure knowledge transfer in bridge networks, and adaptation of models across different environmental conditions. The main challenges involve determining optimal transfer strategies and avoiding negative transfer, while opportunities exist in developing domain adaptation metrics and automated transfer learning pipelines for large-scale SHM deployments.

Federated learning. The mathematical framework of FL addresses distributed learning through a decentralized training paradigm where multiple local nodes collaboratively update a global model by exchanging model parameters (gradients or weights) rather than raw data [113]. The core algorithm, Federated Averaging, aggregates local model updates from participating devices that perform training on their private datasets. The aggregation mechanism must handle non-IID (non-independent and identically distributed) data distributions, which is common in SHM where different structures exhibit distinct behavior patterns, environmental conditions, or damage characteristics. In SHM, FL has been applied to large-scale sensor networks deployed across bridges, buildings, or pipelines, where data locality, privacy concerns, and bandwidth constraints are prominent [164]. Applications include damage diagnosis, vibration classification, and health indexing across distributed infrastructure, allowing each site to adapt to local structural behavior while contributing to a globally robust model. The primary advantages are data privacy preservation, reduced bandwidth usage, and enhanced system scalability, with architecture naturally aligned with edge and fog computing paradigms. However, FL faces challenges including non-IID data distributions, convergence rate and communication efficiency in resource-constrained deployments, and potential security vulnerabilities. Advanced FL algorithms address these through weighted aggregation, clustering of similar clients, or personalization strategies. Potential SHM applications include collaborative learning across infrastructure networks, privacy-preserving model training for sensitive structures, and adaptive learning in dynamic sensor networks. The main challenges involve handling heterogeneous data distributions and ensuring convergence under communication constraints, while opportunities exist in developing SHM-specific FL algorithms and integrating FL with digital twins for enhanced model generalization. However, compared to other AI methods, FL applications in SHM remain relatively scarce, and cases combining FL with edge computing are even rarer, representing a significant gap and opportunity for future research.

Reinforcement learning. The mathematical foundation of RL is based on Markov Decision Processes (MDPs), which formulate sequential decision-making as an interaction between an agent and its environment, where the agent learns a policy (a mapping from states to actions) that maximizes long-term cumulative rewards [101]. The policy is learned through exploration and exploitation, balancing the need to try new strategies with exploiting known good strategies. In SHM, RL has been applied to energy-aware sensor activation, real-time vibration suppression, and dynamic task allocation in changing environments [165,166]. The state space typically includes sensor readings, structural condition indicators, and environmental factors, while actions involve sensor activation, sampling rate adjustment, or alert triggering. The reward function must carefully balance multiple objectives such as monitoring quality, energy consumption, and system reliability. The primary advantages are that RL does not require labeled datasets and learns optimal behaviors through experience, making it highly relevant for real-world SHM systems where conditions evolve continuously. However, RL faces significant challenges including low training efficiency, as it typically requires extensive interactions with the environment to converge to optimal policies, making real-world training costly and time-consuming. This training inefficiency becomes particularly problematic when deploying RL on edge devices, where limited computational resources result in slow training processes and constrained battery capacity further restricts the number of training iterations that can be performed. Additional challenges include reward function design complexity and convergence stability. Transfer learning and simulation-based pretraining can significantly accelerate learning by leveraging knowledge from related tasks or digital twin environments, but the fundamental training efficiency limitations remain a key barrier for edge deployment. Potential SHM applications include adaptive sensor scheduling, autonomous structural control, and dynamic resource allocation in multi-sensor networks. The main challenges involve sample efficiency and reward function design, while opportunities exist in developing model-based RL for faster learning and integrating RL with digital twins for safe exploration.

Multi-agent systems. MAS is grounded in distributed artificial intelligence, where complex system behavior emerges from interactions of autonomous entities operating on partial observations and coordinating via explicit communication or implicit strategy adaptation [167]. Coordination mechanisms range from centralized to distributed or hybrid approaches, with game-theoretic frameworks providing foundations for optimal collective decisions [168]. Agent interactions can adopt competitive, cooperative, or hybrid modes, and through such collective interactions, emergent intelligence can arise from the system, which has the potential to fundamentally transform the operational paradigm of SHM sensor networks. In SHM, this paradigm maps to sensor networks where each node functions as an agent with local sensing, processing, and communication capabilities. Yuan et al. have made foundational contributions, establishing distributed SHM systems using smart wireless sensors and multi-agent technology [169], developing design strategies for large-scale monitoring [168], evaluating collaborative wireless sensor networks [170], and advancing multi-agent coordination and fusion frameworks [171], collectively demonstrating the evolution from early distributed sensing to sophisticated coordination systems. Applications include distributed damage localization [109], intelligent sensing in bridge monitoring [114], event-triggered sensing, and region-specific model adaptation, offering advantages in scalability, fault tolerance, and real-time collaboration. However, MAS faces challenges including coordination complexity, communication overhead, and convergence guarantees in large-scale systems. Integration with reinforcement learning enables decentralized policy learning, forming multi-agent reinforcement learning (MARL) [140], though this introduces complexity as agents learn in non-stationary environments. A critical research gap exists in transitioning from rule-based, manually-designed workflows in current WSN-based MAS toward adaptive, edge-intelligent agents capable of autonomous learning and self-organization, representing a paradigm shift from deterministic coordination to emergent intelligence. Opportunities include integrating MAS with edge computing and digital twins for localized structural intelligence, and notably, the development of onboard AI-driven agents represents a highly promising and transformative research direction with immense potential, enabling true sensor-level intelligence where each node becomes an autonomous decision-making entity capable of real-time adaptation, local inference, and collaborative learning without centralized control or predefined rules.

Large language models (LLMs). The mathematical foundation of LLMs lies in the transformer architecture, which uses multi-head self-attention and positional encoding to learn complex syntactic, semantic, and contextual representations from massive textual corpora [101]. The attention mechanism allows LLMs to capture long-range dependencies and contextual relationships, enabling impressive generalization across diverse tasks, including natural language understanding, reasoning, and code generation. Models such as DeepSeekR1 [172] represent a paradigm shift toward general-purpose AI systems capable of understanding and generating human-like text, code, and multimodal content. As part of the broader generative AI revolution, LLMs are reshaping SHM through their ability to synthesize knowledge, generate insights, and enable natural language interfaces [15]. In SHM, LLMs have been applied to intelligent querying, automated report generation, and fault explanation in natural language, facilitating human–system interaction and improving the accessibility of SHM insights [173,174]. For structural damage identification, LLM-based systems have demonstrated impressive performance, with accuracy reaching 95.24%, a result that matches or even surpasses many traditional methods [174]. Foundation models specifically designed for SHM demonstrate the potential for domain-adapted LLMs that can understand structural engineering concepts and provide specialized monitoring capabilities [175]. The application of large models extends beyond SHM to broader machine monitoring and fault diagnostics, offering insights into opportunities, challenges, and future directions for deploying LLMs in engineering applications [176]. The integration of LLMs with generative AI capabilities enables multimodal synthesis, where visual, textual, and numerical SHM data can be combined to create comprehensive structural health narratives. The primary advantages include natural language interaction, knowledge synthesis capabilities, and multimodal content generation. However, LLMs face significant challenges including adapting to domain-specific vocabularies, ensuring response reliability in safety-critical environments, and optimizing computational efficiency for deployment on edge or fog platforms. Beyond passive assistance, LLMs are increasingly used as the cognitive core of autonomous agents capable of memory management, tool use, and iterative planning. It is important to distinguish LLM-based agents from the agents in MAS: LLM-based agents are primarily deployed in resource-rich computing environments where they can tackle complex, cognitively demanding tasks requiring deep reasoning, extensive context understanding, and sophisticated planning capabilities, whereas edge-deployed agents face stringent resource constraints, necessitating a design philosophy centered on lightweight, specialized, and task-specific architectures that prioritize efficiency over generality. Potential SHM applications include LLM-based agents for orchestrating monitoring workflows, translating between human queries and sensor-level commands, coordinating information across distributed nodes, and providing intelligent decision support. The main challenges involve domain adaptation, response reliability, and computational efficiency, while opportunities exist in developing SHM-specific LLMs through fine-tuning, prompt engineering, or retrieval-augmented generation, and deploying compressed models on edge platforms through model compression and knowledge distillation.

The ascendancy of AI-based methods over traditional knowledge-based systems represents a fundamental paradigm shift in SHM, heralding a new era where computational intelligence transcends deterministic rule-following to embrace adaptive, scalable, and uncertainty-resilient reasoning. AI-based methods offer significant advantages over traditional knowledge-based systems in terms of adaptability, scalability, and performance under uncertainty, making them well-suited for the increasingly complex and dynamic environments of SHM. However, their reliance on large-scale data, limited interpretability, and challenges in model validation remain key concerns, particularly in safety-critical applications. As summarized in Table 4, the two paradigms differ in reasoning mechanisms, operational flexibility, and trustworthiness. The convergence of distributed computing paradigms with AI, particularly edge intelligence, amplifies this transformation, enabling intelligence to permeate every layer of the monitoring ecosystem, from sensor nodes to fog gateways to cloud orchestrators, fundamentally redefining the spatial and temporal boundaries of SHM through real-time, context-aware decision-making at the point of data generation. To harness their complementary strengths, a growing body of research focuses on hybrid approaches that integrate physical constraints, expert priors, or semantic structure into learning processes. Representative techniques include physics-informed neural networks, Bayesian neural networks, and interpretable deep learning frameworks, all of which aim to bridge the gap between empirical adaptability and engineering reliability. These hybrid methods represent a promising direction for SHM,

Table 4
Comparison between knowledge-based and AI-based methods in IoT-based SHM.

Aspect	Knowledge-based	AI-based
Principle	Expert rules and physics models	Data-driven learning
Dependency	Domain knowledge	Large datasets
Adaptability	Low; rule-bound	High; learns patterns
Interpretability	Clear and traceable	Often opaque
Data need	Low	High
Typical tasks	Rule-based alerts, logic checks	Fault detection, prediction
Strengths	Reliable, explainable	Flexible, scalable
Limitations	Hard to adapt, rigid	Needs data, less transparent

enabling systems that are not only data-efficient and context-aware but also physically consistent and auditable. Ultimately, the transition from knowledge-based to AI-based computation, when synergized with distributed computing architectures and edge intelligence, represents a tectonic shift in SHM, moving from centralized, deterministic, expert-guided reasoning toward autonomous, distributed, and self-evolving intelligence that operates seamlessly across edge, fog, and cloud layers. As sensor networks proliferate and computational layers become more decentralized, AI will increasingly form the core of resilient, real-time SHM systems capable of addressing the scale, complexity, and uncertainty of modern infrastructure.

5. SHM applications

This section adopts an application-driven perspective grounded in engineering practice, highlighting how ubiquitous computing and intelligence transform the core tasks of SHM. Rather than classifying methods by architecture or concept, it organizes computational approaches according to their functional roles within practical SHM workflows, emphasizing how ubiquitous computing enables seamless integration of computational capabilities across edge, fog, and cloud layers. Specifically, it examines five interdependent stages: measurement, system identification, damage assessment, damage localization, and damage quantification. The first two focus on ubiquitous data acquisition and intelligent structural modeling, while the latter three form a progressive chain of intelligent damage assessment, from autonomously identifying abnormal behavior to intelligently pinpointing its location and quantifying its severity. This process-oriented structure reflects how modern SHM systems operate in the field through ubiquitous computing paradigms, and underscores how ubiquitous computing and intelligence not only facilitate timely and scalable monitoring, but also serve as critical enablers in advancing SHM systems toward higher levels of autonomy, adaptability, and intelligence across the full monitoring lifecycle.

5.1. Measurement

Measurement constitutes the entry point of SHM and represents the most fundamental embodiment of ubiquitous computing principles, where sensor data are collected directly at the data source to capture both structural responses and environmental conditions. As the closest layer to the physical world, measurement epitomizes the ubiquitous computing paradigm by embedding computational capabilities directly within the sensing infrastructure, enabling distributed intelligence and autonomous operation at the network periphery. Typical measured quantities include displacement, acceleration, strain, stress, temperature, and humidity, depending on the monitoring objectives [17]. These data are typically obtained from field-deployed sensors such as accelerometers and strain gauges, as described in Section 2.1.

The core objective of measurement is to produce reliable data suitable for downstream analysis while maintaining the ubiquitous computing philosophy of seamless, context-aware data acquisition. Achieving this entails addressing challenges related to signal resolution, synchronization, completeness, and latency, each of which introduces specific computational demands that are ideally resolved through ubiquitous computing approaches [68,74]. Techniques such as denoising and filtering improve signal fidelity, while clock correction and alignment resolve temporal inconsistencies. Missing data can be addressed through anomaly detection and imputation, and data buffering, compression, or prioritization techniques help manage bandwidth and latency under resource-constrained conditions. Measurement strategies generally fall into two categories: batch acquisition and live streaming. The former supports offline analysis and long-term evaluation, while the latter enables real-time decision-making, including event-triggered responses. Streaming-based workflows increasingly leverage edge computing for low-latency processing and adaptive data handling close to the sensing source, exemplifying the ubiquitous computing principle of bringing computation to where data originates. As ubiquitous computing and AI transform SHM, future measurement will evolve toward context-aware, on-demand acquisition strategies, with AI-driven agent-controlled systems representing a promising direction where intelligent agents autonomously decide when, what, and how to measure based on environmental understanding [72,74].

Ultimately, robust measurement underpins all subsequent stages of SHM. However, raw sensor data are not inherently meaningful until they are structured, interpreted, and linked to physical behavior through analytical frameworks. This transformation begins with system identification, which extracts dynamic characteristics from measurements and provides a quantitative foundation for condition assessment, model updating [177], and decision-making in modern SHM systems.

5.2. System identification

System identification serves as the bridge between raw sensor measurements and meaningful structural interpretation. It extracts dynamic parameters such as natural frequencies, damping ratios, and mode shapes, which together define a structure's baseline behavior and provide critical input for model-based diagnostics, health tracking, and performance evaluation [94,178]. In practical SHM deployments, especially under ambient or uncontrolled excitations, challenges arise due to low signal-to-noise ratios, time-varying disturbances, and sparse or non-collocated sensor layouts. These conditions require robust identification methods that function effectively with limited data and uncertain input characteristics. Boundary condition uncertainty, arising from sensor mounting, structural connections, or environmental variations, significantly affects modal parameter identification and can be addressed through Bayesian approaches, uncertainty quantification techniques, or multi-model strategies [95,148].

Several analytical strategies are widely used to meet these demands. Time-domain methods, including the eigensystem realization algorithm (ERA) [179,180] and stochastic subspace identification (SSI) [181], estimate dynamic properties by reconstructing state-space models directly from output time-series. These techniques are particularly effective when input excitation is not measured, and they are well-suited for civil structures operating under ambient conditions [50,73,182]. Frequency-domain approaches, such as peak picking in spectral data or frequency response function analysis, are more appropriate when excitation is stationary, offering intuitive insights into resonant behavior and modal separation [183–186]. In addition, time–frequency methods, including wavelet transforms [187] and Hilbert-Huang transforms [188,189], provide localized representations of signal content in both time and frequency. This enables better characterization of non-stationary behavior, such as sudden impacts or environmental changes, which are frequently encountered in field-deployed SHM systems.

Alongside methodological innovations, advances in embedded computing have facilitated real-time and distributed implementations of system identification [109]. Techniques such as streaming modal analysis, recursive subspace tracking, and reduced-order modeling can now operate on edge or fog devices, enabling timely structural assessment without the need for centralized post-processing [190–192]. As ubiquitous computing and intelligence evolve, specialized methods for distributed system identification have emerged, leveraging decentralized architectures and embedded computing for efficient modal parameter extraction across sensor networks [193,194], yet this field remains largely unexplored with significant research potential. These lightweight and scalable algorithms allow early detection of anomalies and support context-aware monitoring in constrained environments. As SHM systems evolve toward greater autonomy and responsiveness, system identification plays an increasingly pivotal role in connecting measurement with decision-making, ensuring that structural assessments are both timely and physically meaningful.

5.3. Damage detection

Damage detection addresses a fundamental question: does the current structural state deviate from its undamaged baseline? This task initiates the transition from passive sensing to active inference in SHM, enabling early alerts and proactive decision-making [11,195–197]. While system identification can extract current responses, establishing reliable baselines remains challenging due to environmental variability, material degradation, and the absence of ground truth in operational settings. The core difficulty lies in both quantifying deviation and distinguishing true structural anomalies from benign fluctuations. Two principal strategies address this challenge: model-based methods leverage numerical simulations or expert-informed rules to define reference behavior, offering interpretability and engineering rigor but requiring high-fidelity models and labor-intensive calibration; data-driven methods recast detection as unsupervised anomaly detection, learning normal behavior patterns from historical data without explicit models, offering greater adaptability but increased sensitivity to operational drift and sensor noise [198–200].

Statistical techniques, including Statistical Process Control (SPC), Principal Component Analysis (PCA), and Mahalanobis Distance (MD), remain widely used for their simplicity, low computational cost, and effectiveness under limited data conditions, making them particularly suitable for edge deployment [7,195,201–203,203]. Unsupervised learning models such as autoencoders learn latent representations of healthy states and detect subtle nonlinear anomalies through reconstruction error analysis [204–206]. AI-based detection methods, particularly deep learning approaches, demonstrate superior performance with high accuracies and reduced false positive rates in controlled laboratory settings, though field deployments show more modest improvements due to environmental variability and operational uncertainties, highlighting the importance of robust training and adaptation strategies [195,198–200,205]. In practical applications, AI-driven damage detection systems have demonstrated significant effectiveness in structural condition assessment. For instance, systems employing Gaussian process regression for anomaly detection achieve substantial performance gains, with processing efficiency improvements of 64-fold and power consumption reductions of approximately 33-fold compared to traditional cloud-based approaches, while maintaining effective damage detection capabilities [7]. Furthermore, intelligent trigger sensing systems integrating Bayesian optimization with edge computing demonstrate notable improvements in detection performance metrics, with computational efficiency enhanced by multiple orders of magnitude [72]. To address environmental variability and operational uncertainties, hybrid approaches incorporating physical priors, statistical normalization, or domain adaptation are increasingly explored. Boundary condition uncertainty, arising from uncertain sensor mounting or structural connections, can cause response variations misinterpreted as damage, requiring environmental normalization, adaptive thresholds, and uncertainty-aware methods that explicitly model boundary condition uncertainty to reduce false alarms while maintaining sensitivity to genuine structural deterioration.

With the rise of edge and fog computing, damage assessment is progressively being migrated to local platforms, where data can be processed close to its source. This shift enables real-time alerts, reduces transmission burden, and enhances system scalability. When properly integrated with system identification outputs, detection provides a crucial trigger for follow-up localization and severity assessment tasks, forming the first computational layer of intelligent structural diagnostics.

5.4. Damage localization

Once damage has been detected, the next critical task is to determine its spatial location. Localization assigns geographic or geometric context to anomalies, enabling targeted inspection, repair planning, and risk containment. This is especially important in large-scale or complex structures where comprehensive manual examination is not feasible.

Localization methods primarily rely on analyzing spatial variations in dynamic structural responses. Modal-based techniques detect shifts in structural behavior by tracking changes in mode shapes and related energy distribution. Curvature mode shape analysis identifies local stiffness loss by examining deviations in the curvature of vibration modes, while the Modal Strain Energy (MSE) method estimates the redistribution of vibrational energy across the structure, which tends to concentrate around damaged regions [207,208]. These methods are particularly effective under ambient vibration conditions and output-only settings, making them widely applicable in operational SHM environments. Traditional modal-based localization methods achieve reasonable accuracy, with performance depending on sensor density and modal parameter estimation quality [208]. AI-enhanced localization approaches, leveraging deep learning and pattern recognition, have demonstrated improved performance with reduced localization errors in laboratory and controlled field conditions [195,200].

In scenarios involving transient or propagating signals, such as impact detection or guided wave monitoring, time-domain approaches are commonly used. Techniques like Time Difference of Arrival (TDoA) estimate the source location of an event by calculating the arrival time differences across multiple sensor nodes [209]. This requires precise synchronization and high temporal resolution but offers accurate localization in real time.

Signal decomposition techniques are often employed to improve robustness under noisy or complex conditions. Wavelet transforms enable time–frequency localization of transient features, enhancing sensitivity to local damage signatures. Independent Component Analysis (ICA) helps separate spatially mixed signals, allowing overlapping structural responses to be untangled and attributed to specific sources [210–212]. From a system architecture perspective, localization increasingly benefits from distributed processing. Edge and fog nodes are capable of computing spatial indicators locally, thereby reducing communication latency and bandwidth usage. By performing intermediate analysis closer to the sensing point, these architectures support timely response and improve the scalability of SHM systems. Notably, localized damage inference can also inform data prioritization strategies by reclassifying sensor streams based on their spatial relevance. Signals from sensors near suspected damage zones may be flagged for high-priority transmission, while less relevant data can be compressed or deferred. This importance-aware transmission approach enhances communication efficiency and ensures that critical information is delivered promptly for downstream diagnostics or decision-making. Accurate localization not only focuses subsequent inspection efforts but also establishes a spatial reference frame for severity evaluation and long-term condition tracking.

5.5. Damage quantification

Damage quantification estimates the severity of identified damage, translating abstract detection signals into engineering-relevant metrics such as stiffness loss, damping variation, or remaining structural capacity. This process is essential for prioritizing maintenance, evaluating safety margins, and informing lifecycle decision-making.

Quantification methods typically assess changes in system dynamics. Frequency-domain techniques compare pre- and post-event frequency response functions to detect degradation in structural properties such as stiffness or damping [184]. These approaches provide a spectral view of damage and are particularly suited to systems where excitation and response can be reliably measured at multiple locations. Modal-parameter-based approaches quantify severity through changes in global modal properties. Techniques like stochastic subspace identification (SSI) extract modal frequencies and damping ratios, which shift measurably in response to structural deterioration [181].

To improve spatial resolution, energy-based techniques such as the MSE index are often used. These methods highlight localized stiffness reductions by calculating the distribution and intensity of vibrational energy under excitation [208]. MSE-based indicators can effectively track progressive damage in multi-story buildings, bridges, or other spatially distributed systems. Meanwhile, data-driven approaches increasingly contribute to quantification through machine learning regression models. Trained on labeled datasets from simulations or historical inspections, these models predict physical parameters such as crack length, damage index, or failure probability based on extracted signal features.

Quantification is also being integrated into digital twin frameworks and automated condition rating systems [213]. These platforms allow quantification metrics to be visualized, trended over time, and combined with simulation-based predictions. Real-time execution on edge devices supports continuous evaluation without overburdening central servers, making quantification compatible with distributed SHM deployments. Ultimately, quantification completes the inference chain by converting sensed anomalies into actionable structural assessments, enabling informed decisions regarding inspection urgency, repair prioritization, or decommissioning strategy.

6. Case studies

This section examines representative IoT-based SHM systems that demonstrate ubiquitous computing and intelligence principles in practice. We analyze over twenty SHM systems to understand how ubiquitous computing enables seamless integration of computational capabilities across edge, fog, and cloud layers, and how intelligence advances SHM toward autonomous, distributed monitoring.

Table Overview. Table 5 presents case studies that exemplify ubiquitous computing and intelligence in IoT-based SHM, enabling analysis of how these principles manifest across different device types, computing paradigms, and application domains. The analysis reveals distinct patterns in how ubiquitous computing and intelligence are implemented across different deployment contexts.

Computing Patterns. Examining the device and architectural choices reveals how ubiquitous computing principles are applied in practice. Academic studies favor MPU platforms for prototyping ubiquitous computing concepts, while practical deployments prefer MCU platforms that better embody ubiquitous computing's goal of embedding intelligence everywhere. This preference reflects the fundamental challenge of ubiquitous computing: bringing computational capabilities to resource-constrained environments. Moreover, a clear trend toward distributed architectures demonstrates ubiquitous computing principles, where sensing, processing, and intelligent decision-making occur collaboratively across nodes, enabling autonomous operation in SHM systems.

Intelligence Integration. Beyond architectural choices, the integration of intelligence presents another critical dimension. A divide exists between system design studies using knowledge-based validation and algorithm-driven research adopting AI methods. The integration of advanced AI techniques with field-ready SHM systems remains limited, revealing untapped potential in distributed intelligence. Most current AI applications use basic models, while advanced methods like federated learning and embodied intelligence have limited uptake due to embedded platform constraints. This gap between theoretical AI capabilities and practical ubiquitous computing implementations highlights a key opportunity: combining resource-efficient IoT architectures with high-level SHM functions to enable intelligent, real-time diagnostics through ubiquitous computing and intelligence.

These case studies collectively demonstrate the convergence of ubiquitous computing and intelligence in SHM, highlighting the need for integrating advanced computational methods with deployable IoT architectures to realize truly pervasive and intelligent structural monitoring.

7. Discussion

This comprehensive review reveals two fundamental trends shaping the evolution of IoT-based SHM systems. First, there is a clear shift from centralized to distributed computing paradigms, where computational capabilities are increasingly embedded throughout the monitoring ecosystem from edge sensors to cloud platforms, enabling real-time responsiveness and autonomous operation. Second, there is a transition from model- and knowledge-driven approaches toward data- and AI-driven methods, where adaptive learning and intelligent inference complement traditional rule-based reasoning, enabling systems to learn from data and evolve autonomously. Building on these observations, this section synthesizes the key challenges and enablers that shape the evolution of ubiquitous computing and intelligence in IoT-based SHM systems (see Fig. 13), and presents engineering considerations and practical insights for real-world deployment. The discussion is organized into three complementary parts. First, challenges examines the fundamental obstacles to achieving efficient, accurate, and reliable ubiquitous computing and intelligence, organized thematically to reflect their interconnected nature, where multiple challenges may overlap and require integrated solutions. Second, potential enablers identifies the technologies, platforms, and paradigms that can address these challenges, recognizing that multiple enablers may collectively address a single challenge. Third, engineering considerations and practical insights translates the comprehensive review findings into actionable guidance, highlighting the anticipated advantages and implementation strategies for adopting ubiquitous computing and intelligence in IoT-based SHM systems.

7.1. Challenges

Cost, constraints and performance. Balancing deployment costs with performance and resource limitations is a fundamental challenge in realizing ubiquitous computing and intelligence in IoT-based SHM. Edge computing nodes operate under limited power, processing capacity, and memory constraints, making efficient resource management crucial for intelligent processing at the network periphery, especially in long-term deployments requiring continuous, autonomous operation in remote areas. Cost-effective strategies include selecting appropriate sensor types, leveraging low-power communication protocols (e.g., LoRa, NB-IoT) for remote areas, adopting edge computing to reduce transmission costs, and implementing modular architectures with intelligent data reduction at the edge.

Data Quality and Management. Ensuring data quality throughout the SHM data pipeline is crucial for accurate monitoring and reliable intelligent decision-making. In ubiquitous computing environments,

Table 5
Representative case studies in IoT-based structural health monitoring.

Ref.	Year	Device	Paradigm	Algorithm	Application	Highlights
[199]	2018	MPU	Centralized	AI	Damage assessment	1D CNN real-time inference
[11]	2018	MCU	Distributed	AI	Damage assessment	Real-time lightweight damage assessment
[68]	2020	MCU	Distributed	Knowledge	Measurement	Autonomous railway bridge implementation
[79]	2021	MCU	Distributed	Knowledge	Measurement	Battery lifespan enhancement for IoT WSN
[127]	2021	MPU	Distributed	Knowledge	Damage assessment	Arduino/Raspberry Pi/laboratory validation
[35]	2022	MCU	Centralized	Knowledge	Measurement	ESP32/STM32 WSN for synchronized sensing
[178]	2022	MCU	Distributed	Knowledge	System identification	STM32/system identification at extreme edge
[119]	2022	MCU	Distributed	Knowledge	System identification	Edge/fog/cloud collaborative architecture
[3]	2022	MPU	Distributed	AI	System identification	Raspberry Pi 4B/NB-IoT/low-cost IoT platform
[214]	2023	MCU	Centralized	Knowledge	Damage assessment	Real railway bridge implementation
[215]	2023	MCU	Distributed	Knowledge	System identification	Low latency real-time computing and streaming
[216]	2024	MCU	Centralized	Knowledge	System identification	ESP32 low-cost IoT node prototyping
[164]	2024	MCU	Distributed	AI	Measurement	Federated learning/smart home
[134]	2024	MCU	Centralized	Knowledge	System identification	Low-cost, low-power/long-term field monitoring
[65]	2024	MCU	Distributed	Knowledge	System identification	Edge–fog–cloud computing combined
[217]	2024	MCU	Distributed	AI	Damage assessment	OpenMV/MCU–MPU combined
[218]	2024	MPU	Distributed	AI	System identification	Nvidia Jetson/computer vision
[18]	2024	MPU	Distributed	AI	Damage assessment	Hong Kong–Zhuhai–Macao Bridge
[105]	2013	MPU	Centralized	Knowledge	System identification	Shanghai Tower (632 m)
[118]	2025	MPU	Centralized	Knowledge	System identification	Tsing Ma Suspension Bridge
[107]	2025	MPU	Distributed	AI	Measurement	Distributed intelligence/knowledge distillation
[110]	2025	MCU	Distributed	AI	Measurement	MCU onboard AI/memory management
[7]	2025	MCU	Distributed	AI	Damage assessment	Adaptive edge intelligence/full scale validation

data flows across multiple layers from edge sensors to cloud platforms, where quality issues can propagate through the entire intelligent processing chain, affecting AI algorithm reliability and autonomous decision-making. Effective noise management requires a holistic approach addressing noise at multiple stages: hardware-level strategies (sensor selection, mounting, shielding), preprocessing techniques (filtering, denoising, regularization), and uncertainty-aware data fusion methods that account for varying noise levels across sensors. Quality assurance requires careful device selection, noise reduction, storage solutions, and robust data management strategies that maintain accuracy, consistency, and timeliness across the ubiquitous computing infrastructure.

Privacy and Data Governance. Data ownership and privacy concerns introduce significant non-technical challenges in SHM. SHM data often belongs to specific organizations, limiting data sharing due to its sensitive nature, despite potential benefits in reducing redundant collection costs and enhancing analysis. Metadata management and data interpretability become increasingly complex with advanced AI models, potentially reducing transparency. Effective data governance and standardization efforts are needed to balance data sharing benefits with privacy protections.

Real-Time and Communication. Achieving real-time processing capabilities is essential for intelligent SHM applications requiring autonomous responses, such as earthquake early warning and emergency response. Ubiquitous computing architectures must balance computational demands of intelligent algorithms with distributed processing constraints, requiring efficient data handling through edge computing (resource-constrained) or cloud computing (network-dependent), with algorithms distributed across the computing hierarchy. Reliable communication faces challenges from latency, bandwidth limitations, packet loss, and data distortion in time-sensitive applications, demanding well-designed distributed computing approaches that combine edge and cloud resources with intelligent strategies like adaptive redundancy, error correction, and data compression.

Scalability and Adaptability. Long-term SHM deployments in remote and challenging environments necessitate both adaptability and scalability, fundamental to ubiquitous computing and intelligence paradigms. Adaptability enables intelligent systems to respond to environmental changes and evolving requirements through autonomous learning and reconfiguration, while scalability allows seamless integration of additional sensors or nodes without disrupting the infrastructure. Addressing these needs requires flexible architectures supporting modular configurations and intelligent adaptation, enabling systems to grow and evolve autonomously as monitoring needs change.

Error, Uncertainty, and Reliability. Numerical errors and uncertainties inherent in SHM data processing, arising from sensor inaccuracies, model assumptions, and data inconsistencies, are particularly critical in ubiquitous computing and intelligence systems where errors can propagate through distributed processing chains and compromise autonomous decision-making reliability. Uncertainty-aware fusion becomes essential, explicitly accounting for varying data quality and uncertainty levels across heterogeneous sensors, preventing unreliable sources from unduly influencing critical decisions. Ubiquitous computing systems must maintain consistent performance across diverse environmental conditions and extended operational periods, requiring effective error control, uncertainty quantification, and reliability assurance techniques to ensure accurate, reliable outputs supporting autonomous operation under varying conditions and potential component failures.

Vulnerability and Resilience. IoT-based SHM systems face inherent vulnerabilities from node failures, network disruptions, and environmental hazards that can compromise monitoring continuity [219]. Resilience patterns include redundancy-based (duplicate components), diversity-based (heterogeneous implementations), modularity-based (failure isolation), and autonomy-based (local decision-making) approaches [220]. Distributed computing paradigms inherently provide better resilience than centralized systems through local autonomy and redundant paths [52], though they require careful design to balance resilience with complexity and resource consumption.

Automation and Interoperability. Current SHM systems often rely on human intervention for fine-tuning, troubleshooting, and decision-making, limiting ubiquitous computing and intelligence potential. For time-sensitive applications, limited automation can delay responses and impact reliability, particularly where autonomous operation is essential. Integrating connected data flows and automated processes through intelligent algorithms can improve performance and responsiveness. Furthermore, interoperability between devices and data formats remains challenging as SHM systems become more diverse and distributed, requiring standardization efforts to facilitate seamless communication between intelligent components across edge, fog, and cloud layers.

Each of these challenges presents specific hurdles to achieving efficient, accurate, and reliable ubiquitous computing and intelligence in IoT-based SHM systems. Together, they emphasize the need for

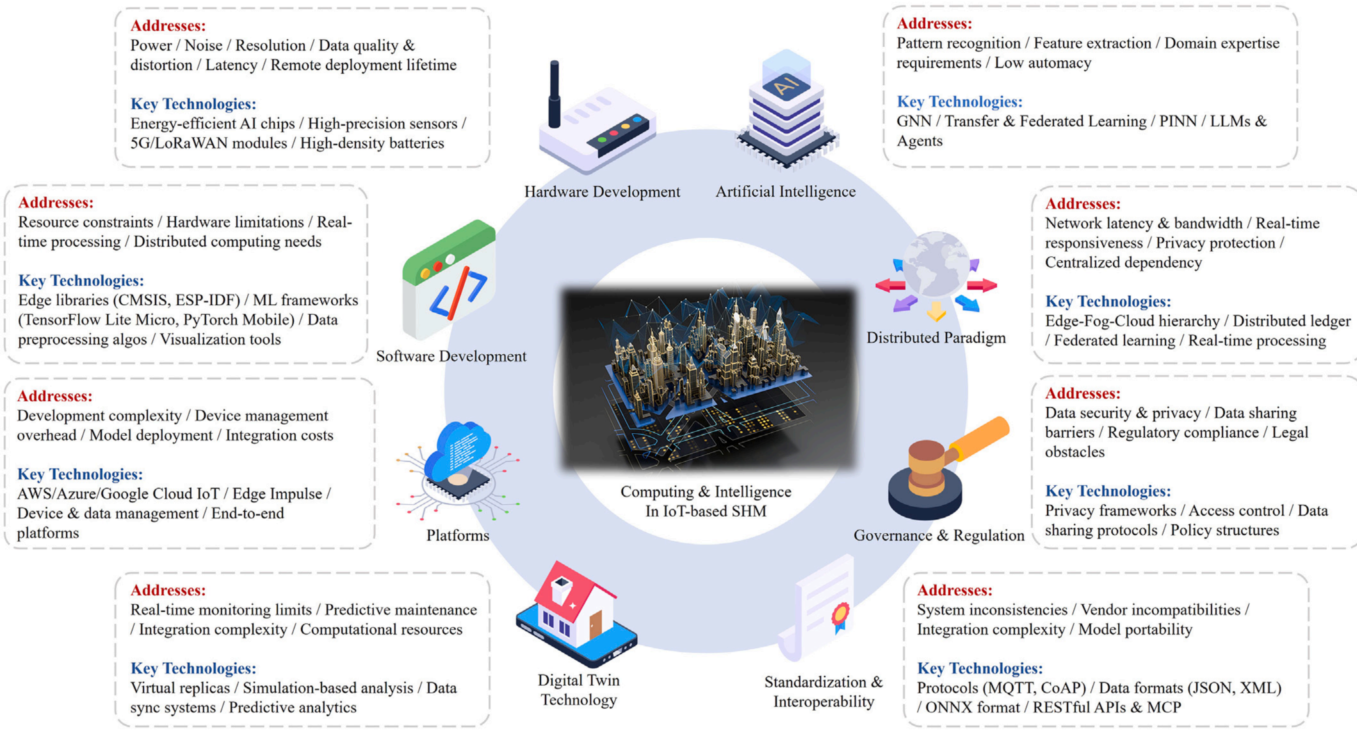

Fig. 13. Overview of potential enablers for computing and intelligence in IoT-based SHM systems: challenges addressed and key technologies.

cohesive design approaches that consider both technical and non-technical factors while advancing toward truly pervasive and intelligent structural monitoring.

7.2. Potential enablers

Hardware development. Hardware developments, including new materials, architectures, and configurations, can fundamentally address critical challenges in IoT-based SHM. Advances in chip design reduce power consumption and enhance computational capacity, enabling more complex processing tasks directly on edge devices [221], while energy-efficient AI implementations are increasingly important for sustainable deployments [222]. Enhanced sensor designs improve data quality and minimize distortion [223], improved actuators enable faster and more precise responses, and high-density batteries extend operational lifetimes for remote deployments. Innovations in communication technology reduce latency and overhead, enabling faster and more reliable data transmission. However, these solutions require collaborative, industry-wide efforts and may not materialize in the short term. For SHM-specific applications, hardware developments should balance cost-effectiveness with performance improvements.

Software development. Well-designed software can unlock the full potential of IoT hardware and compensate for certain hardware limitations. For IoT-based SHM, software encompasses data collection, processing, storage, management, analysis, simulation, and visualization. Lightweight edge libraries like CMSIS [130–132,224] and ESP-IDF [225,226] support efficient processing, while cloud computing frameworks facilitate high-performance computations. AI and machine learning frameworks like TensorFlow [128] and PyTorch [227] are critical for advanced analytics. As computing paradigms shift from centralized to distributed, there is a growing need for high-performance algorithms and libraries specifically designed for resource-constrained edge and fog computing environments [133,225].

Platforms. IoT platforms can streamline the development and deployment of IoT-based SHM systems, offering comprehensive tools for device and data management, as well as AI model training and deployment. Platforms such as AWS IoT, Azure IoT, and Google Cloud IoT support seamless device and data management, while Edge Impulse simplifies edge AI model training and deployment. These end-to-end platforms reduce development costs and time, enabling engineers to focus on unique SHM requirements, though additional customization may be necessary to adapt them to domain-specific SHM needs.

Digital Twin technology. Digital Twin technology creates real-time virtual replicas of physical structures that continuously synchronize with sensor data, enabling predictive maintenance through simulation-based analysis [228]. This technology facilitates seamless integration between physical sensors and virtual models, providing comprehensive structural health assessment combining real-time monitoring with historical data and predictive analytics, while supporting advanced visualization and decision-making. However, effective implementation requires sophisticated modeling capabilities, high-fidelity data synchronization, and substantial computational resources, particularly for complex structures with numerous sensors and dynamic environmental conditions.

Standardization and interoperability. Standardization is vital for addressing inconsistencies and incompatibilities within IoT-based SHM systems, enabling easier integration across devices, algorithms, models, and data sources from different vendors. Common protocols such as MQTT and CoAP, data formats like JSON and XML, and interfaces such as RESTful APIs facilitate communication and data exchange. For AI applications, the Open Neural Network Exchange (ONNX) format [229] supports model portability across frameworks. In the context of LLMs and autonomous agents, emerging specifications such as the Model Communication Protocol (MCP) offer structured guidance for model communication and collaboration [141]. The SHM domain, while beginning to adopt some of these conventions, still lacks unified standards tailored to its unique sensing, modeling, and inference workflows. Advancing standardization will be essential to reduce integration complexity and enhance interoperability.

Governance and regulation. In the digital era, data governance and regulation are critical for IoT-based SHM, as they must balance the dual priorities of data security and accessibility. While protecting data privacy is essential to prevent unauthorized access and ensure compliance with legal standards, promoting data sharing across systems can reduce redundant collection efforts and enhance analytical effectiveness. Achieving this balance requires governance frameworks that provide secure and controlled access to data while simultaneously facilitating its responsible use. In many cases, social and legal barriers to data sharing present greater obstacles than technical limitations, highlighting the need for clearly defined regulatory and policy structures that align with the broader goals of SHM.

Shifting computing paradigms. Evolving computing paradigms, particularly the shift from centralized to distributed models, are redefining how IoT-based SHM systems operate. Traditional centralized computing offers powerful data processing capabilities but is limited by network conditions (e.g., bandwidth, latency). As the need for responsiveness and privacy protection grows, edge and fog computing bring processing closer to data sources, improving real-time performance and reducing dependency on centralized resources, though requiring more sophisticated hardware, optimized algorithms, and reliable networks. The future of SHM lies in striking an optimal balance between edge and cloud computing, leveraging the strengths of both paradigms.

Artificial intelligence. AI is transforming problem-solving across industries, offering promising advancements in SHM for monitoring, diagnosing, and predicting structural health [230–233]. AI algorithms translate complex tasks into basic categories like classification, regression, clustering, and dimensionality reduction, enabling automatic feature extraction from data. While foundational AI methods are well-established, advanced techniques such as graph neural networks [234], transfer learning, federated learning, reinforcement learning, Bayesian neural networks, and physics-informed neural networks hold potential to address specific SHM challenges. The transformer architecture [235] shows promise for sequence modeling, while the rapid development of LLMs and intelligent agent technologies has significantly lowered domain expertise requirements and reduced human-machine interaction barriers, showing broad prospects for future integration into IoT-based SHM systems.

7.3. Engineering considerations and practical insights

This comprehensive review reveals fundamental insights that directly inform the design, deployment, and operation of IoT-based SHM systems in real-world engineering contexts. Successful systems require a holistic approach integrating architectural, algorithmic, and application perspectives. The convergence of distributed computing and AI intelligence addresses the scale, complexity, and real-time requirements of modern infrastructure monitoring through three critical principles: (1) computational capabilities must be embedded throughout the monitoring ecosystem, from edge sensors to cloud platforms; (2) the choice between knowledge-based and AI-based methods should be driven by data availability, interpretability requirements, and safety-critical considerations, with hybrid approaches offering the most robust solutions; and (3) system design must balance local autonomy with global coordination.

For engineering practitioners, the edge–fog–cloud hierarchy provides a flexible framework that enables distributed processing and intelligent decision-making across different layers, allowing computational tasks to be allocated based on latency requirements, data locality, and resource availability. Algorithm developers should emphasize uncertainty quantification in safety-critical applications, leveraging Bayesian methods and hybrid approaches that combine physical constraints with data-driven learning. The economic and operational benefits of distributed intelligence include reduced communication costs, extended battery life, autonomous operation, and incremental scalability.

Implementation requires careful consideration of practical factors. System design must account for heterogeneous SHM deployments, where different structures and environmental conditions demand tailored solutions. Protocol selection, as illustrated in Table 1, must align with structure type, location, and communication requirements. Data quality management requires a multi-stage approach addressing noise at hardware, preprocessing, and fusion levels, while cost considerations must balance initial deployment, operational, and long-term expenses. Most importantly, successful implementation requires a shift in mindset from viewing SHM systems as passive data collection tools to recognizing them as active, intelligent partners that can learn, adapt, and evolve autonomously.

8. Conclusion

The convergence of ubiquitous computing and intelligence is fundamentally transforming SHM from reactive, human-dependent systems into proactive, autonomous entities capable of pervasive sensing, real-time analysis, and intelligent decision-making. While existing reviews have typically examined individual components in isolation, this comprehensive review establishes ubiquitous computing and intelligence as the central organizing principle, providing the first unified framework that systematically integrates edge-to-cloud computing paradigms across the entire monitoring ecosystem through a novel three-perspective analytical framework. This review systematically examines 7326 publications spanning 2016–2025, revealing a remarkable transformation: the proportion of research employing AI/ML methods has increased from 2.4% in 2016 to 50.5% in 2025, with AI-enabled publications comprising 33.4% of the total analyzed dataset, reflecting the field's evolution toward mature, deployable intelligent systems. This review has systematically examined this paradigm shift through three interconnected lenses: architectural frameworks integrating computational capabilities across edge, fog, and cloud layers; algorithmic approaches encompassing both knowledge-based and AI-driven methods; and application domains spanning the complete monitoring lifecycle from measurement to damage quantification. The result is a vision of SHM systems where intelligence is embedded everywhere, enabling truly autonomous and adaptive structural monitoring.

The architectural evolution represents a profound shift from centralized cloud dependence toward distributed computing paradigms that position intelligence at the network periphery, enabling real-time responsiveness and autonomous operation. The algorithmic landscape reveals an equally compelling evolution: the convergence of knowledge-based and AI-driven methods captures the transition from rule-based reasoning toward adaptive, data-centric learning. Hybrid approaches, including physics-informed neural networks, federated learning, and embodied intelligence, demonstrate unprecedented sophistication in distributed computing environments.

Representative case studies demonstrate performance potential: adaptive edge intelligence systems reported processing time reductions of up to 64-fold and power consumption reductions of approximately 33-fold compared to cloud-based approaches; physics-informed neural networks achieved reconstruction errors as low as 0.1% in structural state inference tasks; and large language models reached damage identification accuracy of 95.24% in specific implementations. These results are derived from individual case studies and should not be interpreted as universal performance guarantees. While many findings from this review generalize across different asset types (bridges, buildings, tunnels, pipelines), certain aspects are asset-specific, including protocol selection, sensor placement strategies, and structure-specific damage patterns. Transfer learning and multi-fidelity training help bridge this gap by enabling knowledge transfer from well-instrumented structures to similar assets.

The path forward requires addressing critical challenges, including resource constraints, data quality management, real-time communication, and system reliability, through innovative solutions spanning hardware development, software frameworks, platform integration, and standardization efforts. The future of SHM lies in systems where intelligence transcends traditional boundaries, becoming an integral, living component of the infrastructure itself. By establishing ubiquitous computing as the fundamental paradigm and providing a comprehensive synthesis spanning the entire edge-to-cloud computing spectrum, this review offers both a timely synthesis of the current state-of-the-art and a forward-looking roadmap for next-generation autonomous and intelligent SHM systems.

CRediT authorship contribution statement

Shuaiwen Cui: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Yuguang Fu:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Hao Fu:** Writing – review & editing, Resources, Investigation, Conceptualization. **Wei Shen:** Writing – review & editing, Resources, Investigation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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