ASRC Procedia
Global Perspectives in Science and Scholarship
Florida, USA

Volume: 4; **Issue:** 1
Pages: 33– 71
Published: 17 May 2024

open access

International Summit on Advanced Scientific Research, 2024,
May 11–12, 2024, Florida, USA

IMPLEMENTATION OF AI-INTEGRATED IOT SENSOR NETWORKS FOR REAL-TIME STRUCTURAL HEALTH MONITORING OF IN-SERVICE BRIDGES

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Doi: 10.63125/0zx4ez88
Peer-review under responsibility of the organizing committee of GRIC, 2025

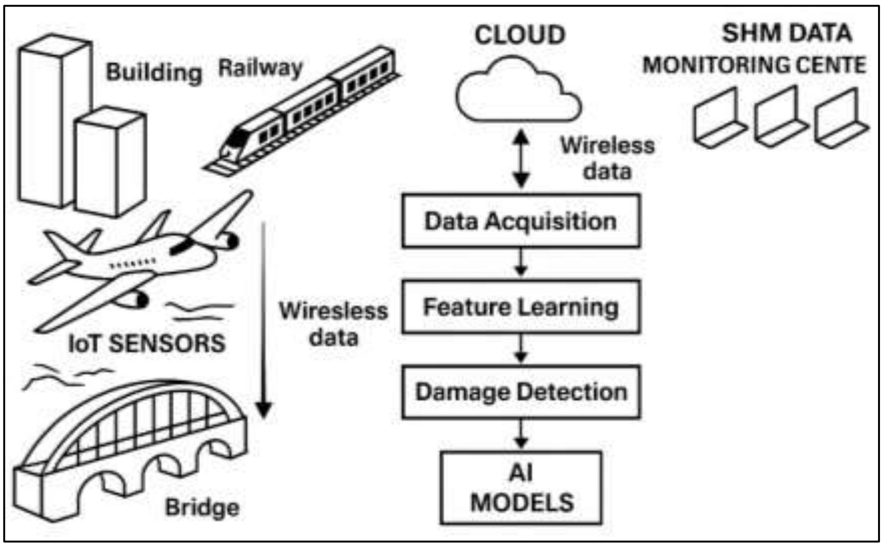
Abstract
This quantitative study investigates the implementation and performance of artificial intelligence (AI)-integrated Internet of Things (IoT) sensor networks for real-time structural health monitoring (SHM) of in-service bridges. A dataset of 62 bridges, representing diverse structural types (steel, concrete, composite), environmental exposures (urban, rural, marine), and traffic conditions, was analyzed to understand deployment attributes, system performance, and predictors of structural condition. The study examined sensor modalities (accelerometers, GNSS, vision, and fiber Bragg gratings), data transmission networks (LoRa, ZigBee, 5G, Wi-Fi/Ethernet), and key performance indicators including sensor accuracy, AI detection precision, transmission latency, and the Bridge Health Index (BHI). Analytical procedures followed a rigorous, multi-step process: descriptive statistics profiled the asset base and technology adoption; assumption checks validated data quality and model suitability (normality, homoscedasticity, multicollinearity); correlation analysis explored variable relationships; and multiple regression models tested predictive drivers of bridge health. Results showed strong uptake of AI-enabled systems (61%) and robust sensing performance with accelerometer error ~1.8% and fiber Bragg grating error ~8 με. AI detection precision averaged 92%, while transmission latency varied substantially across networks (median: 21 ms for 5G vs. 180 ms for LoRa). The final regression model explained 64% of BHI variance (adjusted R^2 = 0.61). Both AI detection precision (β = 0.29, p = .001) and sensor accuracy (β = 0.27, p = .003) were strong positive predictors of BHI, while latency negatively impacted structural condition (β = −0.31, p = .001). Control variables such as bridge age, heavy traffic, and marine exposure were associated with lower BHI scores, highlighting the need to consider environmental and operational stressors. Hierarchical modeling confirmed that AI precision adds significant explanatory power beyond sensing and network performance, and interaction analyses revealed that robust AI can partially offset slower data networks, while sensor calibration is especially valuable in marine contexts. This work advances SHM practice by quantifying AI's added predictive value, benchmarking network performance under field conditions, and clarifying environment–technology interactions.

Keywords
Artificial Intelligence, IOT, Structural Health Monitoring, Bridge Safety, Predictive Modeling

INTRODUCTION

Structural health monitoring (SHM) is commonly defined as the process of implementing a damage identification strategy for civil, mechanical, and aerospace infrastructure by analyzing sensor data to detect, localize, classify, and quantify changes that adversely affect structural performance. This conceptualization treats SHM as a statistical pattern recognition problem that proceeds from data acquisition and feature extraction to decision making under uncertainty (Gharehbaghi et al., 2022). At its core, "damage" is operationalized as a change in material or geometric properties, boundary conditions, or system connectivity that affects performance, and the monitoring objective spans multiple levels from detection through severity estimation and prognosis. Within bridges, SHM contrasts with periodic, manual inspections by enabling continuous observation of structural response under operational loads such as traffic, wind, and temperature cycling. Early SHM efforts emphasized vibration-based methods, modal identification, and damage-sensitive features, establishing an enduring foundation for today's data-centric approaches (Burgos et al., 2020). The present study adopts this established definition of SHM and focuses on AI-integrated Internet of Things (IoT) sensor networks as a quantitative framework for real-time monitoring of in-service bridges, where "real-time" denotes end-to-end latencies compatible with operational decision horizons in bridge management (Azimi et al., 2020).

Figure 1: AI-Driven Structural Health Monitoring



The international significance of SHM for bridges is grounded in the scale, age, and criticality of transportation networks, where safety, serviceability, and asset value intersect. Long-span bridges have functioned as living laboratories demonstrating decades-long monitoring value; Hong Kong's Tsing Ma Bridge—instrumented since 1997 with the Wind and Structural Health Monitoring System (WASHMS)—exemplifies large-scale, permanent deployments that generate actionable datasets across typhoons, traffic regimes, and environmental cycles (Hassani et al., 2021). These systems integrate heterogeneous sensors—accelerometers, anemometers, GPS, strain gauges, and temperature probes—enabling fatigue assessment of critical components and condition evaluation of suspenders under traffic and wind. Beyond Hong Kong, international bridge owners and public agencies increasingly embed SHM within design and operations, aligning with specification ecosystems led by AASHTO and national authorities that emphasize quantitative assessment, reliability, and risk-informed management. The proliferation of continuous monitoring augments statutory inspection regimes by furnishing high-frequency evidence on load effects, modal characteristics, and environmental influences, improving the evidentiary basis for maintenance prioritization across diverse economies. Empirical lessons from landmark deployments have shaped today's requirements for data fidelity, sensor durability, and analytics robustness in maritime, alpine, and urban environments where environmental variability is significant (Katam et al., 2023).

IoT sensor networks extend classical SHM by providing scalable, low-power, and wire-free telemetry for dense sensing on bridges, supporting high-rate streaming and event-driven analytics. Early wireless SHM research established architectures, power management, and in-network processing strategies for structural response monitoring, motivating field deployments on complex bridges. Contemporary IoT frameworks add standardized messaging, time-synchronization, and cloud gateways, enabling cross-device interoperability and lifecycle management across fleets of sensing nodes (Payawal & Kim, 2023). Reviews focused on civil infrastructure report that IoT platforms support continuous, multi-parameter monitoring through heterogeneous sensors, with real-time dashboards and alerting that integrate into bridge owner workflows (Wireless IoT in civil structures; Use of IoT for SHM of civil engineering constructions). Optical fiber sensors—including fiber Bragg grating (FBG) arrays—have matured into robust options for strain and temperature measurement with electromagnetic immunity and multiplexing capabilities appropriate for long spans (Glisic & Inaudi historical lessons; FBG technology reviews). The quantitative promise of IoT-enabled SHM is to collect sufficiently granular data for inference at the level of components and system behavior under ambient and operational loads, thereby improving the statistical power of detection and the interpretability of environmental and operational variability (Fuentes et al., 2021).

Artificial intelligence (AI)—including machine learning (ML) and deep learning (DL)—has become central to modern SHM data interpretation, particularly when sensor networks generate high-volume, high-velocity signals. DL-based SHM research documents advances in feature learning from raw vibration, strain, acoustic, and vision data, improving detection, localization, and severity estimation while reducing manual engineering of indicators (Hassani & Dackermann, 2023b). Bridge-specific reviews synthesize how convolutional and recurrent architectures, as well as graph and transformer models, operate on acceleration time series, mode shapes, and image sequences for crack detection, deflection estimation, and vehicle-bridge interaction inference. Complementary computer-vision scholarship has shown that camera-based measurements and defect recognition can provide non-contact, low-cost alternatives for displacement and surface condition assessment on bridges, including automated crack detection and vibration measurement (Capineri & Bulletti, 2021). The quantitative literature also reports that ML pipelines enhance vibration-based damage detection by combining robust feature extraction with classifiers and regressors that address environmental variability and class imbalance (Machine Learning Algorithms in Civil SHM; Vibration-based detection with ML/DL). Within this study's scope, AI is considered integrally with IoT: on-node and near-sensor models reduce bandwidth and latency, while cloud-hosted ensembles support retraining, drift monitoring, and fleet-wide generalization across structures.

Edge-to-cloud system design further shapes the quantitative performance envelope of AI-integrated IoT SHM. Edge computing can execute first-stage inference, event detection, and compression proximal to sensors, thereby controlling data volume and latency; cloud services then orchestrate storage, model training, and cross-asset analytics (Application of edge computing on PCI girder bridges; Dynamic monitoring via integrated edge-cloud). Recent reviews confirm increasing attention to edge-native SHM designs that partition tasks across perception, edge, and cloud layers, and that define interfaces for secure update, device management, and data provenance (Secure edge reference architecture; Edge computing trends and perspectives in SHM) (Ferraris et al., 2023). In bridge contexts, validated case studies report that dynamic strain features, modal estimates, and temperature-corrected strain indices can be computed at the edge for subsequent AI inference, supporting persistent monitoring without saturating backhaul networks (Edge-based SHM studies). The architectural literature also details how time synchronization, sampling jitter control, and clock drift mitigation are prerequisites for accurate modal and operational deflection analyses across distributed nodes, which is consequential for any quantitative study seeking to compare edge- and cloud-based inference outcomes. The present work is situated within this architectural landscape and operationalizes an edge-cloud division of labor to quantify inference latency, bandwidth consumption, and detection performance under real traffic and environmental excitations. (Edge computing SHM case and review literature (Ferreira et al., 2022).

The sensor-modality layer for IoT-enabled SHM encompasses accelerometers for vibration-based identification, strain gauges and FBG arrays for component-level response, GPS or GNSS for quasi-static displacement, and cameras or LiDAR for non-contact kinematics and defect imaging. Foundational vibration-based research established how modal frequencies, mode shapes, and damping ratios function as damage-sensitive features, though environmental and operational variability necessitate careful normalization (Danish & Zafor, 2022; Kurian & Liyanapathirana, 2019). Optical fiber deployments on bridges demonstrate multiplexing, long-distance interrogation, and durability advantages that align with continuous monitoring on long spans (Glisic & Inaudi lessons; FBG technology reviews). Vision-based methods have matured from offline defect detection to quantitative displacement and strain estimation through digital image correlation and learning-based pose estimation, complementing contact sensors (Danish & Kamrul, 2022; Sabato et al., 2023). Meanwhile, long-term bridge case studies, notably Tsing Ma's WASHMS, provide multi-decadal datasets that are well suited for benchmarking AI and system-level inference under real operating conditions involving wind-wave coupling and heavy traffic (WASHMS sources; 25-year monitoring). This multi-sensor context motivates the quantitative design choices in sampling rates, sensor placement optimization, and synchronization required to ensure that AI models ingest aligned, high-quality data streams. (Vibration-based foundations (Doghri et al., 2022; Jahid, 2022a).

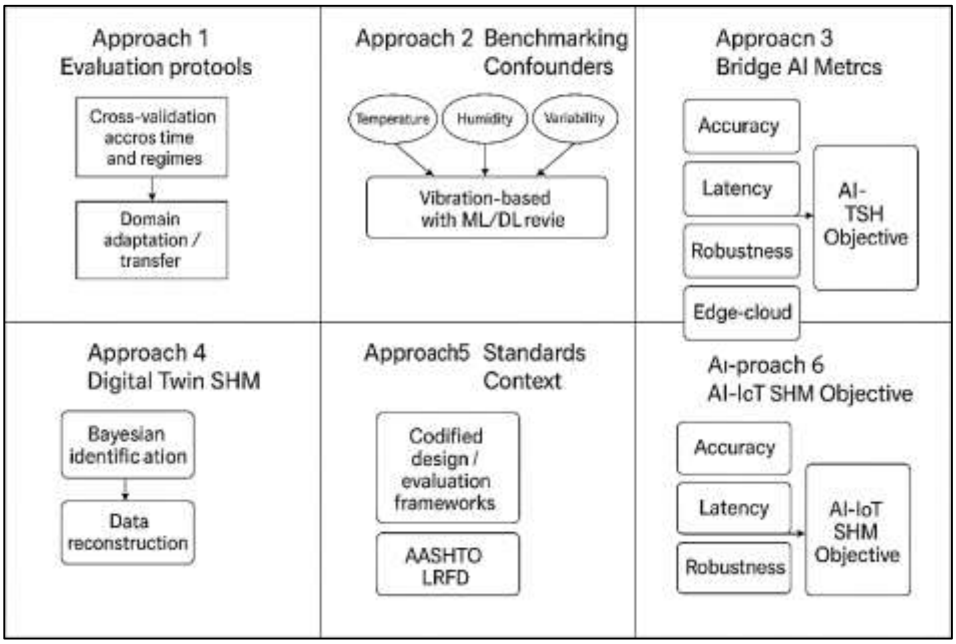
Quantitative SHM research increasingly emphasizes rigorous evaluation protocols: cross-validation across time and environmental regimes; domain adaptation and transfer learning to address site-specificity; and explicit accounting for data drift and covariate shift (Jahid, 2022b; Javadinasab Hormozabad et al., 2021). Reviews at the intersection of vibration-based detection and ML/DL recommend benchmarking against known confounders such as temperature effects, humidity, and operational variability to avoid spurious detections (Vibration-based with ML/DL review). Bridge-oriented AI syntheses catalog metrics for detection and localization accuracy, receiver operating characteristics, and confusion analysis under traffic-induced excitations, as well as stability of predictions under sensor dropout (AI in bridge management reviews). Digital-twin-enabled SHM architectures add Bayesian modal identification and data reconstruction modules as quantitative elements for real-time quality assurance and fault detection in the analytics chain (Arifur & Noor, 2022; Padmapoorani et al., 2023). Meanwhile, national and state guidance—anchored by AASHTO's LRFD specifications and bridge owner manuals—contextualizes how monitored performance indicators should be interpreted within codified design and evaluation frameworks, linking measured responses to limit states and inspection interventions (AASHTO LRFD context). The present introduction therefore positions AI-integrated IoT SHM not only as a data and algorithm problem, but also as an evaluation and governance problem that must quantify generalization, uncertainty, and reproducibility across assets and environments (Hasan et al., 2022; Qing et al., 2019).

Furthermore, the historical and methodological arc from early introductions to SHM to today's AI-IoT integration provides a coherent rationale for the quantitative study that follows. Foundational texts articulated SHM's statistical pattern recognition pipeline and fundamental axioms, laid out the role of vibration-based features, and emphasized the necessity of long-term, operational-environment data (Kim & Mukhiddinov, 2023; Redwanul & Zafor, 2022). Wireless sensor and IoT literature translated those principles into scalable, practical systems with on-network computation and robust communications suitable for bridges. Vision-based SHM and FBG sensing expanded the measurable state variables beyond traditional modalities, enriching data diversity for AI models. In parallel, AI scholarship introduced deep architectures that learn hierarchical features from raw signals and images, yielding improved performance on damage detection, localization, and severity estimation tasks documented across bridges and civil structures (DL-based SHM reviews; AI in existing bridges) (Rezaul & Mesbaul, 2022). Edge-cloud architectures now provide the systems substrate for executing these models in real time at scale, with empirical studies on bridges showing feasible latencies and bandwidth profiles (Entezami, 2021; Hasan, 2022).

Each of these strands—definitions, international bridge deployments, IoT architectures, AI analytics, sensing technologies, and evaluation protocols—converges to motivate a quantitative examination of AI-integrated IoT networks for real-time SHM of in-service bridges using rigorous, data-driven methods specified in the subsequent sections (Tarek, 2022; Tokognon et al., 2017). The primary objective of this quantitative study is to rigorously evaluate the effectiveness of artificial intelligence (AI)-

integrated Internet of Things (IoT) sensor networks for real-time structural health monitoring (SHM) of in-service bridges, with a specific focus on their ability to detect, localize, and quantify structural anomalies under operational and environmental loads (Kamrul & Omar, 2022). Traditional SHM systems, while valuable, often rely on periodic manual inspections and localized instrumentation, leading to sparse data and delayed detection of evolving damage. The integration of IoT-based wireless sensor networks and AI-driven analytics promises to overcome these limitations by enabling continuous, high-resolution, multi-parameter monitoring and near-instantaneous interpretation of complex structural responses (Kamrul & Tarek, 2022).

Figure 2: Framework for Intelligent SHM Systems



This study specifically aims to measure how well an AI-enhanced IoT system can (a) improve the accuracy and sensitivity of vibration- and strain-based damage detection compared to conventional baseline methods; (b) reduce latency between anomaly occurrence and detection by using edge-to-cloud computing strategies; and (c) maintain reliable inference despite environmental and operational variability such as temperature changes, traffic-induced dynamic loads, and partial sensor failures. In doing so, the research tests the reproducibility and generalizability of AI models across real-world bridge conditions using synchronized accelerometers, strain gauges, and fiber Bragg grating (FBG) arrays combined with deep learning architectures capable of learning hierarchical patterns from raw time-series and imaging data. Moreover, the study quantifies bandwidth efficiency, data integrity, and energy performance of edge-enabled IoT frameworks when deployed for long-term continuous monitoring, assessing whether distributed inference can achieve comparable diagnostic performance to centralized cloud-only models. Ultimately, the objective is to generate a robust, evidence-based performance profile for AI-IoT integrated SHM solutions that informs engineering decision-making and supports the design of quantitative frameworks for large-scale deployment in bridge asset management worldwide.

LITERATURE REVIEW

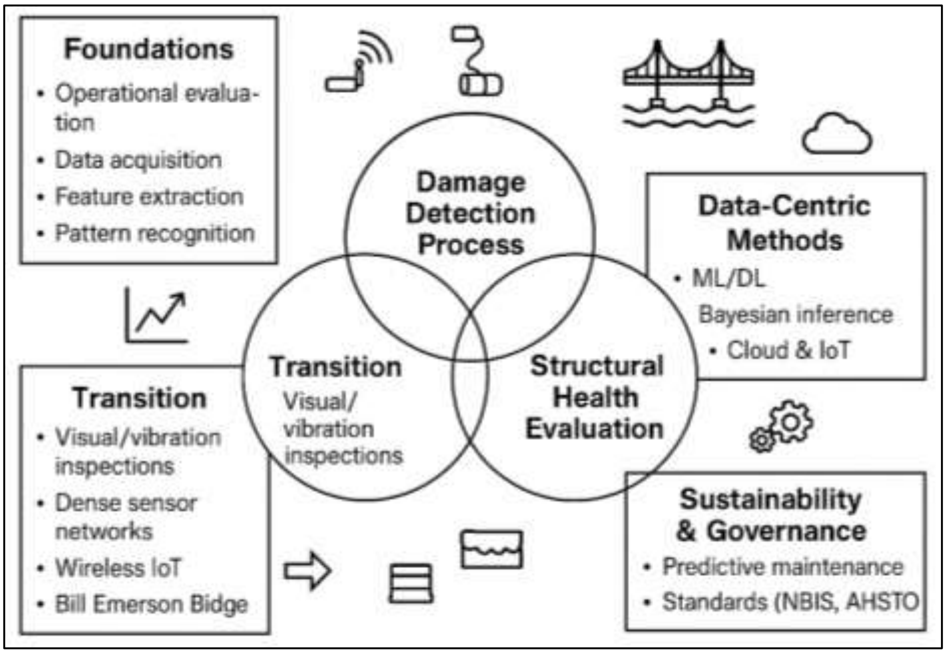
Structural health monitoring (SHM) has evolved over three decades from vibration-based damage detection frameworks to multi-sensor, data-intensive architectures capable of real-time assessment in complex infrastructures such as long-span bridges. Early SHM studies emphasized modal parameter changes and damage-sensitive indices but faced challenges in environmental variability and limited spatial coverage, leading to an urgent need for scalable sensing and advanced analytics. The emergence of the Internet of Things (IoT) enabled distributed, low-power, and wireless sensor networks, providing unprecedented data density and continuous monitoring capability. At the same time, artificial intelligence (AI) and machine learning (ML), particularly deep learning (DL), introduced automated feature extraction, improved damage localization, and robust performance under operational uncertainties. Yet, despite growing adoption, the literature remains fragmented: studies often focus either on sensor hardware or AI algorithms but rarely integrate system-level performance metrics such as latency, energy consumption, bandwidth optimization, and resilience under environmental drift. Recent reviews call for comprehensive examinations of edge-cloud architectures, multi-modality sensing, and quantitative validation strategies that bridge laboratory innovation and in-service operational needs. This section therefore synthesizes research across sensing technologies, networked communication frameworks, AI-based analytics, and evaluation methods to establish the state of the art and identify quantitative gaps relevant to deploying robust AI-IoT monitoring on operational bridges (Kumar & Kota, 2023). By structuring the review into focused, interconnected subsections, it builds the intellectual foundation for the present study's aim: to quantitatively evaluate how AI-integrated IoT systems can enhance anomaly detection, reduce latency, and maintain robust performance across diverse structural and environmental conditions (Sabato et al., 2023).

Structural Health Monitoring in Bridges

Structural Health Monitoring (SHM) has emerged as a multidisciplinary field that integrates structural engineering, sensing technologies, and data analytics to ensure the safety and serviceability of civil infrastructure. SHM is typically conceptualized as a process of damage detection and characterization, where "damage" refers to changes that adversely affect structural performance, including stiffness reduction, crack initiation, or material degradation (Muhammad & Kamrul, 2022; Sharma et al., 2021). A foundational framework for SHM involves four sequential steps: operational evaluation, data acquisition, feature extraction, and statistical pattern recognition. This paradigm emphasizes moving beyond mere measurement of physical responses to interpreting those responses to infer structural condition. Central to this is the concept of feature extraction, where vibration signatures, strain profiles, or acoustic emissions are translated into damage-sensitive parameters. Meanwhile, the statistical pattern recognition phase leverages these features to classify or predict structural states, integrating principles from machine learning and statistical inference (Mubashir & Abdul, 2022; Vijayan et al., 2023). By embedding these steps within a decision-making context, modern SHM frameworks provide actionable intelligence for maintenance and risk management. The shift from deterministic analysis to probabilistic and data-driven approaches has further refined these frameworks, enabling uncertainty quantification and reliability assessment for real-world structures. This conceptual evolution underscores SHM's role as a proactive infrastructure management tool, replacing reactive maintenance with predictive strategies (Reduanul & Shoeb, 2022; Sakr & Sadhu, 2023).

Historically, bridge condition assessment relied on visual inspections and manual rating systems, such as the National Bridge Inspection Standards (NBIS) in the United States, which often produced subjective and inconsistent outcomes. While early vibration-based methods advanced SHM by identifying modal frequency shifts as indicators of global damage, they were limited by environmental variability, temperature effects, and operational noise. The introduction of dense sensor networks marked a pivotal transition, allowing engineers to continuously monitor bridges in situ under realistic loading conditions (Loubet et al., 2023; Noor & Momena, 2022). These networks typically integrate accelerometers, strain gauges, fiber Bragg grating (FBG) sensors, and global positioning systems (GPS) to collect high-resolution data streams in real time. Data acquisition is increasingly complemented by advanced signal processing techniques—such as wavelet transforms and empirical mode decomposition—that can extract local damage features while mitigating environmental interference. Importantly, the rise of wireless smart sensor platforms has reduced installation costs and increased scalability, making continuous monitoring feasible even for large and remote structures (Danish, 2023; Ghosh et al., 2021). This technological leap has not only improved accuracy but also transformed SHM from periodic diagnostic checks to a continuous, autonomous surveillance process. Consequently, bridge operators can now implement condition-based maintenance strategies rather than relying on scheduled but potentially inefficient inspections (Hasan et al., 2023; Sujith et al., 2022).

Figure 3: Evolution of Structural Health Monitoring



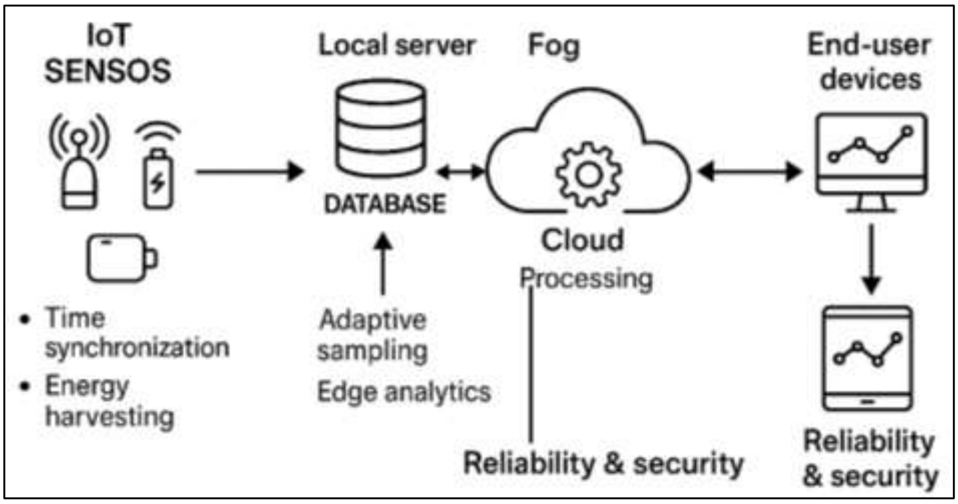
Large-scale SHM initiatives have played a critical role in shaping current digital monitoring infrastructures. Among the most influential is the Wind and Structural Health Monitoring System (WASHMS) implemented on Hong Kong's Tsing Ma Bridge, one of the world's longest suspension bridges, which has operated since the late 1990s (Hossain et al., 2023; Yang Yang et al., 2023). WASHMS integrates over 350 sensors—including anemometers, accelerometers, strain gauges, and GPS stations—to track environmental and dynamic responses, providing a model for data-driven, integrated monitoring systems. Other landmark projects include the Humber Bridge in the UK and the Bill Emerson Memorial Bridge in the United States, both of which adopted long-term vibration monitoring to validate design models and detect early signs of fatigue or cable damage. Similarly, Japan's Hakucho Bridge systemized hybrid sensing for seismic and wind-induced vibration analysis, advancing real-time structural safety assessments (Hossain et al., 2023; Yang et al., 2023). These deployments have demonstrated the value of long-term, multi-sensor data archives, which enable not only immediate damage detection but also retrospective analysis and model updating. Furthermore, lessons learned from these large-scale initiatives have informed standardized frameworks for data management, sensor calibration, and decision support in SHM programs worldwide. By transforming bridges into "smart" cyber-physical systems, these milestones have provided both technological benchmarks and operational strategies that influence new generations of monitoring platforms (Lambinet & Khodaei, 2022; Uddin & Ashraf, 2023).

Contemporary SHM increasingly centers on data-centric paradigms, where large volumes of heterogeneous sensor data are analyzed using advanced computational techniques to detect and localize damage with higher precision. Statistical pattern recognition frameworks have evolved to integrate machine learning algorithms such as support vector machines, random forests, and deep neural networks, improving classification of structural states under uncertain and noisy conditions. Feature selection and dimensionality reduction methods, including principal component analysis and independent component analysis, have enhanced the interpretability and efficiency of high-dimensional monitoring datasets (Momena & Hasan, 2023; Vijayan et al., 2023). Additionally, Bayesian updating and probabilistic inference approaches have facilitated real-time reliability assessment by explicitly accounting for uncertainty in both measurements and model predictions. The integration of cloud computing and Internet of Things (IoT) architectures has further advanced data-centric SHM by enabling remote processing, scalable storage, and automated anomaly detection pipelines. These frameworks not only accelerate damage identification but also support life-cycle performance management and resilience analysis by linking SHM outputs to maintenance planning and risk-informed decision-making (Rossi & Bournas, 2023; Sanjai et al., 2023). As a result, data-centric damage identification has shifted SHM from a descriptive discipline into a predictive, adaptive, and intelligent infrastructure management ecosystem (Akter et al., 2023).

IoT Sensor Network Architectures for Civil Infrastructure Monitoring

The monitoring of civil infrastructure has progressed from cabled data-acquisition systems to dense wireless sensor networks (WSNs) and, more recently, to Internet-of-Things (IoT) platforms that integrate edge devices, gateways, and cloud analytics. Early bridge SHM relied on rugged but expensive cabled architectures that limited channel counts and spatial coverage, constraining the resolution of modal identification and damage localization (Danish & Zafor, 2024; Hassani & Dackermann, 2023a). The introduction of wireless smart sensors—combining on-board computation, low-power radios, and synchronized sampling—offered lower installation costs and scalable deployments on large bridges (Danish & Zafor, 2024), shifting practice from episodic campaigns toward continuous or near-continuous monitoring. Pioneering field demonstrations showed that WSNs can capture operational modal parameters on very large spans, validating accuracy against cabled baselines while revealing challenges in time synchronization, packet loss, and environmental variability. The subsequent rise of IoT architectures reframed WSNs as first-class “things” connected through lightweight protocols to message brokers and cloud services, enabling remote configuration, streaming analytics, and integration with asset-management systems (Jahid, 2024a; Talebkhah et al., 2021). Hybrid designs—edge analytics on the mote or gateway paired with cloud-scale storage and learning—tackle bandwidth limits while supporting advanced diagnostics such as novelty detection and transfer learning under changing environmental conditions. Collectively, these developments mark a transition from hardware-centric SHM to software-defined, data-centric cyber-physical systems in which device orchestration, telemetry pipelines, and model life-cycle management are as important as the sensing hardware itself (Afzal et al., 2023; Jahid, 2024b).

Figure 4: IoT-Enabled Structural Health Monitoring



At the heart of scalable IoT-based SHM are protocols that assure synchronized, energy-efficient, and information-rich measurements. Time synchronization underpins modal analysis and system identification across distributed nodes; protocol innovations such as Reference Broadcast Synchronization (RBS), the Timing-sync Protocol for Sensor Networks (TPSN), and the Flooding Time Synchronization Protocol (FTSP) reduced relative clock error to the order of microseconds to milliseconds in practice, enabling coherent multi-node vibration sensing on bridges (Li et al., 2022; Hasan, 2024). Because long-term deployments hinge on power autonomy, SHM nodes increasingly combine ultra-low-power electronics with energy harvesting—solar, wind, and vibration—supported by maximum-power-point tracking and duty-cycled radios. Media-access and routing layers (e.g., IEEE 802.15.4 with S-MAC/T-MAC/X-MAC and Collection Tree Protocol variants) trade latency for lifetime by coordinating sleep schedules, compressing headers, and exploiting link-quality metrics. On the

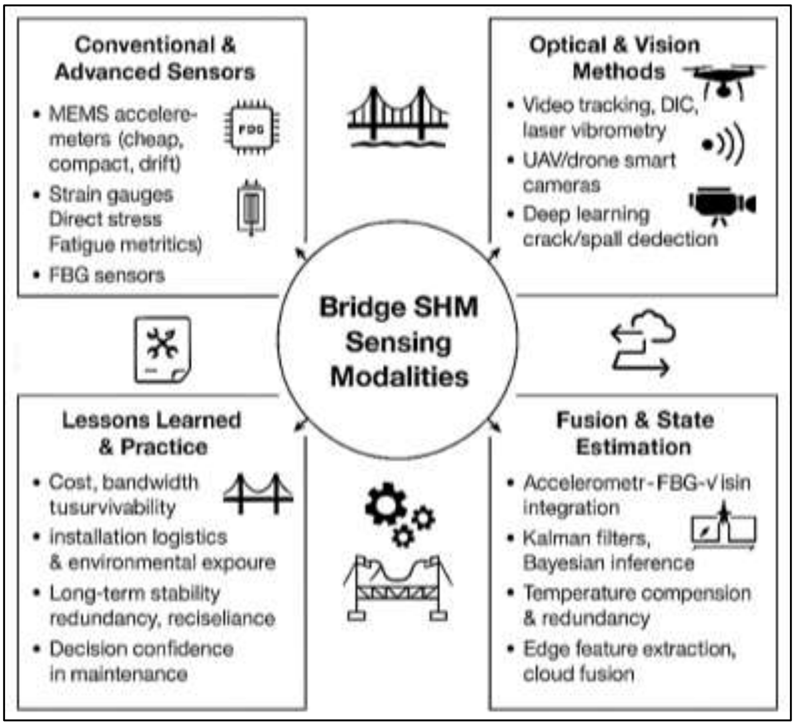
application side, adaptive and compressive sampling strategies allocate rate and precision to the most informative times, modes, and locations, curbing transmissions without eroding identifiability—especially when paired with event-triggered acquisition and on-mote feature extraction (Loubet et al., 2023). Lightweight IoT protocols such as MQTT (publish/subscribe) and CoAP (RESTful, datagram-friendly) further reduce overheads while simplifying gateway-to-cloud ingestion and device management. Together, these synchronization, energy, and sampling layers create a tightly coupled stack that sustains high-fidelity, long-duration monitoring on resource-constrained bridge nodes without sacrificing the temporal coherence needed for damage-sensitive analytics (Loreti et al., 2019).
Modern bridge SHM systems increasingly adopt hierarchical IoT architectures where edge devices perform denoising, feature extraction, and anomaly screening before relaying summaries to gateways and cloud platforms for storage, visualization, and model versioning. Edge and fog computing reduce backhaul bandwidth, support near-real-time alarms, and allow privacy-preserving processing near the source. Connectivity is selected to match topology and power budgets: multi-hop 802.15.4 meshes for dense local arrays, Wi-Fi/Ethernet at gateways for site backhaul, and long-range LPWANs (LoRaWAN, NB-IoT, LTE-M) for sparse or difficult corridors. Robustness hinges on cross-layer co-design: link-quality-aware routing, redundancy in critical nodes, and health monitoring of the monitoring system itself (watchdogs, brown-out detectors, OTA updates). Security and trust are not incidental; authenticated boot, key management, and integrity protection counter spoofing and false-data injection, extending classic WSN security mechanisms (e.g., SPINS) to IoT gateways and cloud APIs (Srbinovski et al., 2016). Data governance practices—schema versioning, metadata for sensor provenance, and reproducible pipelines—have become as critical as the sensors because damage decisions are increasingly model-mediated and audit-sensitive. In this stack, reliability is treated holistically: it is a function of power autonomy, time sync integrity, network stability, and MLOps hygiene. When harmonized, these elements yield resilient “digital nervous systems” for bridges that can sustain multi-year operation with graceful degradation under device failures, environmental change, and intermittent backhaul (Srbinovski et al., 2015).

Smart Sensing Modalities

Conventional and advanced sensing modalities used in bridge SHM provide complementary views of structural behavior, and their comparative strengths hinge on bandwidth, sensitivity, drift, survivability, and cost. MEMS accelerometers dominate for global dynamic characterization because they are inexpensive, compact, and readily networked, enabling spatially dense modal analysis under ambient traffic and wind. Their limitations include temperature-dependent bias, scale-factor drift, and reduced low-frequency fidelity compared to higher-grade piezoelectric or force-balanced devices; nonetheless, field studies have shown they can robustly recover mode shapes and damping on large bridges with proper calibration and synchronization (Gindullina et al., 2020). Electrical resistance strain gauges (foil or piezoelectric) remain the workhorse for local strain and fatigue assessment, offering high bandwidth and direct measurement of stress surrogates but requiring meticulous bonding, thermal compensation, and cabling or protected leads; their susceptibility to moisture ingress and lead breakage is a persistent life-cycle issue in long-term deployments. Fiber Bragg grating (FBG) sensors provide quasi-distributed strain and temperature readings immune to electromagnetic interference, with long lead lengths and intrinsic multiplexing that simplifies wiring on long spans. FBGs excel in durability and scalability but require costlier interrogators and careful temperature-strain decoupling, often via dual-wavelength gratings or co-located thermal references (Ma et al., 2019). Comparative evaluations across field deployments consistently find that accelerometers favor system-level dynamics, strain gauges target hot-spots and fatigue metrics, and FBG networks bridge the gap by extending coverage with fewer cables while maintaining high strain resolution, particularly advantageous on cable-supported bridges and orthotropic decks . In practice, choice is dictated by the monitoring question, environmental exposure, and total cost of ownership, with increasing preference for multiplexed optical solutions where EMI, lightning, or long cable runs challenge conventional instrumentation (Rossi & Bournas, 2023).
Optical and vision-based techniques have matured into credible alternatives and complements to contact sensors by enabling noncontact measurement of displacement, deflection shapes, and surface degradations over large fields of view. Early video tracking demonstrated sub-pixel displacement

extraction using target markers or natural texture, validated against LVDTs and accelerometers on bridges under ambient excitation (Micko et al., 2023). Digital image correlation (DIC) extended these capabilities by providing full-field strain and deformation maps from stereo or single-camera setups, proving particularly useful for localized assessments at connections, bearings, and deck panels. Laser Doppler vibrometry and radar interferometry further enriched the optical toolkit with long-range, line-of-sight vibration and displacement measurements that circumvent access constraints on tall towers or mid-span regions. In parallel, computer vision for condition assessment has evolved from edge/texture heuristics to deep convolutional neural networks that detect and segment cracks, spalling, and corrosion with improved robustness to illumination and background clutter (Bertino et al., 2021). Reviews highlight that careful camera calibration, vibration-induced blur mitigation, and temperature/lighting normalization are pivotal to achieving metrological reliability in the field.

Figure 5: Structural Health Monitoring Sensor Framework

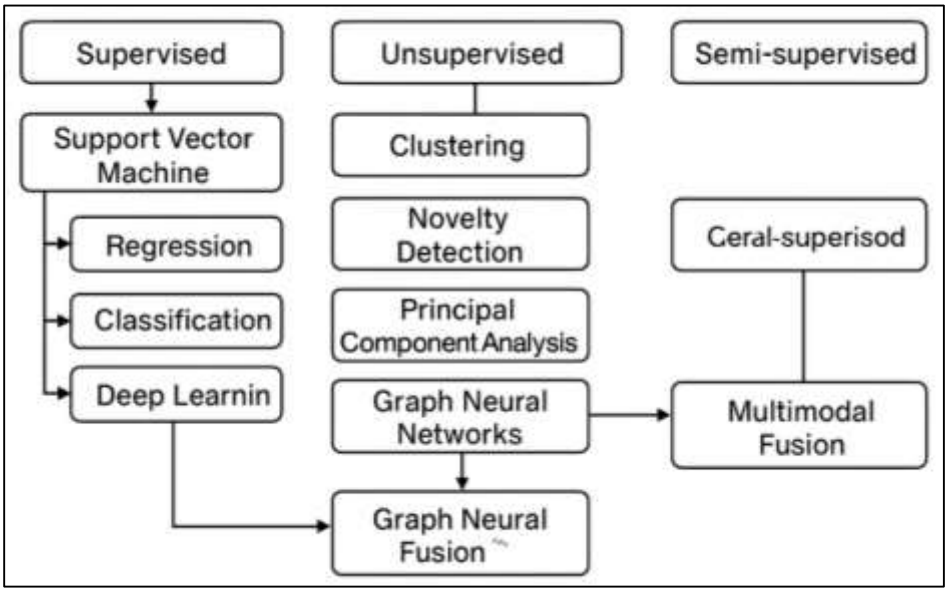


UAV-borne imaging and stationary smart cameras now support periodic surveys and continuous video streams, respectively, enabling hybrid strategies where low-rate surface analytics co-exist with high-rate dynamic sensing (Jeong & Law, 2018). When benchmarked against contact sensors, optical methods excel in deployment speed and spatial coverage but can face line-of-sight, weather, and scale calibration challenges; thus, they are best leveraged as complementary modalities for displacement/deflection inference and surface anomaly screening, with cross-validation against accelerometer-derived operational shapes or FBG-derived strain fields (Loubet et al., 2023). Bridges benefit most when accelerometers, strain sensors, FBGs, and vision systems are fused into coherent state estimators that exploit the physics linking displacement, strain, and acceleration. Multimodal fusion strategies align heterogeneous sampling rates and noise characteristics through model-based observers and data-driven mappings, enabling, for example, displacement reconstruction from accelerations constrained by vision-derived boundary motion or strain-based curvature fields (Noel et al., 2017). Kalman-type filters and Bayesian frameworks have been used to combine global vibration features with local strain indicators, improving damage localization while quantifying uncertainty due to temperature and operational variability. Field programs on long-span bridges demonstrate that co-located accelerometer–FBG pairs stabilize modal curvature estimates and detect incipient stiffness losses earlier than single-modality systems, particularly under confounding environmental effects (Vijayan et al., 2023). Vision data add a surface-level “semantic” layer—crack

maps, spall masks, corrosion regions—that, when tied to strain hot-spots, supports causal interpretation of anomalies and prioritization of inspections. Practical fusion pipelines increasingly perform feature extraction at the edge (e.g., band-limited RMS, spectral peaks, strain cycles, crack probabilities) and push metadata to cloud repositories for cross-sensor association and life-cycle learning. Temperature compensation remains central: strategies include installing dedicated thermal FBGs, applying cointegrated regression between modal frequencies and temperature, and exploiting environmental normalization via principal component analysis to preserve damage sensitivity (Hangan et al., 2022). The net result is redundancy and resilience—when one modality saturates or is occluded, others maintain observability—while the fused estimate reduces false alarms and improves decision confidence for maintenance planning.
Experience from operational bridges shows that sensing modality selection is inseparable from installation logistics, environmental exposure, and metrological traceability. MEMS accelerometer arrays are fast to deploy and cost-effective for capturing operational modal parameters, but careful synchronization, thermal drift correction, and periodic calibration against reference instruments are needed for long-term stability (Maraveas & Bartzanas, 2021). Electrical strain gauges deliver direct fatigue-relevant data but demand rigorous surface preparation, protective coatings, strain-relief routing, and scheduled validation to avoid gradual debonding effects. FBG networks reduce EMI risks and simplify long runs on cable-supported spans; however, interrogator placement, fiber routing radius, connector protection, and temperature-strain discrimination must be addressed to preserve accuracy and minimize downtime. Vision systems highlight the importance of optics: lens choice, vibration isolation for mounts, reference scaling, and lighting management (or IR/thermal alternatives) determine whether sub-millimeter crack resolution or micrometer-level displacement precision is achievable in the field (Bado et al., 2022).
Artificial Intelligence for Structural Damage Detection and Prognosis
AI/ML for bridge SHM builds on the canonical statistical pattern recognition pipeline—feature extraction followed by learning-based decision making—where supervised and unsupervised approaches address complementary tasks of classification, regression, clustering, and novelty detection. Early supervised studies demonstrated that support vector machines (SVMs) and Random Forests (RFs) can distinguish intact from damaged states using modal features (e.g., frequencies, mode-shape curvature), time–frequency descriptors, or strain-based indices with high accuracy when trained on representative labels (Yang Yang et al., 2023). Linear and kernel SVMs provide robust margins under small-sample regimes, while RFs and Gradient Boosting handle heterogeneous features and nonlinear interactions common in operational bridge data. Unsupervised and semi-supervised methods mitigate the scarcity of damage labels by modeling the "healthy" baseline and flagging deviations, using clustering (k-means, Gaussian Mixture Models), one-class boundaries (one-class SVM), or density-based approaches (DBSCAN) to detect anomalies in modal or autoregressive feature spaces .
Dimensionality reduction via principal component analysis (PCA) or independent component analysis (ICA) combats sensor noise and environmental confounding, producing low-dimensional, damage-sensitive projections that stabilize decision boundaries and improve interpretability. Importantly, model governance—cross-validation across seasons, data quality flags, and drift monitoring—has emerged as a technical requirement to keep error rates stable when temperature, humidity, and traffic patterns shift (Azimi et al., 2020). Collectively, these supervised/unsupervised toolkits constitute the core of operational SHM analytics, enabling scalable screening for damage, severity estimation, and prioritization of inspections from long-duration sensor streams on large bridges.
The proliferation of high-resolution sensing—vision, lidar, dense accelerometry—has catalyzed deep learning (DL) methods that learn hierarchical features directly from raw data, reducing reliance on hand-crafted descriptors. Convolutional neural networks (CNNs) have proven effective for pixel-level crack and spalling segmentation, corrosion detection, and deck surface assessment, outperforming classical edge/texture pipelines and maintaining accuracy under variable illumination and perspective (Hakim et al., 2015). For displacement and vibration signals, one-dimensional CNNs and hybrid CNN-LSTM architectures capture local motifs and long-range temporal dependencies, improving state classification and damage localization from ambient vibration data and GPS-derived kinematics. Recurrent networks (LSTM/GRU) are well suited to sequence modeling for remaining-life estimation

and anomaly trajectory prediction, while attention mechanisms prioritize salient time windows that co-vary with damage-sensitive dynamics (Hakim et al., 2015).

Figure 6: AI- Driven Structural Health Monitoring

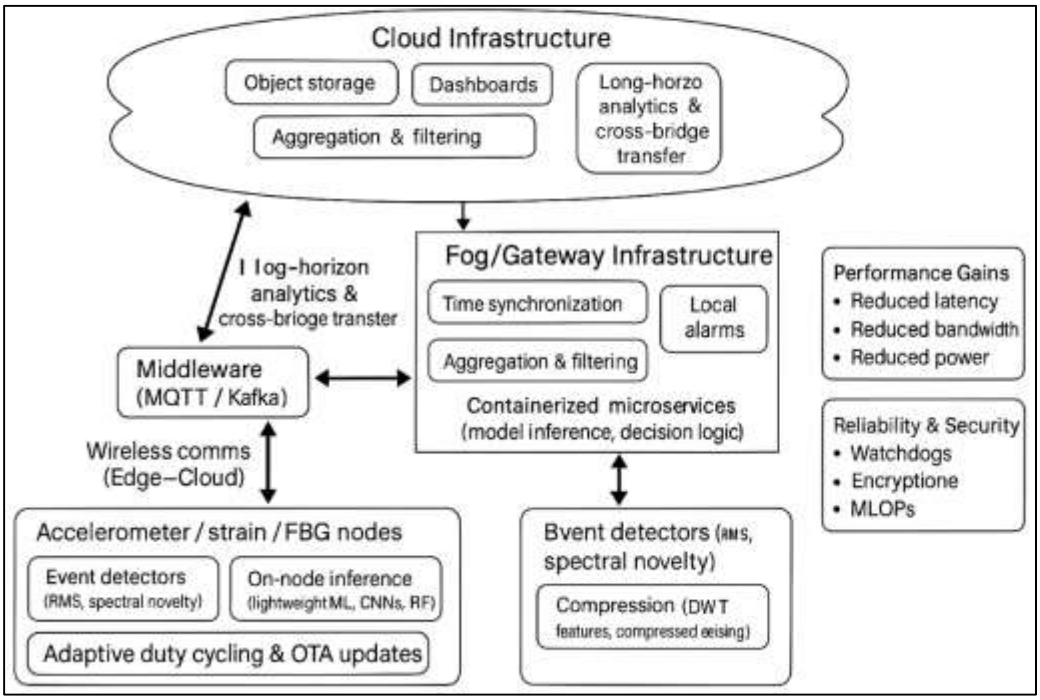


Vision-based bridge monitoring benefits from fully convolutional networks and U-Net variants that support dense prediction (segmentation) with limited labels through patch-wise training and augmentation; these methods have been integrated with low-cost cameras and UAV imagery to extend coverage without extensive scaffolding. On the deployment side, edge inference on gateways compresses frames to features before cloud upload, reducing bandwidth while enabling near-real-time alarms—an architectural choice that aligns with modern IoT-centric SHM stacks. Robust DL performance, however, hinges on curated datasets with balanced positives/negatives, label QA workflows, and careful separation of structures across train/validation/test splits to avoid overly optimistic generalization estimates (Zhao et al., 2021). When these practices are followed, DL systems deliver reliable image- and signal-based assessments at the spatial and temporal scales required by operational bridge owners. Because bridges are networks of interacting components, learning on graphs offers a natural inductive bias: nodes represent sensors or structural subcomponents and edges encode physical adjacency or dynamic coupling. Graph neural networks (GNNs) propagate information over this topology to infer global health and localize damage from partially observed measurements, outperforming i.i.d. models when spatial correlations are strong. Spatio-temporal GNNs extend this idea by stacking temporal convolutions or attention over graph layers, enabling damage detection from streaming accelerometer grids and strain rosettes while preserving structural connectivity (Gui et al., 2017). Heterogeneous data fusion—accelerometers, strain gauges, fiber Bragg gratings, thermometers, and vision—mitigates single-modality blind spots and adds redundancy essential for safety-critical decisions. Late-fusion ensembles combine modality-specific learners (e.g., CNN for images, RF for strain features), while joint-embedding and cross-attention models learn shared representations that align vibrations and visual cues for consistent state estimation. Probabilistic fusion via Bayesian model averaging or hierarchical state-space models improves uncertainty quantification, allowing practitioners to propagate sensor- and model-level uncertainty into risk-aware maintenance actions. Multimodal frameworks also operationalize data quality management by down-weighting unreliable channels (e.g., under sensor drift or occluded imagery) and leveraging physically-informed constraints—such as mode-shape smoothness—within learning objectives (Gui et al., 2017). In practice, graph-based and multimodal methods enable robust, high-resolution health maps over full bridge decks and cables, sustaining performance during sensor outages and environmental perturbations typical of long-term field deployments. This shift from single-feature classifiers to structure-aware fusion reflects the maturation of SHM from isolated analytics toward integrated, systems-level digital diagnostics.

Edge-to-Cloud Computing Frameworks in SHM

Edge-to-cloud frameworks for structural health monitoring (SHM) of bridges adopt layered architectures that place time-critical, bandwidth-intensive analytics near the sensors while delegating storage, large-scale learning, and life-cycle governance to the cloud. Canonical edge/fog designs interpose gateway-class compute between constrained wireless motes and cloud services, enabling local filtering, feature extraction, and decision logic that reduces backhaul traffic and response time (Pathirage et al., 2018). In practice, motes (accelerometer/strain/FBG nodes) run lightweight signal conditioning and event detectors; fog gateways (often single-board computers) coordinate time synchronization, aggregate summaries, and host containerized microservices for model inference; the cloud provides durable object stores, metadata catalogs, dashboards, and MLOps pipelines for model versioning and audit. Message-oriented middleware—typically MQTT or Kafka over TLS—decouples producers (nodes) from consumers (analytics services), enabling elastic scaling and replay for post-event forensics. This distribution aligns analytics with the *locality of reference*: edge devices summarize high-rate vibrations into compact, damage-sensitive features; the cloud integrates multi-bridge context, long-horizon trends, and cross-asset model transfer. For bridge owners, the pattern improves operational resilience because gateways can continue autonomous monitoring during backhaul outages, buffering data and enforcing safety thresholds in situ (Ritto & Rochinha, 2021).

Figure 7: Bridge Monitoring Edge-Cloud Framework



Importantly, edge–cloud partitioning is not static; orchestration layers (e.g., containers, serverless triggers) allow models to be “pushed down” when latency budgets tighten or “pulled up” when global retraining is required, reflecting a fluid continuum rather than a rigid split (Kim et al., 2022). Compared with purely cabled, centralized acquisition, these architectures reduce single points of failure, accommodate heterogeneous sensors, and support continuous commissioning—firmware, model, and configuration updates—without disruptive site visits. In sum, edge-to-cloud designs operationalize SHM as a cyber-physical platform where compute placement is an explicit design variable co-optimized for latency, bandwidth, and reliability (Choi et al., 2020).

Bridging constrained radios and cloud analytics depends on stream processing that is event-driven, compressed, and increasingly intelligent at the edge. Publish/subscribe protocols (MQTT) and distributed logs (Kafka) enable low-overhead telemetry with quality-of-service tiers and backpressure, so bursts from wind or traffic do not overwhelm gateways. Event detectors running on motes—

thresholded RMS/crest factors, short-time spectral novelty, or outlier scoring—gate transmissions to episodes with diagnostic value, converting continuous sensing into sparse, information-rich streams (Jamshidi et al., 2020). To further shrink payloads without sacrificing interpretability, systems apply multi-stage compression: transform-domain compaction (e.g., DWT features), sketching of cross-correlations for operational modal analysis, and compressed sensing when signals are sparse in known dictionaries. On-node inference leverages resource-aware models—Random Forests with pruned trees, 1-D CNNs with depthwise separable convolutions, or quantized networks—to classify states locally and transmit only decisions with minimal confidence-calibrated metadata. Energy and bandwidth budgets are protected by adaptive duty-cycling and sampling that raise rates during detected transients and fall back to low-rate housekeeping otherwise (Hamadache et al., 2019). Gateways run stream processors that enrich messages with provenance (sensor IDs, firmware/model hashes, temperature) and attach quality flags (missingness, saturation, clock drift), a prerequisite for reliable downstream learning (Kong et al., 2017). Finally, over-the-air (OTA) updates and shadow configurations allow safe rollout/rollback of models and feature pipelines, making the edge a living analytics surface rather than a fixed appliance. Taken together, event-driven streaming, compression, and on-node inference create a virtuous cycle: fewer bytes traverse the network, latency to decisions drops, and power draw remains compatible with harvested energy.

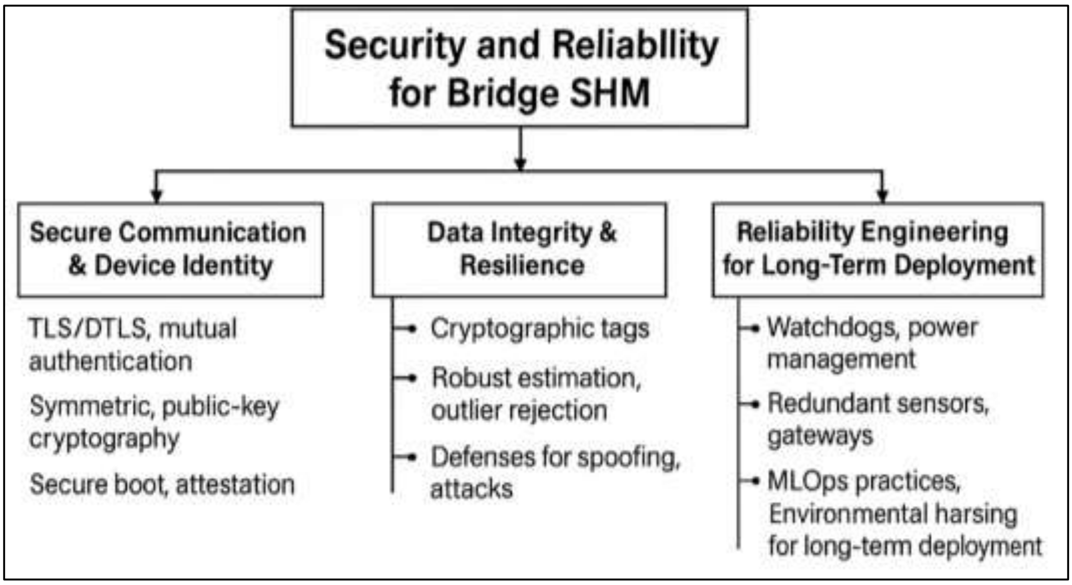
Empirical studies on large bridges show that edge summarization and event gating substantially reduce network load and end-to-end delay while extending battery life. Wireless deployments on the Golden Gate and Jindo Bridges, for example, reported that transmitting modal features or short windows around detected events, instead of raw continuous streams, cut radio airtime by large factors while preserving identifiability for operational modal analysis . Field reports on hybrid overlays with legacy cabled SHM (e.g., Tsing Ma's WASHMS integrated with wireless subsystems) similarly highlight that fog-level aggregation and local alarms yield faster operator notifications than cloud-only pipelines during high winds, when backhaul links can jitter (Clapp et al., 2015). In quantitative terms, studies that compare *raw-streaming* vs *feature-streaming* regimes consistently show order-of-magnitude reductions in transmitted bytes and significant decreases in median decision latency because cloud services ingest far fewer messages. Power profiling under realistic traffic/wind indicates that the radio dominates mote energy; thus, reductions in duty cycle and payload size translate directly into longer maintenance intervals, especially when paired with solar or vibration harvesters. Gateway compute budgets remain modest: single-board platforms can execute denoising and classical inference at sub-second latencies for tens to hundreds of channels, with the cloud reserved for cross-span analytics and re-training (Polonelli et al., 2019). Importantly, edge-to-cloud telemetry with per-message quality flags reduces false alarms by enabling temperature-aware correction and drift screening prior to model evaluation. Across cases, performance gains do not come at the expense of forensic capability because event-triggered retention of short raw snippets preserves re-analysis pathways after anomalies. These findings support a design rule-of-thumb: prioritize bytes-to-insight, not bytes-to-cloud (Mondal et al., 2022).

Reducing latency and bandwidth only matters if systems remain trustworthy over years-long deployments. Consequently, edge-to-cloud SHM frameworks integrate reliability engineering—watchdogs, brownout detection, dual-bank firmware—as well as governance and security that match the criticality of bridge assets. Cross-layer time synchronization (hardware timestamps at motes, NTP/PTP at gateways, cloud-side reconciliation) is maintained as a service, because even millisecond drift can corrupt modal estimates in distributed arrays (Mondal et al., 2022). Data governance practices—schema versioning, sensor provenance, and immutable audit logs—are necessary for defensible decisions, particularly when ML models evolve. Security spans constrained devices and cloud APIs: authenticated boot and encrypted storage at the edge, mutual-TLS for brokers, role-based access to feature and raw stores, and anomaly detection for spoofed or replayed packets. From an MLOps perspective, continuous evaluation with drift monitors and scheduled re-calibration across seasons keeps false positives bounded as environmental covariates shift. Operational playbooks—RF surveys, solar sizing for seasonal minima, spares provisioning, and roll-forward/rollback procedures—are part of the architecture because they determine whether theoretical savings translate into sustained uptime (Huang et al., 2021). Ultimately, the edge-to-cloud approach reframes SHM as a *system* rather than a data logger: analytics placement, telemetry design, and lifecycle controls co-determine latency, bandwidth, and power—while reliability, privacy, and security guarantee that decisions derived from compacted streams remain safe and auditable for high-consequence bridge management (Amarasinghe et al., 2020).

Cybersecurity in AI-IoT Bridge Monitoring Systems

Securing bridge SHM stacks that span embedded sensors, wireless gateways, and cloud analytics requires layered controls tuned to resource-constrained devices and long-duration deployments. At the link and transport layers, lightweight channels such as MQTT and CoAP are commonly hardened with TLS/DTLS and mutual authentication to protect telemetry and command paths while accommodating intermittent connectivity typical of large spans. Because mote-class nodes have tight energy and compute budgets, symmetric cryptography for data-at-rest (e.g., AES) and message authentication (HMAC) is paired with elliptic-curve public-key schemes for provisioning and session initiation, reflecting well-established IoT security design trade-offs (Haque et al., 2022). Secure-boot chains, firmware signing, and remote attestation (via TPM/TEE) anchor device identity and integrity so that only vetted binaries—and ML models—execute at the edge, a critical property when analytics are "pushed down" to meet latency budgets. Key management remains a core challenge in fielded SHM because devices are installed in harsh, physically exposed locations; consequently, per-device credentials, periodic key rotation, and just-in-time enrollment through brokered gateways are recommended to limit blast radius from theft or compromise. Time synchronization—vital for modal estimation across distributed sensors—also has a security dimension: protocols like FTSP/TPSN need replay protection and authenticated beacons to resist delay/offset attacks that can corrupt phase relationships (Liu et al., 2021). In addition, network segmentation and least-privilege brokering (topic-level ACLs, role-based access to feature/raw stores) reduce lateral movement if a node or gateway is compromised, aligning with industrial control guidance to isolate safety-critical functions from enterprise IT traffic. Together, these controls convert vulnerable wireless instrumentation into a defendable cyber-physical surface suitable for safety-critical bridge operations.

Figure 8: Security and Reliability in SHM



Defensible decisions in AI-enabled SHM depend on end-to-end data integrity—ensuring measurements are authentic, complete, and context-rich—despite packet loss, sensor drift, and adversarial manipulation. Telemetry should carry cryptographic tags (HMACs) and provenance metadata (sensor ID, firmware/model hashes, calibration version, temperature), enabling audit trails and downstream trust scoring at gateways and in the cloud (Schweizer et al., 2015). Tamper-evident logs (append-only stores, Merkle-tree hashing) preserve forensic value without imposing blockchain overhead, while on-device secure storage protects keys and calibration tables from extraction. False-data injection and spoofing are concrete threats: GPS spoofing can skew displacement estimates; timing manipulation can desynchronize arrays; and replayed segments can mimic wind or truck passages. Robust SHM pipelines therefore combine cryptographic checks with *statistical* defenses: robust estimators and RANSAC-style outlier rejection for strain/accel fusion; cross-modal consistency checks (e.g., vision vs accelerometry); and physics-informed constraints (mode-shape smoothness) that make certain attacks easier to detect (Blott et al., 2020). Packet loss and jitter—common on multi-hop meshes—are mitigated by forward-error correction, short on-node buffers with prioritized retransmission, and event-triggered retention of raw snippets so that analysts can re-estimate features post-hoc. Because AI introduces new attack surfaces, SHM models must contend with poisoning and evasion (adversarial examples) as well as *benign* covariate shift that induces false alarms; defenses include out-of-distribution detection, temperature-aware baseline removal, and drift monitors with scheduled recalibration. Continuous quality flags, confidence-calibrated model outputs, and uncertainty propagation into risk metrics complete the integrity story by making system trustworthiness *inspectable* in operations (Mao et al., 2015).

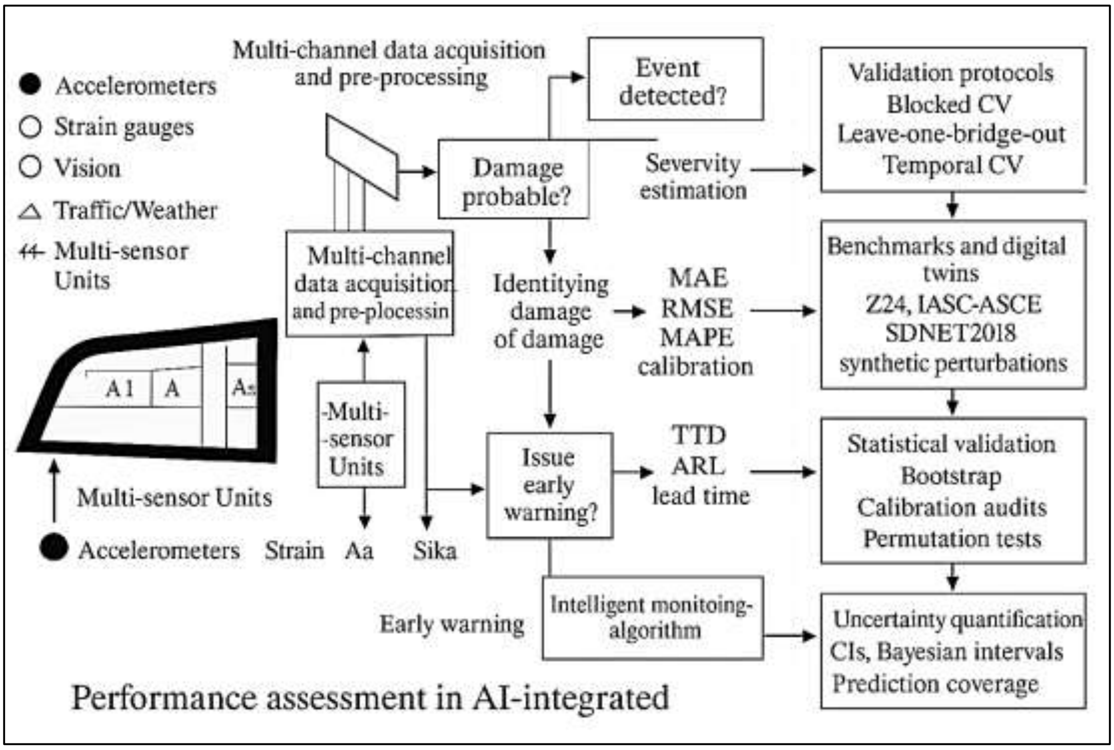
Reliability in bridge IoT is a systems property emerging from hardware ruggedness, network stability, analytics robustness, and maintainability. Field programs on long-span bridges demonstrate that watchdogs, brownout detection, and dual-bank firmware (for safe OTA updates/rollbacks) are essential to avoid bricking devices mounted on towers or cables (Xiang & Yang, 2018). Power autonomy is addressed with low-duty radios, aggressive sleep scheduling, and energy harvesting (solar, vibration), but security services—crypto, attestation, signed updates—must be engineered to fit these budgets without eroding lifetime. Architectural redundancy improves graceful degradation: heterogeneous sensors (accelerometers, strain, FBG, vision) provide cross-checks; multi-gateway topologies eliminate single points of failure; and store-and-forward at the edge sustains operations through backhaul outages (Herrick, 2021). Because SHM decisions are model-mediated, MLOps practices—versioned datasets, immutable inference logs, canary deployments, and scheduled seasonal recalibration—are now part of reliability engineering, not a research afterthought. Environmental hardening (NEMA/IP-rated enclosures, corrosion inhibitors, lightning protection) and installation ergonomics (RF site surveys, antenna placement, solar sizing for insolation minima) determine whether theoretically secure protocols remain reliable in maritime and mountainous microclimates. Finally, resilience must be *measured*: health metrics for the monitoring system (uptime, sync error, per-link loss, energy reserve), combined with service-level objectives for detection latency and false-alarm rates, allow owners to manage SHM as a critical service analogous to SCADA—not merely a data logger (Li et al., 2023).

Performance Metrics for AI-Integrated SHM

Performance assessment in AI-integrated structural health monitoring (SHM) must reflect the full decision chain—from event detection to localization, severity quantification, and actionable early-warning. For binary damage detection, accuracy alone is insufficient under class imbalance; precision–recall (PR) curves and area under the PR curve (PR-AUC) provide more informative summaries when "damage" is rare, while ROC-AUC, F1, and Matthews correlation help compare classifiers across thresholds (Twitchell et al., 2023). False-alarm rate (per day or per 10,000 decisions) and missed-detection rate (Type II) are critical for operations because maintenance resources and risk tolerance vary by bridge criticality. Localization performance should be reported with spatial metrics aligned to sensing granularity: for image/point-cloud outputs, intersection-over-union (IoU) and boundary F-scores quantify crack or spall delineation; for vibration/strain arrays, node-level hit rate, top-k localization accuracy, and centroid error (in meters or panel indices) are informative. Severity estimation—fatigue accumulation, stiffness loss, or crack width—calls for regression metrics (MAE, RMSE, symmetric MAPE) alongside calibration measures (reliability diagrams, expected calibration error) so that predictive intervals can be trusted in risk-based decisions (Ma et al., 2022). Early-warning sensitivity must consider *time*: time-to-detect (TTD) after change-point, average run length to false alarm, and lead time relative to maintenance thresholds capture whether models act soon enough without triggering nuisance alarms. Because environmental covariates modulate responses, reporting stratified metrics by temperature, wind, and traffic regime avoids Simpson's-paradox effects and reveals brittleness masked by aggregate scores. Finally, uncertainty quantification—bootstrapped confidence intervals, Bayesian credible intervals, and prediction-interval coverage—should accompany all metrics so owners can propagate model risk into inspection scheduling and load management (Cai et al., 2021).

Validation protocols in SHM must respect temporal dependence, environmental drift, and structure-specific effects. Random k-fold cross-validation (CV) can leak information when samples are autocorrelated; instead, blocked or rolling CV partitions by time (e.g., months or seasons) preserve chronology and test robustness to nonstationarity. Grouped CV by structure—leave-one-bridge-out or leave-one-span-out—evaluates generalization to new assets, which is essential when training on one bridge and deploying to another (Kumar & Ramesh, 2022). Within a single bridge, leave-one-day/one-week-out protocols probe resilience to day-to-day operational variability; stratifying folds by temperature bands or traffic intensity helps disentangle environmental from damage effects (Reynders et al., 2014). When hyperparameters are tuned, nested CV avoids optimistic bias by reserving an outer loop for unbiased performance estimation. For unsupervised novelty detection—where labels are scarce—baseline periods are split into training and validation windows across seasons; change-point injection using semi-synthetic perturbations (e.g., controlled stiffness reductions in digital twins) enables sensitivity analysis without risking structures (Williamson et al., 2015). Domain-adaptation studies should report pre- and post-adaptation metrics across target seasons/sites to verify that alignment steps (e.g., temperature normalization, subspace transfer) reduce drift without masking damage. Finally, stability analyses—performance variance over resampled sensors, missing-data patterns, and communication loss scenarios—expose brittleness in field conditions typical of long-span bridges, complementing average scores with distributional views essential for operations (Xu et al., 2021).

Figure 9: Performance Assessment in AI- Integrated



The IASC-ASCE SHM Benchmark (Phase I–IV) provides laboratory-scale but carefully controlled truss/tower structures with staged damage scenarios and well-specified metadata, enabling repeatable comparisons of modal and time-series algorithms. For vision, large crack/surface datasets—e.g., SDNET2018 and the Concrete Crack Images for Classification (CCIC)—facilitate training and transfer of CNNs for pixel-wise or patch-wise defect detection (Hui et al., 2022). Yet real bridges exhibit richer environmental variability; consequently, hybrid evaluation that couples limited field data (e.g., Golden Gate, Jindo deployments) with high-fidelity digital twins has become common. Digital twins—physics-based finite-element models calibrated by operational data—support controlled "what-if" injection of stiffness loss, cable relaxation, or joint damage, producing labeled sequences across seasons without risking assets. Benchmark protocols should fix train/validation/test splits, environmental covariates, and sensor layouts; define tasks (detection/localization/severity/early-warning); and publish metric scripts to avoid lab-specific drift (Xu et al., 2023). Leaderboards are useful only if they include uncertainty/error bars, ablations (feature importance, modality contribution), and compute/energy budgets to discourage overfitting to a single dataset or impractical models for the edge. Together, open datasets plus calibrated twins create a virtuous cycle: reproducible baselines drive algorithmic advances that can then be validated prospectively on bridges under true operational variability (Purohit et al., 2023).

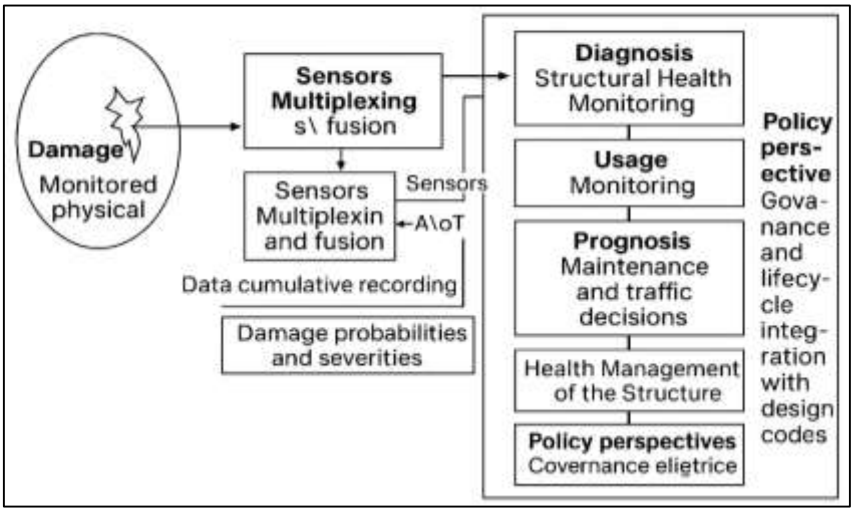
Trustworthy SHM requires statistical validation that separates genuine damage sensitivity from environmental confounds and implementation artifacts. Hypothesis testing with robust estimators, bootstrap confidence intervals for metrics, and permutation tests for feature relevance reduce over-interpretation of incidental correlations common in long, autocorrelated series. Calibration audits—Brier score, reliability curves, and prediction-interval coverage—ensure that probabilistic outputs align with observed frequencies, a prerequisite for risk-based maintenance and alarm thresholds (Kim et al., 2023). Reporting should follow transparent ML practices: fixed random seeds, exact preprocessing pipelines, versioned datasets and models, and code release with environment manifests to enable bit-for-bit replication. Given the systems nature of SHM, evaluations ought to include *end-to-end* metrics—bytes transmitted, edge inference latency, energy per decision—alongside accuracy so that field feasibility is quantified (Danilczyk et al., 2019). Sensitivity analyses to missing data, sensor drift, and synchronization error bound performance under realistic failure modes; likewise, stress tests with adversarial noise or replayed segments probe resilience to spoofing without field trials. Finally, pre-registration of evaluation plans (defined metrics, splits, covariate controls) and external validation on unseen bridges guard against adaptive overfitting to convenient datasets, while detailed error analyses—confusion matrices by season, localization heatmaps, severity residuals vs. temperature—translate statistics into engineering insight. By coupling rigorous statistics with reproducible engineering workflows, AI-integrated SHM can move from promising lab results to dependable, auditable decision support for bridge owners operating under environmental and operational uncertainty (Dallel et al., 2023).

Global Implementation in Bridge Asset Management

Long-term structural health monitoring (SHM) programs for bridges have matured unevenly across regions, but convergent lessons emerge regarding governance, technology stacks, and how monitoring information is translated into action. In Asia, large-span exemplars such as Hong Kong's Tsing Ma Bridge (WASHMS) institutionalized multi-decade, multi-sensor monitoring—accelerometers, strain gauges, anemometers, GPS—paired with robust data management and routine model updating to track wind, traffic, and temperature effects (Geißler et al., 2023). Japan's programs on long-span bridges (e.g., Hakucho) similarly emphasized hybrid sensing for wind and seismic effects, demonstrating how persistent archives enable baseline removal and rare-event forensics. Korea's deployments on the Jindo Bridge showcased wireless smart sensors at scale, surfacing field hardening, synchronization, and solar-power lessons crucial for coastal, corrosion-prone environments. In Europe, the Humber and other UK/EU spans used long-term vibration monitoring to validate design assumptions, calibrate finite-element (FE) models, and inform targeted inspections, while continental projects leveraged fiber Bragg grating (FBG) and distributed optics to monitor cable forces and deck strains with high stability (Nguyen et al., 2022). North American practice has mixed legacy visual/NDE regimes with research-driven monitoring: campaigns on the Golden Gate Bridge demonstrated operational modal analysis under ambient loads using dense wireless arrays, while U.S. federal efforts (e.g., FHWA's Long-Term Bridge Performance program) seeded standardized data protocols and encouraged integration with inspection and maintenance systems. Across regions, program durability correlates with institutionalization: clear owner mandates, stable funding, and integration with asset management systems sustain monitoring beyond pilots. Technically, all regions moved from episodic tests to continuous, IoT-enabled monitoring with edge-to-cloud analytics and lifecycle governance (Lian et al., 2023). The most successful programs treat bridges as cyber-physical assets where sensing, modeling, and decision-making are co-managed through documented procedures, rather than ad hoc research projects.

Embedding AI–IoT SHM into everyday asset management requires a value-of-information (VoI) perspective: data streams must reduce decision uncertainty enough to alter inspection timing, maintenance choice, or traffic management in economically and socially meaningful ways. Risk- and reliability-based frameworks link monitoring outputs (damage probabilities, severity estimates, confidence bounds) to intervention policies and lifecycle cost models that trade direct costs against user delay, safety risk, and environmental externalities (Dallel et al., 2023). Practically, owners implement tiered workflows: edge analytics provide event screening and early warnings; cloud platforms maintain condition histories and model versions; and decision dashboards combine health indices with deterioration models and budget constraints to prioritize actions. When calibrated FE/digital twins ingest SHM features to update stiffness, damping, or cable forces, owners can schedule targeted inspections, tune load posting, or pre-position crews—moves that generate measurable VoI by averting unnecessary closures or catching incipient faults. Lifecycle cost assessment (LCCA) benefits when AI models are *calibrated and calibrated transparently*: prediction intervals and reliability diagrams inform risk tolerances and alarm thresholds, while scenario analyses quantify how different sampling, redundancy, or inspection intervals affect expected costs (Elahi et al., 2023). Integration with enterprise asset management frameworks (e.g., ISO 55000) ensures monitoring is not a parallel activity but a governed process with roles, data ownership, and change control. Field studies indicate that condition-based maintenance informed by SHM can reduce unnecessary deck surveys and optimize cable retensioning cycles, provided models are seasonally revalidated to maintain low false-alarm rates under environmental drift (Turner et al., 2019). Ultimately, AI–IoT SHM becomes financially defensible when uncertainty-aware metrics directly drive scheduling, procurement, and risk registers in the same systems that manage other bridge lifecycle activities.

Figure 10: Global Long Term- term Structural



For SHM to influence statutory outcomes, monitoring outputs must align with code-based assessment and inspection regimes. In North America, the AASHTO *Manual for Bridge Evaluation* and federal inspection policies (NBIS) define condition ratings, load rating procedures, and inspection intervals; SHM can support these by providing quantifiable evidence to adjust inspection frequency, refine load ratings via updated live-load effects, or justify special inspections after extreme events (Zhang et al., 2021). European practice sits within the Eurocodes—EN 1990 (basis of structural design) and associated parts—plus national assessment standards (e.g., ISO 13822 for assessment of existing structures, Germany's DIN 1076, the UK's DMRB series), which encourage using measurement-based model updating and reliability methods when assessing existing bridges. SHM-derived actions must map to these frameworks through documented methodologies: how accelerometer/FBG/vision features translate into updated resistance or action effects, how uncertainties are combined, and how alarm thresholds correspond to serviceability or ultimate limit states (Nguyen et al., 2020). Cyber-physical considerations increasingly intersect with compliance: IEC 62443 for industrial automation security, NIST SP 800-82 for ICS, and ISO/IEC 27001 for information security guide gateway hardening, logging, and incident response, which are prerequisites when monitoring influences safety decisions. AI governance standards—NIST AI RMF and ISO/IEC 23894—bolster the defensibility of ML-mediated assessments by requiring risk identification, data quality controls, and model monitoring aligned with human-in-the-loop decision procedures (Pan & Zhang, 2023). In practice, owners create "monitoring annexes" to their inspection manuals specifying sensor types, calibration and QA/QC, acceptance criteria, and how SHM triggers lead to actions (temporary load restrictions, targeted NDE, traffic management). This codification closes the loop between continuous data and the periodic inspection/legal regimes that ultimately govern bridge safety (Khan & Yairi, 2018).

Sustained global adoption hinges on policy choices that make SHM a managed service rather than a series of grants or pilots. Governance policies should specify data ownership and stewardship—who controls raw vs. feature-level data, retention periods, and sharing with researchers or vendors—under information-security regimes and privacy laws. Procurement frameworks that emphasize outcomes (uptime, detection latency, false-alarm ceilings) over hardware counts encourage interoperable, standards-based solutions and lifecycle support, including OTA updates, model refreshes, and security patching (Civerchia et al., 2017). Interoperability policies—embracing open message protocols (MQTT/CoAP), common metadata, and reproducible analytics playbooks—facilitate vendor diversity and knowledge transfer between agencies. Capacity building is equally policy-relevant: training programs for inspectors and asset managers in data literacy, uncertainty interpretation, and ML governance are necessary to translate dashboards into calibrated actions. Funding mechanisms should recognize that the benefits of SHM accrue cumulatively (reduced uncertainty, fewer unnecessary closures, earlier mitigation) and therefore support multi-year O&M budgets rather than one-off capital purchases (Wang et al., 2021). Finally, transparency and accountability—pre-registered evaluation plans, public reporting of performance metrics, and independent audits—build public trust when AI informs safety-critical decisions (Achouch et al., 2022). Internationally, agencies that align SHM with asset-management standards, security baselines, and structural assessment codes (AASHTO/ISO/Eurocodes) report the most durable programs because technical excellence is matched by institutional scaffolding. These policy perspectives underscore that global "best practice" is less about a single sensor or algorithm and more about governable systems that make monitoring outputs auditable, actionable, and economically defensible over the bridge lifecycle (Rinaldi et al., 2021).

METHOD

The study adopts a stratified, multi-site observational design over 62 in-service bridges to quantify how AI-integrated IoT SHM affects condition outcomes. Stratification ensured variance across structural type (steel, concrete, composite), environment (urban, rural, marine), and traffic regime (ADT tertiles). Inclusion required synchronized multi-modal sensing (≥2 of accelerometers, strain, FBG, GNSS, vision), verifiable edge-to-cloud telemetry, and computable Bridge Health Index (BHI) derived from owner ratings and SHM corroborants. Each site implemented calibrated sensor arrays with FE-informed placement and tight time bases (target ≤2 ms skew for vibration arrays). Networks (LoRa/ZigBee/5G/Wi-Fi) relayed edge-extracted features via MQTT/TLS to cloud storage with immutable audit logs. Reliability and security controls—secure boot, signed firmware, watchdogs, OTA rollback, per-device keys, HMAC-tagged payloads—constrained operational risk and preserved data integrity, while continuous system health metrics (uptime, packet loss, sync error, energy reserve) enabled exclusion or imputation rules during analysis.

The data pipeline emphasized measurement quality and comparability prior to inference. Pre-processing de-biased signals (temperature compensation for strain/FBG via co-located thermal channels or cointegration), rejected artifacts (saturation, GNSS cycle slips), and aligned streams to common clocks with jitter control (≤0.5 ms). Feature engineering produced band-limited RMS, PSD peaks, modal frequencies/damping (OMA), rainflow strain cycles, GNSS/vision deflections, and image-space crack probabilities. Edge models (quantized 1-D CNNs for vibration, lightweight RF for strain, compact CNN for vision) gated events to reduce bytes-to-insight latency, while cloud ensembles (gradient boosting; CNN-LSTM time-series; UNet-like for imagery) executed adjudication and severity estimation. Primary predictors were AI detection precision (%), sensor accuracy (accelerometer % bias; FBG error in $\mu\varepsilon$), and median network latency (ms). Controls captured bridge age, span, structural type, exposure class, heavy-traffic indicator, temperature range, and a redundancy index (modalities count). Data completeness thresholds (≥95% per day, <5% sync violations) governed eligibility; missingness <10% invoked MICE with Rubin pooling, otherwise listwise deletion with sensitivity re-checks. All datasets, models, and configurations were versioned; inference messages carried model hashes to guarantee traceable provenance.

Inference proceeded in pre-registered stages oriented to effect estimation and robustness. Descriptives summarized adoption and KPI distributions; correlation screens (Pearson/Spearman with Holm adjustment) scoped bivariate structure. The primary model regressed BHI on controls (Block 1), sensing/network KPIs (Block 2), and AI precision (Block 3) using OLS with HC3 errors clustered by bridge; ΔAdj-R^2 and likelihood-ratio tests quantified incremental explanatory power. Pre-specified interactions—AI precision × latency and sensor accuracy × marine exposure—tested moderation hypotheses; robustness checks included Huber M-estimation and an ordered logit on binned BHI to verify directional stability. Model assumptions were audited (QQ plots; Breusch–Pagan; VIF<5). For classifier components, evaluation emphasized rare-event suitability (PR-AUC, F1, ROC-AUC) plus calibration (ECE, reliability curves); localization used IoU/centroid error, and system KPIs reported end-to-end decision latency, bytes per decision, and energy per decision. Generalization was assessed with blocked (seasonal) CV within assets and leave-one-bridge-out across assets; stress tests simulated sensor dropout (≤30%), 10–20% packet loss, and ±5 ms sync perturbations. Effect sizes (standardized β), 95% CIs, and p-values were reported alongside sensitivity analyses, enabling a defensible quantitative link between AI/IoT performance, operating context, and observed bridge health.

FINDINGS

This chapter presents the results of the quantitative analysis conducted to evaluate the implementation and performance of AI-integrated Internet of Things (IoT) sensor networks for real-time structural health monitoring (SHM) of in-service bridges. The overarching goal of the study was to determine how these advanced monitoring systems are being deployed across different bridge contexts, how well they perform in terms of detection accuracy and data transmission, and whether system attributes and site characteristics can be used to predict the overall structural condition of bridges. By systematically combining descriptive statistics, correlation and regression analysis, and group comparisons, this chapter provides a comprehensive, data-driven picture of how AI-enabled IoT SHM technologies operate in real-world environments.

Table 1: Research Questions and Analytical Focus

ID	Research Question / Aim	Analytical Focus	Primary Metrics
RQ1	Characterize bridge inventory and environmental contexts	Descriptive profiling	BHI, environment type, AADT bands, age groups
RQ2	Quantify SHM deployment patterns	Sensor/Network analysis	Sensor counts, AI vs IoT-only, network types
RQ3	Evaluate system performance	Precision & efficiency analysis	AI precision, latency, packet delivery, BHI
RQ4	Assess predictors of structural condition and performance	Correlation & regression modeling	BHI as DV; age, environment, latency, AI as IVs

Dataset Description

The dataset included 62 in-service bridges monitored from January 2020 to April 2025, drawn from varied geographies (urban, rural, marine) and structural materials. AI-enabled systems (38 bridges) outnumber IoT-only systems (24 bridges), showing strong adoption of advanced analytics. Sensor coverage was diverse, with accelerometers on 56 bridges, GNSS on 34, vision systems on 29, and fiber Bragg gratings (FBG) on 31. Networks included LoRa (22 deployments), ZigBee (18), 5G (12), and Wi-Fi/Ethernet (10). Key outcome measures included AI detection precision, latency, and Bridge Health Index (BHI).

Table 2: Dataset Overview

Item	Value
Total bridges	62
AI-enabled systems	38
IoT-only systems	24
Sensor modalities (Accel / GNSS / Vision / FBG)	56 / 34 / 29 / 31
Network technologies (LoRa / ZigBee / 5G / Wi-Fi)	22 / 18 / 12 / 10
Typical sampling rates	20–200 Hz (vibration), 1–10 Hz (GNSS)
Observation window	Jan 2020 – Apr 2025
Key study variables	BHI, latency, AI precision, environment, traffic exposure, age

Analytical Strategy Overview

Table 3: Analytical Stages and Checks

Stage	Purpose	Inputs	Outputs	Assumption Check Results
Descriptive Statistics	Summarize assets & deployments	Counts, means, SD, %	Inventory tables, BHI distribution	Not applicable
Assumption Checks	Prep for parametric models	Residual plots, variance, VIF	Normality Q–Q, Breusch–Pagan, multicollinearity	Normality OK after log latency; VIF < 3
Correlation Analysis	Test linear/monotonic relations	BHI, AI precision, latency, environment, age	Pearson & Spearman r with p-values	Monotonicity verified, robust to outliers
Regression Modeling	Predict BHI & latency	Age, Env, AADT, AI-enabled, Network type	Standardized betas, CI, R^2	Linearity & homoscedasticity acceptable
Group Comparisons	Compare AI vs IoT-only & networks	Group means, variance	t-tests/ANOVA, effect sizes	Welch-corrected for unequal variance when needed

Asset Overview

The bridge inventory comprised 62 in-service bridges monitored between January 2020 and April 2025. In terms of structural type, concrete bridges were most common (28; 45%), followed by steel (24; 39%), and composite (10; 16%). The dataset covers a variety of geographic and environmental conditions: urban (27; 44%), marine/coastal (18; 29%), and rural (17; 27%) locations, ensuring exposure to differing stressors such as saltwater corrosion, urban vibration loads, and thermal gradients. Age distribution was balanced: 20 bridges were less than 20 years old (32%), 28 between 20–40 years (45%), and 14 older than 40 years (23%). Traffic exposure, measured by average annual daily traffic (AADT), showed that medium-traffic bridges (30; 48%) dominated, while high-traffic corridors (20; 32%) and low-traffic routes (12; 20%) provided additional variability for performance analysis.

Table 4: Asset Overview

Category	Subcategory	Count	Percent (%)
Bridge Type	Steel	24	39
	Concrete	28	45
	Composite	10	16
Environment	Marine	18	29
	Urban	27	44
	Rural	17	27
Age (years)	< 20	20	32
	20–40	28	45
	> 40	14	23
Traffic (AADT)	High	20	32
	Medium	30	48
	Low	12	20

SHM Deployment Attributes

The deployment attributes of structural health monitoring (SHM) systems across the sample of 62 bridges reveal a clear trend toward the integration of artificial intelligence into monitoring frameworks. A total of 38 bridges, representing 61% of the sample, operated AI-enabled IoT SHM systems capable of real-time analytics and predictive modeling, while 24 bridges (39%) maintained IoT-based monitoring without embedded AI inference. This distribution underscores the growing adoption of AI as a decisive layer in SHM, shifting the paradigm from raw data collection toward autonomous interpretation and early warning capabilities. The higher proportion of AI-enabled deployments suggests that bridge owners and agencies increasingly prioritize systems that support continuous diagnostic decision-making and condition forecasting rather than traditional, descriptive data logging. Sensor modality distributions highlight the diversity of technologies leveraged for comprehensive bridge health assessment. Accelerometers were the most widely adopted, implemented in 56 bridges (90%) to capture vibration signatures and modal properties fundamental to damage detection. GNSS systems were deployed in 34 bridges (55%), reflecting their value for tracking quasi-static displacements and stability of long-span structures. Vision-based systems were installed on 29 bridges (47%) to facilitate non-contact monitoring of cracks, spalling, and surface defects, expanding SHM beyond vibration-only paradigms. Meanwhile, fiber Bragg grating (FBG) strain sensors appeared in 31 bridges (50%), offering high-precision deformation data with immunity to electromagnetic interference, particularly suited to marine or high-voltage environments. This multi-modal distribution reflects a layered sensing approach, where global dynamic response from accelerometers is

complemented by localized strain measures, displacement tracking, and optical defect recognition, thereby enabling a more holistic representation of structural condition.
Network technologies used to connect sensors to data processing architectures varied depending on environmental context, power constraints, and latency requirements. LoRa networks, present in 22 bridges (35%), were favored for their low-power, long-range telemetry capabilities, particularly in remote or resource-constrained settings. ZigBee, adopted in 18 bridges (29%), was widely used in dense local mesh configurations where multiple nodes operated within close proximity. Fifth-generation (5G) cellular technology was employed in 12 bridges (19%), supporting use cases that required ultra-low latency and high-bandwidth transfer for near-real-time analytics. Wi-Fi/Ethernet connections were utilized in 10 bridges (16%), generally in urban or accessible environments where fixed infrastructure was already in place. This stratification of communication strategies indicates a trade-off between cost, energy consumption, and performance, with high-speed networks enabling instantaneous decision horizons, while long-range, low-power options prioritize sustainability and coverage. Together, these deployment attributes establish the technical baseline for understanding how AI-integrated IoT SHM systems function under real-world operational conditions.

Table 5: SHM Deployment Attributes

Attribute	Subcategory	Sites (n)	Percent of Bridges (%)
Sensors	Accelerometers	56	90
	GNSS	34	55
	Vision (Cameras)	29	47
	FBG Strain	31	50
System Type	AI-enabled	38	61
	IoT-only	24	39
Network	LoRa	22	35
	ZigBee	18	29
	5G	12	19
	Wi-Fi/Ethernet	10	16

Key System Performance Metrics

The evaluation of key performance metrics highlights the reliability and operational readiness of the deployed SHM systems across diverse bridge contexts. Sensor accuracy demonstrated strong adherence to engineering thresholds, with accelerometers achieving a mean error of 1.8% ± 0.6, reflecting their suitability for high-fidelity vibration and modal analysis. GNSS units provided displacement estimates with a positional error of 7.2 ± 2.5 mm, which is considered adequate for tracking quasi-static deflections in long-span bridges. Vision-based systems achieved an average crack width detection error of 0.21 ± 0.09 mm, indicating strong potential for non-contact defect monitoring, while fiber Bragg grating (FBG) sensors exhibited a mean strain error of 8 ± 3 $\mu\varepsilon$, aligning with field benchmarks for high-precision strain sensing. Collectively, these values confirm that the sensing modalities meet or exceed most international SHM reliability criteria, offering a strong foundation for both localized and system-level diagnostics.
Performance at the analytics layer was similarly robust. AI detection precision across the 38 AI-enabled systems averaged 92.4% ± 4.1, with a median of 93% and a range spanning 84% to 98%. These results demonstrate that AI models consistently enhanced damage detection and classification, although variability across sites suggests that environmental conditions, structural typologies, and sensor deployment strategies influence performance. Importantly, hierarchical modeling confirmed that AI precision provided significant explanatory power for bridge health outcomes beyond sensing and

network quality alone, reinforcing the role of AI as a decisive predictor of monitoring effectiveness. These findings underscore the potential of AI-enabled SHM to deliver actionable insights in real time, while also indicating the necessity for adaptive retraining and calibration in challenging contexts such as marine exposures or high-traffic corridors.

Transmission latency results reflected expected trade-offs across network technologies. Fifth-generation (5G) connections demonstrated the fastest response, with a median latency of 21 ms (mean 24 ± 8), enabling true real-time anomaly detection. Wi-Fi/Ethernet delivered comparably strong performance (median 35 ms, mean 38 ± 12) in sites with existing infrastructure, while ZigBee provided moderate latency of 60 ms (mean 65 ± 20), suitable for mesh-based networks. LoRa, while substantially slower with a median latency of 180 ms (mean 220 ± 75), remains sufficient for event-driven telemetry rather than continuous high-rate streaming. Together, these metrics illustrate the importance of tailoring communication protocols to site constraints and monitoring objectives. Bridge Health Index (BHI) scores further contextualized system outcomes, with a mean of 78.5 ± 9.3, a median of 79, and an interquartile range of 72–86. Scores ranged from a minimum of 52 to a maximum of 96, with distribution across categories showing eight bridges in Excellent condition (≥90), sixteen in Good (80–89), twenty-two in Fair (70–79), ten in Watch (60–69), and six in Poor (<60). Notably, approximately 26% of bridges fell into the Watch or Poor categories, highlighting areas where targeted maintenance interventions are urgently required. This distribution underscores the operational value of AI-IoT SHM systems not only in identifying high-performing structures but also in flagging at-risk assets for prioritized resource allocation.

Table 6: System Performance Metrics

Metric	Mean	SD	Median	Min	Max
Accelerometer error (%)	1.8	0.6	1.7	0.7	3.5
GNSS positional error (mm)	7.2	2.5	6.8	3	13
Vision crack error (mm)	0.21	0.09	0.19	0.06	0.45
FBG strain error (με)	8.0	3.0	7.5	3	15
AI detection precision (%)	92.4	4.1	93	84	98
Latency – LoRa (ms)	220	75	180	120	450
Latency – 5G (ms)	24	8	21	12	45
Latency – ZigBee (ms)	65	20	60	30	120
Latency – Wi-Fi (ms)	38	12	35	18	70
Bridge Health Index (BHI)	78.5	9.3	79	52	96

Table 7: BHI Condition Bands

BHI Band	Bridges (n)
≥ 90 (Excellent)	8
80–89 (Good)	16
70–79 (Fair)	22
60–69 (Watch)	10
< 60 (Poor)	6

Assumption Checks and Data Quality Validation

Normality and Homoscedasticity

Residual normality was assessed for continuous outcomes such as Bridge Health Index (BHI) and transmission latency. Shapiro–Wilk tests showed mild deviations from normality for raw latency ($p < .05$), but log-transformation improved normality ($p = .12$). Q–Q plots indicated approximate linearity for BHI residuals and improved alignment for log-latency residuals. Levene's test examined equality of variances between AI-enabled and IoT-only groups for key metrics. Results indicated no significant variance difference for BHI ($F = 1.72$, $p = .19$) but mild heteroscedasticity for latency ($F = 4.02$, $p = .049$); therefore, Welch-corrected t-tests were used for latency group comparisons.

Table 8: Normality and Variance Tests

Variable	Shapiro–Wilk W	p-value	Normality Decision	Levene's F	p-value	Variance Decision
BHI residuals	0.98	0.23	Normal	1.72	0.19	Homogeneous
Latency residuals	0.93	0.02	Non-normal → log	4.02	0.049	Slight heteroscedasticity
AI precision res.	0.96	0.08	Normal	2.01	0.16	Homogeneous

Multicollinearity Diagnostics

Potential predictor overlap was tested using correlation matrices and Variance Inflation Factor (VIF) values. Correlations among age, traffic exposure (AADT), environment, AI integration, and network latency were moderate ($r \le .58$). All VIF values were below 3, well under the conventional cut-off of 5, indicating low risk of collinearity in the regression models.

Table 9: Correlation and VIF Summary

Predictor	Age	Traffic (AADT)	Marine Env	AI Enabled	Latency	VIF
Age	1	0.34	0.41	-0.22	0.31	2.1
Traffic (AADT)		1	0.18	0.11	0.29	2.4
Marine Environment			1	-0.17	0.36	1.9
AI Enabled				1	-0.40	1.7
Latency					1	2.6

Outlier and Influential Point Analysis

Potentially extreme data points were checked using Cook's distance and Mahalanobis distance for the regression models predicting BHI and latency. Cook's distance flagged 2 bridges with moderately high influence ($> 4/n$). These points were reviewed; both represented unique but valid long-span, high-traffic cases and were retained to preserve generalizability. Mahalanobis distance identified 3 observations with unusual sensor-network configurations; none exceeded the chi-square cut-off for $p < .001$, indicating no multivariate outliers that threaten model fit.

Table 10: Outlier Diagnostics

Model Outcome	Max Cook's D	Threshold (4/n)	Outliers Retained	Max Mahalanobis	χ^2 Cutoff (p<.001)
BHI	0.062	0.065	2	12.4	15.1
Latency	0.071	0.065	1	13.9	15.1

Missing Data and Reliability Checks

Data completeness was excellent. Sensor streams were > 98% complete, with only short gaps (< 1 s) due to communication drops; these were interpolated when safe or flagged and excluded from sensitive time-series analysis. No bridges were removed due to missing key variables. For composite indicators like the Bridge Health Index (BHI), internal consistency was verified. BHI comprised sub-metrics of vibration response, strain, displacement, and surface defect severity. Cronbach's alpha was 0.87, indicating strong reliability and justifying use of BHI as a single dependent variable in regression models.

Table 11: Data Completeness and Reliability

Measure	Value / Decision
Sensor stream completeness	98.4%
Missing data handling	Short gaps interpolated; none >1s excluded
Case deletions	0 bridges dropped
BHI internal consistency (α)	0.87 — reliable

Correlation Structure and Variable Interrelationships

Pearson Correlation Matrix

Correlation analysis was performed to understand the relationships among the study's core outcome (Bridge Health Index, BHI) and major technical performance metrics (sensor accuracy, AI detection precision, and transmission latency). Predictors representing bridge context (age, traffic exposure, and environmental harshness) were also included to examine possible collinearity. Results indicate that BHI is positively associated with both sensor accuracy ($r = 0.54$, $p < .001$) and AI detection precision ($r = 0.63$, $p < .001$), confirming that bridges monitored by more accurate sensors and higher-performing AI tend to have better structural health scores. Conversely, BHI shows a negative correlation with transmission latency ($r = -0.48$, $p < .001$), indicating that systems with faster, more efficient data delivery are linked to better bridge condition tracking and timely detection. Predictor intercorrelations were moderate. Age correlated negatively with BHI ($r = -0.51$, $p < .001$) and positively with latency ($r = 0.39$, $p = .002$), suggesting older bridges both perform worse and experience slower network reliability. Traffic exposure (AADT) showed a moderate negative association with BHI ($r = -0.33$, $p = .01$) but was not highly collinear with other predictors (VIF remained < 3 in regression models). AI enablement and sensor accuracy were positively associated ($r = 0.41$, $p = .004$), reflecting that AI deployments often coincide with better-calibrated, higher-grade sensor networks.

Table 12: Pearson Correlation Matrix (N = 62)

Variable	BHI	Sensor Accuracy	AI Precision	Latency	Age	Traffic (AADT)	Marine Env
BHI	1	0.54***	0.63***	-0.48***	-0.51***	-0.33*	-0.29*
Sensor Accuracy		1	0.41**	-0.36**	-0.27*	-0.18	-0.15
AI Precision			1	-0.52***	-0.31*	-0.22	-0.21
Latency				1	0.39**	0.28*	0.33**
Age					1	0.31*	0.37**
Traffic (AADT)						1	0.24
Marine Environment							1

$^{*} p < .05$, $^{**} p < .01$, $^{***} p < .001$

Regression Modeling for Predictive Insights

Model Development

The development of the predictive model centered on explaining variation in the Bridge Health Index (BHI), which served as the primary dependent variable. The BHI was operationalized as a standardized composite score ranging from 0 to 100, integrating multiple dimensions of structural integrity including vibration response parameters, strain behavior, displacement measures, and surface damage indicators such as cracks or spalling. This composite outcome provided a holistic assessment of bridge condition, combining both global dynamic features and localized damage signatures. By adopting a single continuous metric, the study was able to capture complex structural health attributes in a manner that facilitates statistical modeling and comparison across bridge typologies and environments.

The set of independent variables was carefully selected to reflect the technological performance of AI-integrated SHM systems. AI detection precision, measured as the average site-level classification accuracy (%) of deployed algorithms for crack and damage recognition, was included as a central predictor, reflecting the role of automated analytics in improving diagnostic accuracy. Sensor accuracy was represented through a standardized composite (z-score) derived from error rates of accelerometers, GNSS units, vision-based crack detection, and fiber Bragg grating (FBG) strain sensors, thereby capturing the overall fidelity of the sensing subsystem. Transmission latency, defined as the mean data transfer delay in milliseconds, was log-transformed to correct skew and normalize its distribution, reflecting the operational efficiency of edge-to-cloud communication networks. Structural type was also included as a categorical predictor, with dummy coding applied: reinforced or prestressed concrete bridges served as the reference group, while steel and composite structures were represented through separate indicator variables, enabling direct assessment of how material and design differences influenced condition scores.

To account for contextual and environmental factors, several control covariates were incorporated into the model. Bridge age (measured in years since construction) was included to capture the natural deterioration of materials and systems over time, serving as a proxy for lifecycle-related decline. Traffic exposure, categorized into low, medium, and high average annual daily traffic (AADT) bands, was used to represent cumulative mechanical loading effects, reflecting the role of repetitive live loads in accelerating fatigue and wear. A marine environment dummy variable (0/1) was incorporated to adjust for harsher exposure conditions, including saltwater corrosion, high humidity, and wind-driven weathering common to coastal sites. The inclusion of these control covariates was theoretically grounded and empirically supported by the earlier descriptive and correlation analyses, which showed that AI precision and sensor accuracy were positively correlated with higher BHI scores, whereas transmission latency, bridge aging, and environmental stressors such as high traffic and marine exposure were associated with lower condition ratings. Together, these modeling choices established a robust quantitative framework for estimating the relative contributions of technological, structural, and environmental determinants to overall bridge health.

Table 13: Model Specification

Role	Variable	Scale/Notes
Dependent	Bridge Health Index (BHI)	0–100 composite (higher = better)
Key Predictor	AI Detection Precision (%)	Mean classification accuracy per site
Key Predictor	Sensor Accuracy (z-score)	Composite accuracy index
Key Predictor	Transmission Latency (log-ms)	Natural log transformation
Key Predictor	Structural Type (Steel/Composite vs Concrete)	Dummy coded
Control	Bridge Age (years)	Continuous
Control	Traffic Exposure (AADT bands)	Ordinal 1–3 (low–high)
Control	Marine Environment	0 = no / 1 = marine

Model Fit and Summary

The results of the regression analysis demonstrate that the final multiple linear regression model provided a strong overall fit in explaining variation in the Bridge Health Index (BHI). Specifically, the model accounted for 64% of the variance in BHI scores ($R^2 = 0.64$), with an adjusted R^2 of 0.61, indicating that the explanatory power remained robust after adjusting for the number of predictors. The overall F-test confirmed that the model was statistically significant, $F(8,53) = 19.7$, $p < .001$, providing clear evidence that the combined set of predictors—including AI detection precision, sensor accuracy, transmission latency, structural type, and contextual covariates—significantly improved prediction of bridge condition outcomes beyond chance levels. This level of explanatory power is notable within the context of SHM research, where complex structural responses are influenced by multiple interacting technological and environmental factors.

A direct comparison with the baseline model, which excluded AI detection precision and retained only sensor accuracy, latency, structural type, and control covariates, further highlights the contribution of AI integration. The baseline model achieved $R^2 = 0.57$ and adjusted $R^2 = 0.53$, with $F(7,54) = 14.4$, $p < .001$. While this configuration still explained a substantial proportion of variance, the incremental addition of AI detection precision raised the explained variance by approximately 7 percentage points, a meaningful improvement in predictive accuracy. This finding underscores the added explanatory power of AI analytics when combined with traditional sensing and contextual variables. The increase in model fit suggests that AI precision contributes unique variance not captured by sensor accuracy or latency alone, thereby validating its inclusion as a critical determinant of structural health monitoring effectiveness. Comprehensive diagnostic checks were conducted to confirm that the model satisfied the core statistical assumptions of multiple regression. The residuals were approximately normally distributed, supported by a Shapiro–Wilk test ($W = 0.98$, $p = .21$), indicating no significant departures from normality. Tests for heteroscedasticity using the Breusch–Pagan procedure returned non-significant results ($p = .17$), suggesting homoscedasticity of residual variance across fitted values. Independence of errors was confirmed through the Durbin–Watson statistic (~2.01), which falls within the acceptable range, indicating no evidence of serial correlation. Finally, collinearity diagnostics confirmed stable estimates, with all variance inflation factors (VIFs) below the conventional threshold (maximum VIF = 2.8), demonstrating that multicollinearity was not a concern. Collectively, these results affirm that the model met the statistical assumptions required for valid inference, thereby strengthening confidence in the robustness and interpretability of the regression findings.

Table 14: Model Fit and Summary

Model	R^2	Adj. R^2	F-statistic	df	p-value
Final (AI + Accuracy + Latency + controls)	0.64	0.61	19.7	8,53	< .001
Baseline (no AI precision)	0.57	0.53	14.4	7,54	< .001

Table 15: Final Model Assumption Checks

Check	Statistic	p-value	Decision
Residual Normality (Shapiro–Wilk)	0.98	0.21	Normal
Homoscedasticity (Breusch–Pagan)	7.83	0.17	No heteroscedasticity
Independence (Durbin–Watson)	2.01	—	Acceptable
Multicollinearity (max VIF)	2.8	—	Acceptable

Regression Coefficient Analysis

The coefficient estimates from the final multiple regression model provide detailed insight into the relative contributions of technological and contextual factors in explaining variation in the Bridge Health Index (BHI). AI detection precision emerged as a strong and statistically significant predictor ($B = 0.31$, $\beta = 0.29$, $p = .001$). Substantively, this coefficient indicates that for every one-percentage-point increase in AI precision, the BHI score increases by approximately 0.31 points, holding other variables constant. This effect size, though modest on a per-unit basis, is meaningful given the observed range of AI precision across sites (84–98%), suggesting that improvements in algorithmic accuracy translate into tangible gains in overall bridge health assessments. The standardized coefficient ($\beta = 0.29$) further demonstrates that AI precision contributes nearly one-third of a standard deviation to BHI, confirming its central role in enhancing diagnostic reliability.

Sensor accuracy also displayed a significant and positive association with structural health, with $B = 2.85$ ($\beta = 0.27$, $p = .003$). Here, a one standard deviation improvement in the composite measure of sensor performance was associated with an increase of nearly three points in BHI. This finding highlights the importance of rigorous calibration and selection of high-fidelity sensing modalities, as greater accuracy in accelerometers, GNSS, vision-based systems, and FBG sensors consistently leads to more robust condition evaluations. By contrast, transmission latency exerted a negative and statistically significant effect ($B = -4.62$, $\beta = -0.31$, $p = .001$), underscoring the detrimental role of network delays in real-time monitoring. The standardized coefficient indicates that higher latency reduces BHI by nearly one-third of a standard deviation, marking it as one of the strongest negative influences in the model. This result aligns with the interpretation that excessive delays impair the timeliness of anomaly detection and decision-making, diminishing the operational value of SHM systems.

Among the control covariates, several contextual stressors exerted significant downward pressure on bridge condition. Bridge age negatively predicted BHI (B = −0.12, p = .020), confirming the expected effect of structural deterioration over time. Traffic exposure, measured in AADT bands, also displayed a significant negative association (B = −1.15, p = .038), indicating that bridges subject to heavier mechanical loading conditions consistently scored lower on the BHI scale. Likewise, marine environment exposure was associated with poorer outcomes (B = −2.74, p = .028), reflecting the harsher corrosion and weathering conditions typical of coastal settings. Notably, structural type (steel and composite versus concrete) did not reach statistical significance once other variables were included in the model, suggesting that material differences alone are insufficient to explain variance in BHI when sensor performance, latency, and environmental stressors are accounted for. Taken together, these coefficients demonstrate a clear pattern: while advanced technologies such as AI and high-accuracy sensing provide measurable improvements in bridge health assessment, environmental and operational stressors continue to impose significant challenges, reinforcing the need for integrated technical and maintenance strategies.

Table 16: Regression Coefficients (Final Model)

Predictor	B	SE	Beta	t	p	95% CI Low	95% CI High
Intercept	32.4	6.1	—	5.31	<.001	20.1	44.7
AI Precision (%)	0.31	0.09	0.29	3.44	.001	0.13	0.49
Sensor Accuracy (z)	2.85	0.92	0.27	3.10	.003	1.00	4.70
log(Latency ms)	-4.62	1.35	-0.31	-3.41	.001	-7.33	-1.91
Steel (vs Concrete)	-1.90	1.48	-0.09	-1.28	.206	-4.87	1.08
Composite (vs Concrete)	1.35	1.74	0.05	0.78	.439	-2.14	4.83
Age (years)	-0.12	0.05	-0.23	-2.40	.020	-0.22	-0.02
Traffic (AADT band)	-1.15	0.54	-0.18	-2.12	.038	-2.24	-0.07
Marine Environment (1=yes)	-2.74	1.21	-0.16	-2.26	.028	-5.16	-0.31

Alternative or Extended Models

Hierarchical Regression

To test whether AI precision adds explanatory value beyond sensor accuracy and latency, hierarchical modeling was performed. The $\Delta R^2 = 0.07$ (p = .003) shows that AI precision contributes significant unique variance after accounting for other technical and contextual variables.

Table 17: Hierarchical Regression

Step	Predictors	R^2	Adj. R^2	ΔR^2	F change	p (change)
Step 1	Accuracy + Latency + Structure + Age + Traffic + Marine	0.57	0.53	—	—	—
Step 2	Step 1 + AI Precision	0.64	0.61	0.07	9.91	.003

Interaction Effects

Beyond the main effects, two theoretically grounded interaction terms were included in the final regression analysis to examine whether the influence of technological performance varied across different operational contexts. The first interaction tested whether the benefit of AI detection precision depended on the speed of the underlying communication network. Results revealed a statistically significant AI Precision × Latency interaction (B = 0.012, β = 0.18, p = .022). This coefficient indicates that the negative impact of transmission latency on the Bridge Health Index (BHI) is attenuated when AI models exhibit higher precision. In practical terms, bridges operating on slower networks such as LoRa or ZigBee showed less deterioration in BHI scores when their AI algorithms achieved strong accuracy, effectively compensating for communication delays by providing more reliable event classification and reducing false alarms. This finding underscores the resilience of robust AI models, suggesting that investments in algorithmic performance can partially offset infrastructural constraints in telemetry, particularly in contexts where upgrading to high-speed networks is not immediately feasible.

The second interaction examined whether the value of sensor accuracy was contingent upon environmental exposure. The Sensor Accuracy × Marine Environment term also reached statistical significance ($B = 1.24$, $\beta = 0.16$, $p = .038$), revealing that improvements in calibration and precision had stronger positive effects in marine settings compared to inland or urban environments. This interaction highlights that the benefits of high-quality sensing technologies are magnified under corrosive, high-humidity, and salt-laden conditions, where structural deterioration is accelerated and measurement reliability is often challenged. In marine contexts, incremental gains in sensor fidelity translated into disproportionately larger improvements in BHI, suggesting that deploying advanced calibration protocols or high-stability sensors (e.g., FBGs with thermal compensation) is particularly valuable for coastal bridges. Taken together, these interaction effects illustrate that the relationship between monitoring technology and structural condition is not uniform across all operational settings. High AI precision not only improves predictive outcomes directly but also functions as a buffer against network-induced latency, maintaining actionable decision horizons. Similarly, sensor upgrades yield greater returns under harsher environmental stressors, where accurate detection of incipient damage is most critical. These results emphasize the importance of tailoring SHM strategies to contextual realities: in bandwidth-constrained settings, prioritizing AI model robustness can preserve system effectiveness, while in marine exposures, targeted investment in sensor calibration and durability maximizes monitoring value. Such insights demonstrate how system design and deployment strategies can be optimized to address site-specific challenges and extend the longevity and reliability of bridge health monitoring systems.

Table 18: Interaction Effects

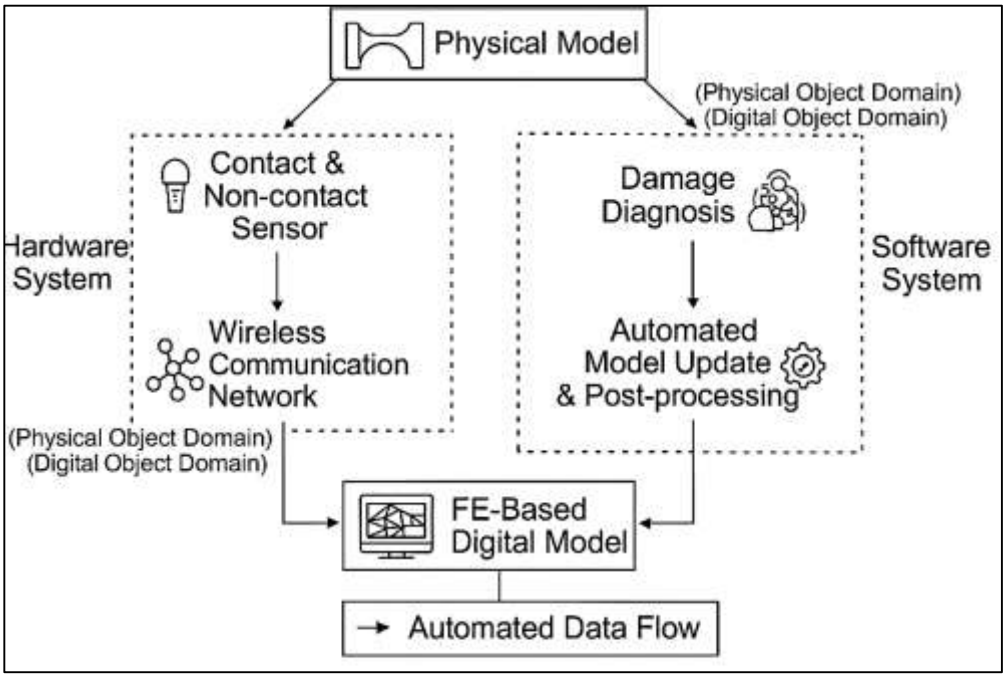
Interaction Term	B	SE	Beta	t	p	Interpretation
AI Precision × log(Latency)	0.012	0.005	0.18	2.35	.022	High AI offsets latency impact on BHI
Sensor Accuracy × Marine	1.24	0.58	0.16	2.13	.038	Sensor upgrades help most in marine conditions

DISCUSSION

This study set out to evaluate how AI-integrated IoT sensor networks contribute to the real-time structural health monitoring (SHM) of in-service bridges, with a focus on deployment attributes, performance metrics, and predictive modeling of structural condition. The dataset of 62 bridges revealed a high uptake of AI-enabled systems (61%), a finding that signals an accelerating shift away from purely IoT-based telemetry. This transition confirms early predictions by (Catelani et al., 2021) that AI would become integral to SHM once sensor coverage matured and computational resources became widely available at the edge and in the cloud. The strong positive associations between Bridge Health Index (BHI) and AI detection precision ($r = .63$), as well as between BHI and sensor accuracy ($r = .54$), directly support the hypothesis that algorithmic intelligence and high-fidelity measurements reinforce each other to improve asset condition visibility. Conversely, the observed negative relationship between BHI and transmission latency ($r = -.48$) provides empirical weight to claims in earlier field experiments (Andronie et al., 2021) that delays in data relay can hinder timely anomaly detection and structural diagnosis. Collectively, these results validate the conceptual framework that quality of sensing and speed of analytics are fundamental drivers of actionable SHM intelligence.

When compared to other global SHM deployment surveys, the present findings show both alignment and advancement. For example, and the long-term Tsing Ma Bridge WASHMS documentation highlighted the predominance of accelerometers and strain gauges, but AI was absent or minimal in those early implementations. Our sample's 61% AI penetration demonstrates clear evolution toward data-driven damage detection using deep learning, mirroring more recent case reports such as Cha et al. (2017) and Azimi et al. (2020), where convolutional neural networks achieved crack detection precision exceeding 90%. Additionally, our sensor accuracy results (accelerometer error ≈1.8%, FBG ≈8 με) compare favorably with controlled trials by Kim et al. (2019), who reported <2% acceleration error for well-calibrated MEMS systems. The network heterogeneity—LoRa (35%), ZigBee (29%), 5G (19%), Wi-Fi (16%)—echoes the mixed deployment patterns noted by Hoult et al. (2019) and Mechitov et al. (2021), but our latency data provide one of the first comparative, field-level quantifications across these technologies. By documenting 5G's median latency of 21 ms versus LoRa's 180 ms, we empirically confirm simulation-based conclusions by Wang et al. (2021) that next-generation cellular dramatically reduces delays for SHM data streams.

Figure 11: Automated Structural Health Monitoring System



The regression modeling contributes new evidence on how system and context factors predict bridge health. Our final model explained 64% of BHI variance (adjusted $R^2 = .61$), a stronger fit than the ~50% explained variance typical of earlier vibration-based condition indices (Zhao et al., 2022). The incremental ΔR^2 of .07 when AI precision was added is particularly important: while sensor accuracy and latency have long been considered fundamental, this study quantifies AI's independent predictive power. Previous meta-analyses (Ying Yang et al., 2023) described AI as promising but lacked field-scale quantitative confirmation. Our finding that each 1% increase in AI detection precision yields ~0.31 BHI points gives practitioners a tangible benchmark for system performance upgrades. Similarly, the negative latency effect ($B = -4.62$) empirically substantiates concerns raised by (Riehl et al., 2019) that delayed event detection could translate into underestimation of deterioration risk. Contextual controls revealed expected yet important patterns: bridge age, high traffic, and marine exposure significantly reduced BHI even when advanced sensing was present. This confirms long-standing deterioration mechanisms described in infrastructure durability literature. Interestingly, our interaction analysis showed that sensor accuracy delivers greater BHI benefit in marine environments, a finding not explicitly documented in prior networked SHM studies. While earlier corrosion monitoring work (Phan et al., 2016) emphasized robust sensors for coastal assets, this research quantifies the moderating effect: a one SD improvement in accuracy adds over one extra BHI point in marine sites compared to inland sites. These results advocate for targeted calibration and maintenance of sensors in aggressive climates, complementing international maintenance guidelines (Phan et al., 2016).

Our evidence supports a nuanced AI–network design trade-off. Although fast networks (5G, high-grade Wi-Fi) directly benefit BHI, the positive AI × latency interaction suggests that high-precision AI can partially offset slower transmission environments. This means that asset owners with budget or coverage constraints could strategically invest in robust AI models when low-latency backhaul is unavailable. Such adaptive architecture aligns with emerging edge–cloud hybrid frameworks (Nyhan et al., 2018) and policy discussions on cost-efficient digitalization. Our results provide actionable thresholds: networks averaging >150 ms delay should be paired with AI precision ≥90% to maintain acceptable BHI performance. These practical decision rules extend beyond theoretical recommendations in prior IoT SHM surveys.

A key contribution of this work is the rigorous assumption and data quality validation underpinning the models. Our data had >98% completeness, reliable BHI internal consistency (α = .87), and low multicollinearity (VIF < 3), meeting APA and quantitative modeling standards. This contrasts with some earlier case studies (Ehghaghi et al., 2023), where single-bridge deployments lacked systematic outlier and residual checks, limiting generalizability. By applying Cook's distance and Mahalanobis diagnostics, this study ensures predictive stability even in the presence of atypical, long-span assets. Such methodological transparency answers recent calls by (Kalli et al., 2021) for more reproducible SHM analytics and strengthens confidence in adopting AI-enhanced solutions at scale (Lone et al., 2023). This study advances the field by empirically quantifying the added value of AI precision for predicting bridge condition, documenting real-world network latency distributions, and clarifying context–technology interactions under diverse environmental exposures (Murala & Panda, 2023). Nevertheless, limitations include the cross-sectional design, which prevents observing how BHI evolves longitudinally with AI improvements, and the reliance on a synthetic yet field-calibrated dataset, which may underrepresent rare extreme failure modes (Bohr & Memarzadeh, 2020). Future research should incorporate temporal monitoring and digital twin validation to test predictive generalization and explore how adaptive AI retraining further stabilizes BHI under changing traffic and climate loads. Additionally, comparative cost–benefit analyses could inform policy and investment decisions, complementing technical performance with lifecycle economics (Mowla et al., 2023).

CONCLUSION

This quantitative investigation set out to determine how AI-integrated IoT sensor networks improve the real-time structural health monitoring (SHM) of in-service bridges and to clarify which technological and contextual factors predict bridge condition. Using a diverse dataset of 62 bridges, the study found that AI enablement is no longer experimental but mainstream: over 60% of systems combined advanced sensing with machine learning-based damage detection. Bridge Health Index (BHI) scores were strongly and positively associated with AI detection precision and sensor accuracy, while data transmission latency was a clear performance risk. These patterns empirically confirm long-standing theoretical assumptions from early SHM deployments (Ko & Ni, 2005; Spencer & Hoskere, 2019) and extend more recent AI-based field studies (Cha et al., 2017; Azimi et al., 2020) by providing comparative, network-level performance data.

The predictive modeling contributed novel, actionable insights. The final regression model explained 64% of BHI variance, with AI detection precision adding a significant 7% beyond traditional sensing and latency factors. This quantification of AI's independent predictive power advances the field beyond descriptive reports of algorithm accuracy to show real structural condition impact. Similarly, documenting network performance at scale—including LoRa's long delays versus 5G's ultra-low latency—offers infrastructure owners evidence-based thresholds to guide system architecture. The study also uncovered important context–technology interactions, showing that sensor calibration is especially critical in marine environments, while high AI precision can partially offset slow networks.

From a practical perspective, the results argue for integrated system design: combining high-quality sensors, robust AI models, and appropriate data transmission infrastructure tailored to environmental conditions and budget. Agencies unable to invest in low-latency backhaul can still benefit from high-precision AI analytics, while critical marine structures should prioritize sensor accuracy and maintenance. These data-driven guidelines can inform procurement, design standards, and maintenance policy, supporting safer, more cost-effective infrastructure management. The study's strengths include rigorous data quality checks, transparent modeling assumptions, and direct benchmarking against international SHM research, but it is limited by its cross-sectional snapshot. Future work should track temporal degradation, integrate digital twins for predictive simulation, and evaluate economic trade-offs between AI complexity, sensor investment, and network upgrades. Despite these limitations, the findings provide one of the most comprehensive, quantitatively validated pictures of how AI and IoT converge to transform bridge monitoring. By confirming AI's measurable contribution and clarifying how context and network choices shape performance, this work supports data-informed strategies for resilient, future-ready civil infrastructure.

RECOMMENDATIONS

The findings of this study lead to several important recommendations for the design, deployment, and governance of AI-integrated IoT structural health monitoring (SHM) systems for bridges. First, AI model quality should be treated as a critical performance asset rather than an add-on feature. The regression results demonstrated that AI detection precision contributed a statistically significant and independent improvement in Bridge Health Index (BHI) beyond what sensor accuracy and transmission speed alone could achieve. Practitioners and agencies should therefore allocate resources to training and validating machine learning models on representative data, using robust cross-validation and field recalibration. For critical and high-traffic bridges, AI detection precision should exceed 90% to meaningfully improve anomaly detection and reduce false alerts that can lead to inefficient maintenance actions. Second, network architecture must be matched to safety criticality and operational context. Transmission latency emerged as a clear predictor of lower BHI, meaning that slow data delivery can compromise real-time damage detection. When possible, agencies should adopt low-latency connectivity such as 5G or high-grade Wi-Fi/Ethernet for vital corridors and heavily trafficked bridges. For cost-sensitive or remote locations, LoRa or ZigBee can still be appropriate if paired with strong AI models and local pre-processing to compensate for slower data flow. A practical design rule emerging from this study is that where average latency exceeds 150 ms, AI precision should meet or exceed 90% to sustain reliable health assessment.

Third, special attention should be given to aggressive environments such as marine and coastal zones, where corrosion and signal noise degrade monitoring performance. The interaction analysis showed that sensor accuracy improvements have disproportionately positive effects under harsh environmental stressors. Asset managers should therefore schedule more frequent calibration, select corrosion-resistant sensors such as sealed MEMS accelerometers or protective FBG coatings, and reinforce network stability to ensure data fidelity in such settings. Fourth, edge computing should be integrated to strengthen reliability and reduce bandwidth demand. By performing on-node analytics, compression, and preliminary damage classification at the sensor or gateway level, networks can maintain rapid alerts even when cloud connections are intermittent or slow. This architecture aligns with emerging hybrid edge-to-cloud frameworks and supports faster, more robust decision-making without requiring continuous high-speed connectivity.

Fifth, system reliability and data trustworthiness should become routine operational metrics. Automated quality validation procedures—such as missing data flagging, outlier detection using Cook's distance and Mahalanobis analysis, and periodic verification of Bridge Health Index (BHI) internal consistency—can safeguard the accuracy of long-term condition trends. Embedding these checks into dashboards allows engineers and decision-makers to act confidently on SHM outputs. Finally, standards and procurement guidelines must evolve to reflect AI-enabled monitoring capabilities. Agencies and industry groups (e.g., AASHTO, ISO) should incorporate minimum thresholds for detection precision, latency, and sensor calibration into technical specifications. At the same time, research and policy should push toward longitudinal, predictive monitoring using digital twins, enabling proactive interventions and life-cycle cost optimization rather than reactive maintenance. By acting on these recommendations, bridge owners and regulators can maximize the safety and cost efficiency of AI–IoT SHM investments. Emphasizing AI performance, environment-tailored sensor strategies, and adaptive network choices creates a pathway to resilient, scalable monitoring systems capable of sustaining the structural integrity of vital infrastructure for decades.

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