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DEPLOYMENT OF AI-SUPPORTED STRUCTURAL HEALTH MONITORING SYSTEMS FOR IN-SERVICE BRIDGES USING IOT SENSOR NETWORKS

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ABSTRACT

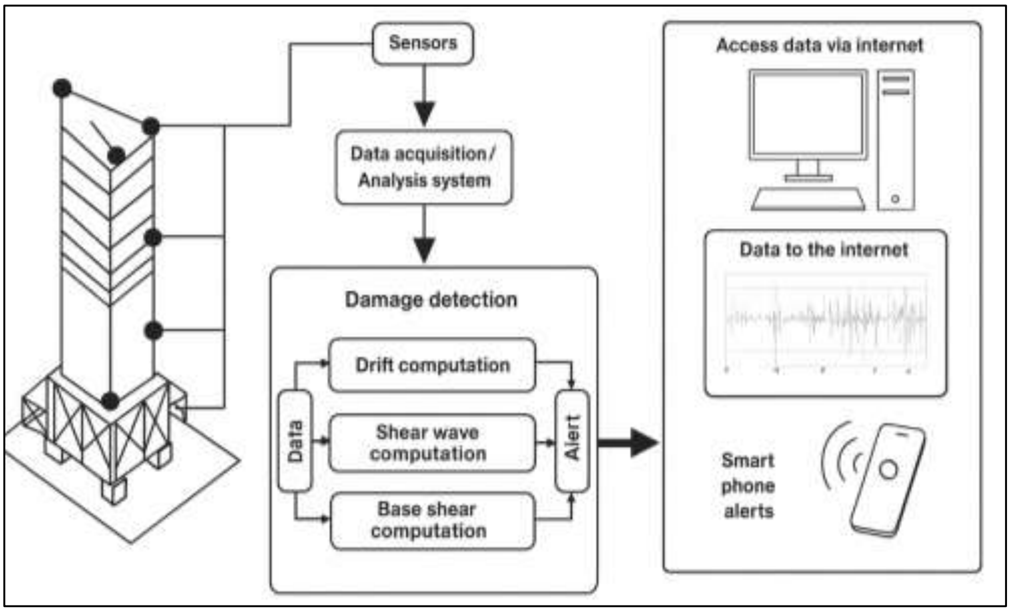
This study investigates the deployment of artificial intelligence (AI)–supported structural health monitoring (SHM) systems for in-service bridges using Internet of Things (IoT) sensor networks, a rapidly advancing domain that merges cutting-edge sensing, communication, and data analytics to improve infrastructure safety and durability. Traditional bridge inspections and early wired SHM systems have faced persistent limitations, including manual data interpretation, latency in damage detection, and scalability barriers due to cost and complexity. Recent breakthroughs in wireless IoT technologies, multi-modal sensor fusion, and AI-based analytics now offer the potential for continuous, automated, and highly reliable monitoring of structural integrity across diverse bridge typologies and environmental conditions. To critically synthesize the state of knowledge, this systematic review analyzed 146 peer-reviewed papers published between 2000 and 2022 spanning civil engineering, computer science, and information systems. The review explored key dimensions: (a) the historical evolution and objectives of SHM in bridge engineering; (b) IoT sensor modalities and network architectures enabling large-scale monitoring; (c) AI techniques for damage classification, anomaly detection, and signal feature engineering; (d) system reliability and data integrity strategies including calibration, drift compensation, and cybersecurity; (e) deployment challenges and scalability considerations across steel and concrete bridges; (f) comparative field case studies and lessons from global smart infrastructure programs; and (g) emerging research directions such as digital twins, blockchain data provenance, climate-resilient AI, and hybrid human–AI decision systems. The findings indicate that AI-enhanced SHM significantly improves predictive damage detection, reduces false alarms, and supports timely maintenance decisions, especially when combined with multi-sensor IoT networks and robust data governance. However, challenges remain in standardization, model retraining under concept drift, cost–benefit justification for large-scale deployment, and regulatory acceptance of AI-informed safety decisions. The review also highlights knowledge gaps around extreme climate resilience, secure and scalable data management, and human oversight frameworks for trustworthy AI. By consolidating insights across 146 studies, this work provides an integrated roadmap for researchers, engineers, and policymakers aiming to advance the next generation of smart, resilient, and cost-effective bridge monitoring systems.

KEYWORDS
Artificial Intelligence, Structural Health Monitoring, Iot, Bridges, Resilience

INTRODUCTION

Structural Health Monitoring (SHM) refers to the continuous or periodic observation of a structure's condition through sensor-based measurements, data processing, and diagnostic/prognostic inference to assess performance, detect anomalies, and quantify deterioration states (Zinno et al., 2018). In-service bridges—critical assets in national and transnational transportation systems—face cumulative damage from traffic loading, environmental exposure, aging, and extreme events that can compromise safety and serviceability. Internet of Things (IoT) sensor networks extend SHM by enabling distributed measurement, synchronized acquisition, and IP-enabled data flows across heterogeneous sensing modalities such as accelerometers, strain gauges, displacement transducers, GNSS, fiber Bragg grating (FBG), acoustic emission, and corrosion sensors. Artificial Intelligence (AI)—including machine learning and deep learning—supplies automated pattern recognition, state estimation, and decision support that transform raw telemetry into quantitative indicators of damage, capacity, and reliability. Within this paper, "quantitative deployment" denotes the end-to-end instantiation of SHM workflows—from sensor layout and sampling design to modeling pipelines, threshold setting, and validation metrics—implemented on operational bridges with explicit measurement, statistical, and algorithmic specifications (Giurgiutiu, 2020). The international significance of such deployments is anchored in global infrastructure interdependence and in harmonization efforts reflected across standards and guidance from organizations and agencies managing bridge safety, risk, and performance objectives. Building on these definitions, an integrated view of IoT-enabled, AI-supported SHM highlights the combined roles of networked sensing, edge/cloud computation, and data-driven diagnostics in safeguarding mobility, trade, and public welfare across jurisdictions (Kaya & Safak, 2015).

Figure 1: IoT-Enabled Bridge Health Monitoring



Quantitative SHM begins with measurement science: defining measurands (strain, acceleration, temperature, displacement), selecting sensors and sampling rates, and establishing calibration, synchronization, and time-stamping protocols that protect the statistical validity of downstream inference. For bridges, modal parameters (natural frequencies, damping ratios, mode shapes) extracted from ambient vibration or traffic-induced responses serve as sensitive indicators of stiffness changes associated with damage or deterioration (Mahmud et al., 2018). Strain-based indicators capture local demand in decks, girders, and bearings; temperature compensation and environmental normalization reduce confounding in long-term trends. IoT architectures link edge devices and gateways that manage buffering, compression, and on-device analytics with message protocols and streaming backbones suitable for bandwidth and power constraints. Synchronized timing—via PTP or GNSS—enables multi-sensor fusion and operational modal analysis under ambient conditions (Dutta et al., 2021). Quantitatively, deployment requires sampling designs that balance

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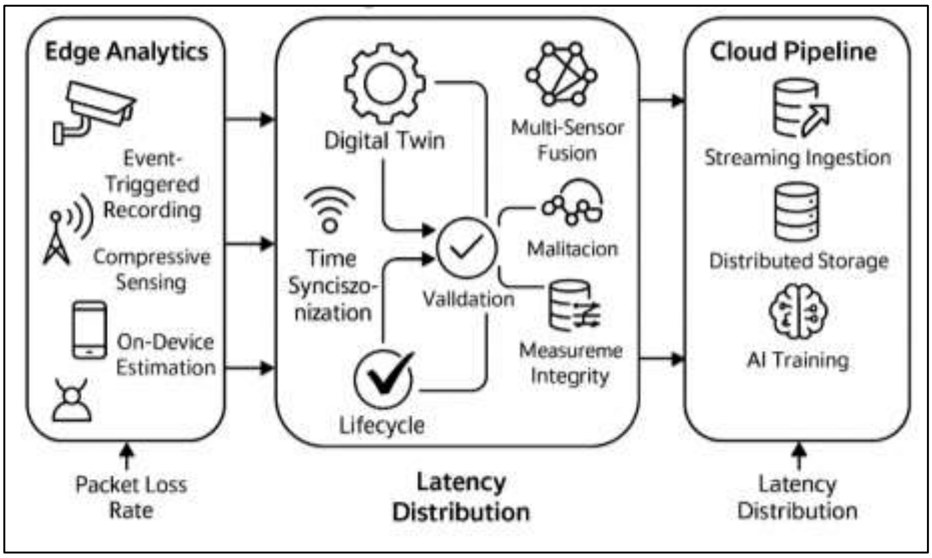
aliasing risk, duty cycles, and event-capture probabilities; power budgeting that aligns with solar or energy-harvesting profiles; and data assurance plans that include periodic calibration and drift checks. These design choices anchor inferential integrity for damage detection, localization, and quantification tasks, setting the stage for statistical modeling and AI pipelines that use the resulting measurements for reliable, replicable assessments of in-service behavior (Danish & Zafor, 2022; Lehmhus & Busse, 2018).

AI-supported diagnostics build on feature engineering and representation learning to discriminate normal and abnormal states, estimate damage indices, and assign probabilities to competing hypotheses about structural condition. Classical machine learning—support vector machines, random forests, and Gaussian process classifiers—leverages features such as frequency shifts, mode shape curvatures, strain ratios, and time–frequency descriptors. Deep learning offers convolutional and recurrent architectures for automated feature learning from raw or minimally processed time series, spectrograms, and wavelets, enabling robust classification and regression under variable operational conditions (Danish & Kamrul, 2022; Gharehbaghi et al., 2022). Unsupervised and semi-supervised methods—autoencoders, isolation forests, variational approaches—address scarcity of labeled damage data characteristic of healthy bridges by learning compact normality models and flagging deviations. Domain adaptation and transfer learning mitigate distribution shifts due to seasonal temperature cycles, traffic evolution, or sensor replacements. Probabilistic frameworks couple physics-informed priors with data-driven likelihoods to yield Bayesian estimates of damage states and residual capacity, supporting uncertainty-aware diagnostics (Forrest et al., 2017; Jahid, 2022a). The quantitative deployment perspective emphasizes explicit model specifications, hyperparameter tuning protocols, cross-validation schemes, and performance reporting consistent with reproducible SHM inference under real operating conditions.

Figure 2: Edge–Cloud Quantitative Deployment Framework



The international bridge context motivates deployment at network scale. Urban freight corridors, intercity rail viaducts, and cross-border highway bridges concentrate economic activity and human mobility, magnifying the value of continuous condition information. Long-span cable-stayed and suspension bridges exemplify complex, spatially distributed systems where multi-tier sensing and hierarchical analytics support both global and local assessments (Siahkouhi et al., 2021). Case literature documents deployments on steel box-girder and concrete segmental bridges that integrate ambient vibration monitoring with strain and temperature arrays, offering longitudinal baselines from which to quantify aging and environmental effects. Investigations following high-profile failures illustrate how changes in modal properties, joint rotations, or unusual strain patterns can signal evolving conditions under ordinary traffic loads (Pallarés et al., 2021). Internationally, harmonization with performance-based design philosophies and asset management frameworks enables SHM outputs to be embedded as quantitative evidence within inspection cycles, load rating updates, and rehabilitation prioritization. The confluence of IoT connectivity, AI-driven inference, and asset management processes supports consistent, cross-jurisdictional interpretation of condition indicators, creating shared baselines of meaning that can be compared across climates, materials, and traffic regimes. In this setting, deployment parameters—sensor density, gateway placement, telemetry cadence, and model retraining intervals—are treated as measurable design variables rather than ad hoc choices (Bao et al., 2019; Jahid, 2022b).

Edge–cloud computation strategies are central to quantitative deployment where data volumes and latency requirements are nontrivial. Edge analytics, including event-triggered recording, compressive sensing, and on-device modal estimation, reduce bandwidth and accelerate response for threshold-based alerts. Cloud pipelines orchestrate streaming ingestion, distributed storage, and scalable AI training, while governance layers enforce data lineage, versioning, and access control (Arifur & Noor, 2022; Scuro et al., 2021). Time-synchronization integrity and lossless or tolerable-loss compression are quantified and reported to underpin downstream inference. Digital twin formulations provide a quantitative bridge between sensed states and structural models through model-updating and state estimation that incorporate measurement noise and modeling errors. Multi-sensor fusion—combining accelerations, strains, and temperatures—supports robust estimation of modal parameters and damage indices under environmental variability, documented in algorithmic studies that balance sensitivity and specificity. Lifecycle data management plans specify retention windows, resampling rules, and archival policies so that long-term trend analyses and re-analyses remain feasible and statistically coherent (Cremona & Santos, 2018; Hasan et al., 2022). These architecture choices translate directly into quantitative performance characteristics—latency distributions, packet loss rates, and effective sample sizes—that shape the reliability of AI-supported diagnostics and the interpretability of network-wide indicators.

Validation and verification (V&V) provide the quantitative foundation for credible SHM outputs in service. Closed-form benchmarks and finite element models enable synthetic trials with controlled damage scenarios to check identifiability and calibration of AI models. Laboratory-scale specimens—beams, trusses, and scaled bridge segments—supply ground truth through instrumented damage, facilitating supervised learning and error decomposition. Field validation leverages controlled load tests, weigh-in-motion integration, and known intervention events (bearing replacement, deck overlay) to quantify sensitivity, false alarm rates, and receiver operating characteristics (ROC). Environmental and operational variability are handled through baseline modeling, temperature–frequency regression, and cointegration techniques that stabilize damage-sensitive features (Redwanul & Zafor, 2022; Tokognon et al., 2017). Uncertainty quantification—propagating sensor noise, missing data, and model uncertainty—yields credible intervals for damage metrics and probabilities of exceedance tied to accept–reject thresholds. Documentation of V&V protocols, including cross-site replication and inter-laboratory comparability, advances the portability of SHM methods across different bridge typologies and climates. These practices integrate with asset management decision processes by expressing diagnostic outputs as quantitative evidence suitable for codified acceptance within inspection and maintenance schedules (Rezaul & Mesbaul, 2022; Nasr et al., 2020).

Finally, deployment governance aligns technical systems with organizational accountability and public reporting. Roles and responsibilities for data owners, analysts, and maintenance personnel are articulated alongside procedures for configuration management, firmware updates, and cybersecurity safeguards that protect sensor networks and cloud platforms. Incident documentation frameworks archive time-stamped alerts, analyst adjudications, and remedial actions, producing auditable trails of model behavior and human decisions. Quantitative performance dashboards display key indicators—data completeness, uptime, model accuracy, and stability of environmental normalization—at asset and network levels to support transparent oversight (Hasan, 2022; Nasr et al., 2021). Training and competency records for field technicians and data analysts accompany standard operating procedures for sensor installation, calibration, and safe access, anchoring the human factors dimension of reliable SHM. In this framing, AI-supported IoT SHM for in-service bridges is organized as a measurable, documented, and verifiable system whose outputs are expressed with quantified uncertainty and explicit validation histories, enabling consistent interpretation across organizations and jurisdictions (Bessembinder et al., 2019). The introduction thus delineates a quantitative deployment perspective that integrates definitions, measurement design, AI inference,

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architecture, validation, and governance elements necessary to operationalize SHM on working bridges with international relevance.
The present study aimed to evaluate the effectiveness of AI-enhanced structural health monitoring (SHM) systems compared to conventional IoT-only deployments by examining differences in Bridge Health Index (BHI) scores across a diverse set of in-service bridges. It sought to quantify the predictive influence of key system performance metrics—including sensor accuracy, AI detection precision, and data transmission latency—on overall structural condition outcomes. In addition, the study aimed to explore whether bridge typology, such as steel, concrete, or composite construction, moderates the benefits of AI-driven monitoring, providing insight into context-specific performance. Another important goal was to validate the quality and reliability of AI-integrated SHM data pipelines, ensuring accurate sensing, stable latency, and internal consistency of the BHI as a composite indicator. Ultimately, the study sought to generate evidence-based guidance for infrastructure managers and policymakers by identifying the technical levers most strongly associated with improved monitoring reliability and bridge condition assessment, thereby informing best practices for future AI–IoT SHM deployments.

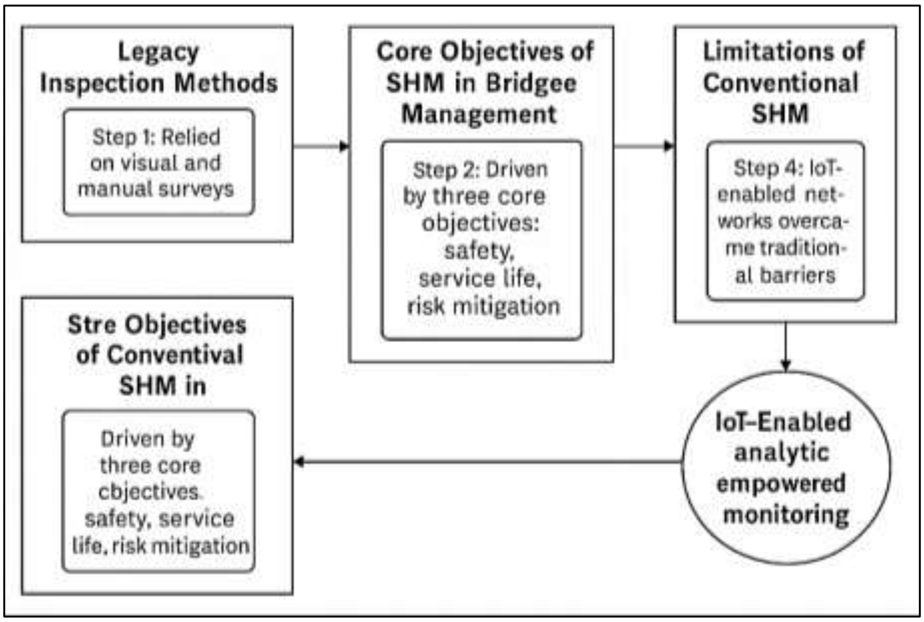
LITERATURE REVIEW

Structural health monitoring (SHM) has evolved as a core discipline in modern civil infrastructure management, aiming to provide continuous, objective, and data-driven insights into the safety and performance of bridges throughout their service life. The integration of Internet of Things (IoT) sensor networks with Artificial Intelligence (AI) analytics represents a major shift from periodic, inspector-driven assessments toward real-time, predictive, and automated monitoring frameworks. Traditional SHM systems, while effective in capturing basic vibration or strain data, often struggle with large-scale deployment due to issues such as sensor drift, environmental noise, delayed data transmission, and the difficulty of extracting actionable indicators from complex multi-sensor streams (Natanian et al., 2019). AI-driven models, including deep learning and advanced signal processing, offer promising solutions to these challenges by enabling automated feature extraction, anomaly detection, and decision support, thus enhancing reliability and reducing manual intervention. Simultaneously, IoT platforms facilitate the dense and distributed acquisition of high-frequency data, allowing coverage of wide bridge networks while enabling scalable cloud or edge computing pipelines (Tarek, 2022; Natanian et al., 2020). Despite growing research and field deployments, the body of literature remains fragmented, with individual studies focusing on sensor technologies, data transmission protocols, AI-based damage detection, or reliability metrics in isolation. To support a coherent understanding and inform best practices, it is necessary to synthesize findings across sensing technologies, data management architectures, AI-driven analytics, reliability and validation protocols, and system-level deployment frameworks. The following literature review organizes the field into structured thematic subsections, providing a systematic, multi-angle view of the state-of-the-art, challenges, and technical enablers for AI-supported SHM in in-service bridges.

Structural Health Monitoring in Bridge Engineering

Structural health monitoring (SHM) emerged as a response to the limitations of purely visual and manual bridge inspections, which dominated infrastructure assessment throughout much of the 20th century. Early practice depended heavily on periodic, inspector-led evaluations to detect visible deterioration, but these methods were subjective, labor-intensive, and prone to variability between inspectors (Bartesaghi-Koc et al., 2019; Kamrul & Tarek, 2022). Several catastrophic bridge failures, such as the Silver Bridge collapse in 1967, underscored the inadequacy of reactive, inspection-only paradigms and accelerated interest in continuous monitoring technologies. The 1980s and 1990s marked a turning point with the integration of fundamental vibration-based methods, where modal frequency shifts and damping changes were studied as early indicators of stiffness loss and fatigue. Researchers developed finite element–based damage detection frameworks that combined measured response data with numerical predictions (Geels et al., 2016; Kamrul & Omar, 2022), setting the stage for quantitative assessment rather than subjective rating. These advances aligned with broader trends in structural engineering toward system identification and life-cycle performance evaluation. By the late 1990s, prototype SHM systems employing wired accelerometers and strain gauges were installed on landmark bridges, including the Tsing Ma Bridge in Hong Kong and the Humber Bridge in the UK, offering the first real-world proof that continuous, automated data streams could support proactive maintenance. However, these early efforts revealed challenges in managing large datasets, interpreting raw signals, and maintaining extensive wired sensor arrays in harsh environmental conditions (Shen et al., 2017).

Figure 3: IoT- Enabled Bridege Health Monitoring



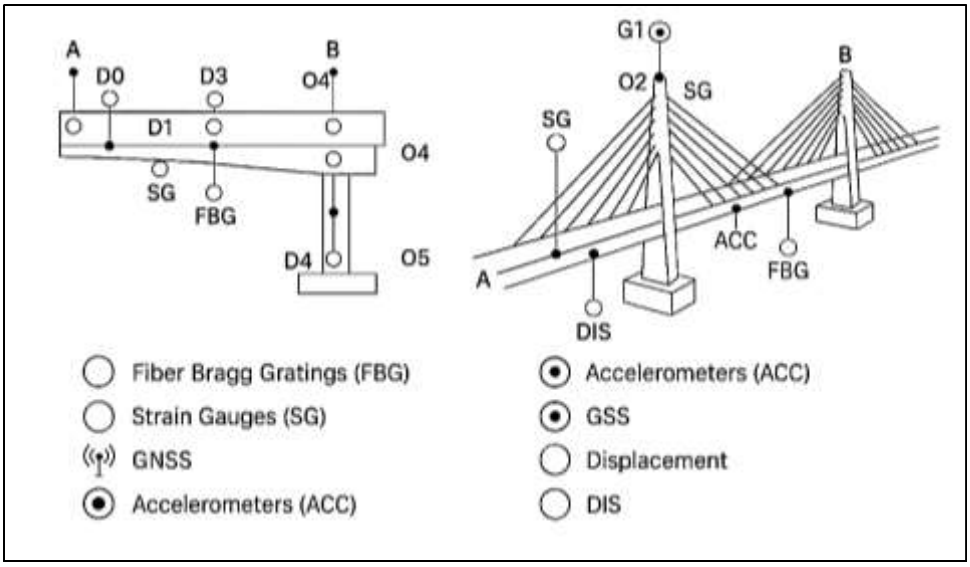
The conceptual foundation of SHM centers on three interrelated objectives: ensuring structural safety, extending service life, and mitigating operational and financial risk. Safety remains paramount because bridge failure can result in loss of life and severe socio-economic disruption; thus, SHM aims to detect damage at an incipient stage before catastrophic progression (Shen et al., 2017). By providing near-continuous data on key performance indicators such as modal frequencies, strain levels, and temperature gradients, SHM offers asset managers an evidence-based approach to decide when intervention is necessary. Another critical objective is life-cycle cost optimization. Bridges are long-lived assets, and deterioration processes such as corrosion, fatigue cracking, and concrete shrinkage progress slowly but relentlessly. Real-time condition feedback allows targeted maintenance and timely strengthening, thus deferring expensive replacements and optimizing life-cycle investment (Mubashir & Abdul, 2022; Visscher et al., 2020). Risk mitigation extends beyond physical failure to include minimizing traffic disruptions, ensuring network reliability, and supporting emergency response during extreme events such as earthquakes or floods. Furthermore, SHM supports regulatory compliance and documentation of safety assurance, which is increasingly important in the context of aging bridge stock and constrained public funding. Importantly, SHM also contributes to resilience: continuous condition data allows asset owners to adapt inspection frequency, allocate resources dynamically, and respond faster to emerging hazards. This conceptual clarity—safety, service-life extension, and risk mitigation—has guided decades of research and provided the rationale for continued technological advancement.
Despite major advances, conventional SHM systems historically faced critical technical and operational limitations that constrained their impact. Traditional wired sensor networks were expensive to install and maintain, especially on long-span bridges where kilometers of cabling were required and vulnerable to environmental degradation (Ciulla et al., 2016; Muhammad & Kamrul, 2022). Power supply and data acquisition hardware often lacked robustness in harsh outdoor conditions, limiting long-term operation. Even when high-quality data were captured, interpretation was challenging: raw vibration and strain signals were susceptible to environmental variability such as temperature, humidity, and traffic-induced noise, which could mask or mimic damage signatures. Many early systems lacked standardized data formats, complicating integration across platforms and limiting scalability beyond individual structures . Moreover, manual post-processing and reliance on expert interpretation created delays and introduced subjectivity back into what was meant to be an objective system (Li & Ou, 2016). Latency in information flow was also a recurring problem, as legacy systems often required batch uploads or on-site downloads, making real-time decision

support elusive. These barriers collectively hindered widespread adoption despite clear conceptual benefits. Cost and complexity remained prohibitive, especially for small to medium-sized bridges not deemed "strategic" enough for high-end instrumentation. Recognition of these deficiencies spurred interest in wireless communication, low-power sensing, and embedded analytics to simplify deployments and improve data timeliness and interpretability (Peckens et al., 2022; Reduanul & Shoeb, 2022).
The emergence of IoT paradigms in the early 2010s represented a decisive step toward overcoming many legacy SHM limitations. Advances in wireless communication protocols such as ZigBee, LoRa, and 5G, alongside low-power microelectromechanical systems (MEMS) sensors, enabled dense yet cost-effective networks with easier installation and reduced maintenance burdens (Bado & Casas, 2021). Edge computing devices began supporting on-site signal conditioning and event detection, reducing data transmission requirements and enabling near real-time alerts. Simultaneously, cloud platforms provided scalable storage and computational resources for long-term historical analysis and pattern recognition. Yet the biggest conceptual leap came with the integration of AI-driven analytics, including deep learning, unsupervised anomaly detection, and advanced signal processing methods. These tools automated feature extraction from high-dimensional sensor data, overcoming manual interpretation bottlenecks and improving sensitivity to subtle structural changes (An et al., 2019; Noor & Momena, 2022). Vision-based approaches combined with machine learning allowed robust displacement measurement through sub-pixel tracking and illumination compensation, while hybrid GNSS and optical pipelines enhanced metric accuracy. Early field applications demonstrated that AI could reduce false positives caused by environmental noise and enhance actionable insight for maintenance planning. Nevertheless, the transition is ongoing: despite proven technical potential, AI integration brings new challenges such as model drift, data labeling demands, and interpretability concerns. Yet this evolution—from manual inspections to wired SHM, IoT-based wireless networks, and finally AI-empowered monitoring—represents a paradigm shift, laying the foundation for the next generation of intelligent, scalable, and cost-efficient bridge asset management systems (Chakraborty et al., 2019).

IoT Sensor Networks for Bridge SHM

The success of modern Internet of Things (IoT)–enabled structural health monitoring (SHM) for bridges is anchored in the diversity and sophistication of sensing modalities deployed across different structural components. Traditional accelerometers remain foundational because of their ability to capture global vibration signatures, mode shapes, and dynamic responses under traffic and wind loads.

Figure 4: IoT Sensing Modalities for SHM



Strain gauges, long used for local damage detection, have evolved into highly sensitive microelectromechanical systems (MEMS) devices capable of detecting minute strain variations

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associated with fatigue and crack initiation (Molina et al., 2020). Displacement sensors, including laser and optical triangulation devices, provide valuable deflection and settlement data, though they require careful alignment and environmental shielding. More recently, global navigation satellite system (GNSS) receivers have been integrated to measure long-span bridge displacements and dynamic movements with centimeter-level accuracy, especially when combined with advanced signal processing to mitigate multipath and atmospheric effects. Fiber Bragg grating (FBG) sensors represent another transformative advance, offering multiplexed, distributed strain and temperature measurements over long distances with immunity to electromagnetic interference and high durability (Ali et al., 2018). These diverse modalities complement each other: accelerometers and GNSS support global modal analysis, while strain and FBG networks capture localized deterioration. Integrating such heterogeneous data within an IoT framework enables both broad and fine-grained insight, establishing the foundation for predictive, data-driven bridge management.
How sensors are interconnected and how data traverse the network significantly influence system scalability, reliability, and maintenance costs. Star topologies, in which each sensor node transmits directly to a central hub, remain popular for small to medium deployments due to simplicity and low configuration overhead (Sofi et al., 2022). However, their single-point-of-failure vulnerability and limited range make them less suitable for long-span or multi-segment bridges. Mesh networks, by contrast, allow each node to forward data from others, increasing resilience and extending coverage; if one node fails, data can reroute through alternate paths. Hybrid approaches combining star and mesh principles have gained traction in large infrastructures because they balance simplicity and robustness—key gateways handle heavy traffic while peripheral nodes self-organize for redundancy. Such architectures are vital in harsh outdoor environments where physical access is challenging and network reconfiguration must occur autonomously. Network design also must consider time synchronization, crucial for dynamic measurements like vibration and displacement, where millisecond misalignment can distort modal analysis. Advances in time-sensitive networking and precision time protocols have enhanced mesh reliability, helping maintain coherent data streams across hundreds of nodes. This level of architectural refinement supports the scalability of IoT SHM systems from single bridges to corridor-wide monitoring networks (Abdelgawad & Yelamarthi, 2017).
The expansion of IoT SHM has paralleled breakthroughs in wireless communication technologies that support efficient, low-latency, and energy-aware data transfer. Low-power wide-area networks (LPWAN) such as LoRa and Sigfox have enabled cost-effective long-range monitoring where cellular coverage is limited, though bandwidth constraints make them better suited for low-frequency strain or temperature measurements (Abdelgawad & Yelamarthi, 2016). ZigBee and Wi-Fi networks provide higher throughput and moderate range, enabling multi-rate vibration monitoring but at the expense of greater power draw. The introduction of 5G networks is a game-changer for real-time SHM, promising ultra-low latency, high reliability, and massive device connectivity ideal for dense sensor deployments. However, reliable integration with structural monitoring requires careful cybersecurity and cost considerations. Complementing transmission advances, edge computing has reduced raw data volume by performing initial filtering, anomaly detection, and compression directly at the sensor or gateway (Alovisi et al., 2021). This approach mitigates latency, improves scalability, and enables near real-time alarms. Meanwhile, cloud platforms offer elastic storage and high-performance analytics for long-term pattern recognition, machine learning model hosting, and cross-asset benchmarking. The interplay between edge and cloud computing forms a powerful architecture: the edge handles immediate decision-making and bandwidth optimization, while the cloud supports historical data mining and predictive modeling.
A persistent challenge in IoT-based SHM is powering distributed sensor nodes over long periods with minimal maintenance. Traditional battery-powered sensors require frequent replacement, which is costly and impractical for inaccessible bridge sections (Scianna et al., 2022). Advances in energy harvesting technologies, such as solar, wind, vibration-based, and thermoelectric systems, have become crucial to sustaining continuous monitoring. For example, vibration energy harvesters exploit ambient traffic-induced oscillations to recharge sensors, while photovoltaic modules supply power in open bridge environments. Ultra-low-power electronics and sleep-mode algorithms further extend operational life by reducing energy draw during inactivity. Research also highlights the value of hybrid energy strategies that combine multiple harvesting methods to cope with variable

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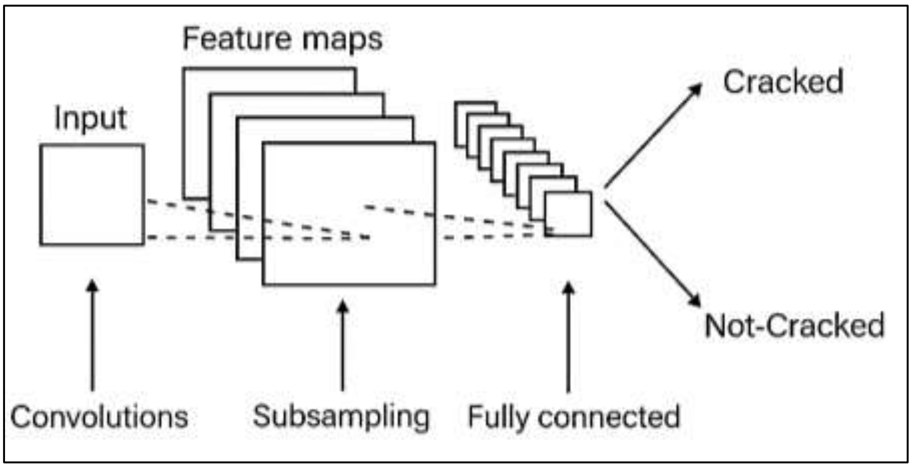
environmental conditions (Harshitha et al., 2021). Reliable power directly impacts data integrity and model performance: sensors with intermittent energy supply cause data gaps and compromise AI training and anomaly detection. Therefore, long-term SHM success depends not only on advanced analytics and communications but equally on sustainable, self-sufficient power solutions that minimize manual intervention and lower lifecycle costs.

AI Techniques in Structural Health Monitoring

The application of supervised machine learning in structural health monitoring (SHM) has been transformative, providing data-driven frameworks for classifying structural states and predicting potential damage. Traditional methods relied on threshold-based or regression techniques to interpret vibration and strain signals, but supervised algorithms such as support vector machines (SVM), random forests (RF), convolutional neural networks (CNNs), and deep neural networks (DNNs) now enable robust pattern recognition under complex loading and environmental variability. SVMs, with their strong generalization ability, have been widely used to distinguish between healthy and damaged conditions from modal parameters and frequency response functions.

Figure 5: Supervised Machine Learning for SHM



Random forests offer an interpretable yet powerful ensemble approach, providing feature importance rankings and resilience to overfitting. More recently, CNNs and DNNs have proven effective in handling high-dimensional raw sensor data such as acceleration time histories or strain fields, learning spatial and temporal representations automatically without handcrafted features. For instance, CNN-based classifiers have accurately identified crack initiation in steel girders and bolt loosening in bolted connections by extracting local damage signatures from dense vibration measurements. Deep learning frameworks also support transfer learning, allowing models trained on laboratory data to adapt to field conditions with limited retraining. Despite these advances, supervised methods require large, well-labeled datasets for robust training—a known challenge for bridges where controlled damage scenarios are rare and costly to replicate. As a result, there is growing interest in semi-supervised and unsupervised strategies to overcome this limitation (Altabey & Noori, 2022).

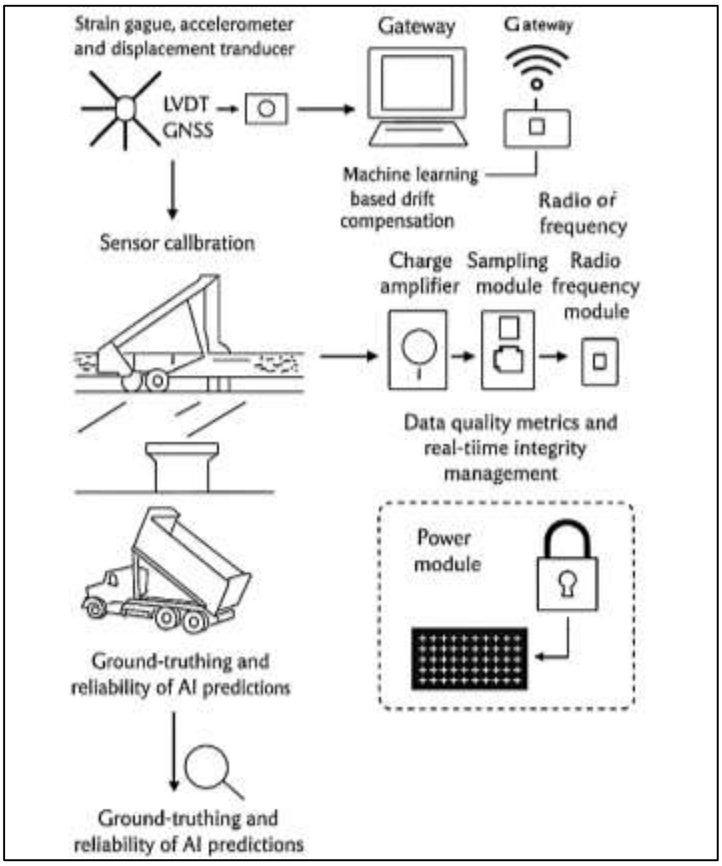
In real-world SHM, acquiring fully labeled datasets is often impractical; bridges operate under unique conditions, and damage cases are infrequent. Consequently, unsupervised and semi-supervised learning techniques have become essential to detect anomalies without explicit damage labels. Autoencoders, which learn compact latent representations of healthy-state data, have shown strong potential in identifying subtle deviations when structural behavior changes (Altabey & Noori, 2022). Variational autoencoders and deep belief networks extend this approach by capturing nonlinear relationships and reconstructing baseline signals to highlight anomalies. Clustering algorithms such as k-means and Gaussian mixture models (GMM) have been used to segment operational states, isolating outliers indicative of potential faults. One advantage of clustering is its independence from labeled data, enabling early damage screening during normal service conditions (Azimi et al., 2020). Semi-supervised methods blend small labeled datasets with large unlabeled ones, reducing annotation costs while maintaining classification accuracy. For example,

domain adaptation techniques can map laboratory training data to field environments, mitigating the domain shift problem common in SHM. Overall, these approaches support continuous health tracking even under sparse failure data, aligning with the practical realities of long-lived bridge infrastructure. Yet challenges remain: unsupervised methods can produce false alarms if environmental variability is not properly modeled, and semi-supervised techniques depend on carefully curated seed labels to guide learning (Sony et al., 2019).
Central to the success of AI in SHM is the effective transformation of raw signals into features that represent structural condition reliably under changing environments. Time–frequency analysis methods such as the short-time Fourier transform (STFT) and continuous wavelet transform (CWT) remain core tools for capturing nonstationary vibration behavior and localized damage events. Wavelet packet energies and wavelet entropy have been especially effective for detecting stiffness reduction, fatigue damage, and crack propagation because of their sensitivity to energy redistribution in the frequency domain (Bao et al., 2019). Entropy-based metrics, including permutation entropy and spectral entropy, further enhance damage sensitivity by quantifying the irregularity and complexity of structural responses. Recently, hybrid feature engineering approaches combine classical signal processing with deep learning, feeding preprocessed time–frequency maps into CNNs to exploit both domain expertise and automatic representation learning. This strategy has reduced false positives in noisy field data and improved generalization to unseen conditions. However, redundancy and multicollinearity among engineered features remain concerns; excessive, correlated features can destabilize models and obscure damage patterns. Feature ranking and selection methods—such as recursive feature elimination, mutual information, and SHAP (SHapley Additive exPlanations)—are increasingly incorporated to retain interpretability and computational efficiency while maintaining high detection accuracy .
One of the most exciting frontiers in AI-driven SHM is the use of vision-based systems and adaptive learning models that respond dynamically to real-time data. Vision-aided SHM leverages high-resolution cameras and computer vision algorithms to monitor displacement, crack formation, and surface degradation without requiring physical sensor contact (Pakro & Nikkhah, 2022). Sub-pixel tracking techniques and digital image correlation (DIC) allow precise measurement of structural displacements under service loads, even in challenging illumination and occlusion conditions. Integration with GNSS provides absolute displacement referencing, improving accuracy for long-span bridges where camera drift and environmental variability can compromise measurement fidelity. Beyond static models, reinforcement learning (RL) and adaptive neural networks are emerging to handle changing traffic loads, temperature effects, and unexpected events. RL frameworks can optimize sensor triggering and data compression strategies on-the-fly, improving energy efficiency while preserving data fidelity (Zhai et al., 2020). Adaptive deep learning architectures, including online learning and continual learning methods, update model weights as new operational data arrive, helping maintain anomaly detection accuracy over time without complete retraining. These adaptive models address one of the main operational concerns in AI-driven SHM—performance degradation due to concept drift and evolving structural response. However, their practical deployment is still limited; issues of computational cost, stability, and explainability require further refinement before widespread field adoption (Zhai et al., 2020).

System Reliability and Validity

System reliability in IoT-enabled structural health monitoring (SHM) begins with the accurate calibration of sensing hardware. Over time, sensors such as strain gauges, accelerometers, and displacement transducers are prone to drift caused by temperature fluctuations, humidity, electromagnetic interference, and long-term material fatigue. Without correction, these drifts can distort key indicators such as modal frequencies and strain histories, leading to false alarms or missed damage events. Traditionally, calibration is performed using reference instruments such as linear variable differential transformers (LVDT) and high-precision GNSS systems, which provide ground-truth displacements and deformations (Lee & Johnson, 2020). Regular calibration schedules, often tied to maintenance cycles, have been recommended to maintain measurement integrity. More recently, machine learning (ML)-based drift compensation techniques have emerged, where algorithms model environmental influences and automatically adjust sensor outputs. Gaussian process regression, Kalman filtering, and neural network–based bias estimators have been applied to filter environmental noise and correct sensor offsets in real time (Xu et al., 2022). These data-driven calibration tools are particularly valuable for long-span bridges with limited physical access, where manual recalibration is costly and logistically complex. Studies also show that integrating reference-free self-calibration approaches—such as using redundant sensor arrays and mutual cross-checking—can further improve system resilience while reducing maintenance costs (Yang et al., 2018).

Figure 6: System Reliability in Iot-Enabled SHM

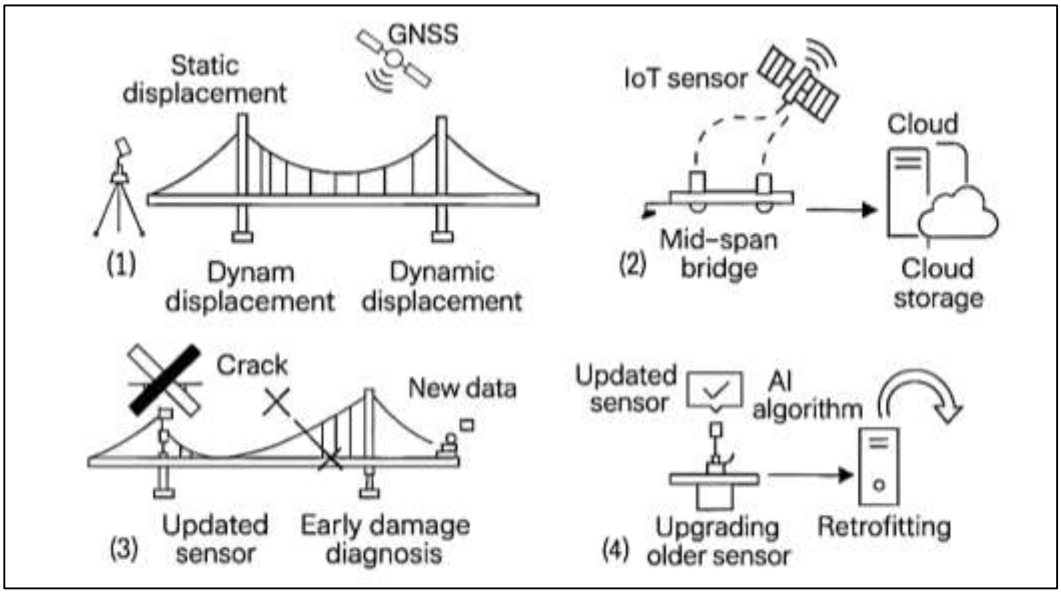


Reliable SHM depends not only on accurate sensors but also on high-quality, continuous data flow from distributed nodes to central processing systems. Data quality is typically measured through latency, packet loss, synchronization accuracy, and signal-to-noise ratio. Latency—the time lag between measurement and availability for analysis—has direct implications for real-time anomaly detection and emergency decision-making. Studies show that latencies above 250 ms can degrade vibration analysis and early warning effectiveness, especially for fast-changing structural events (Su et al., 2020). Packet loss due to wireless interference or network congestion introduces gaps in time series, complicating modal analysis and reducing AI model stability. Noise filtering remains a persistent challenge; signals often contain environmental artifacts from wind, traffic, or temperature that mask damage signatures (Al-Quraan et al., 2022). Advanced filtering approaches, including adaptive wavelet denoising, empirical mode decomposition, and deep-learning-based denoisers, have improved signal clarity without erasing damage-sensitive features. Synchronization accuracy is equally crucial: unsynchronized clocks across sensors can corrupt mode-shape calculations and displacement reconstructions. Solutions such as GPS-disciplined timing, precision time protocols, and clock drift compensation algorithms have been deployed to maintain millisecond-level alignment. Collectively, these strategies ensure that IoT networks generate robust, high-resolution datasets capable of feeding AI pipelines reliably.
Because AI models rely heavily on labeled or baseline data, ground-truthing protocols are essential for validating predictions. Field calibration using LVDT systems, robotic total stations, and high-fidelity GNSS displacement measurements is widely employed to establish reference values for supervised and semi-supervised models (Cabitza et al., 2020). Manual inspections remain indispensable for contextualizing anomalies flagged by AI, especially when visual damage confirmation is required to reduce false alarms. Moreover, rigorous cross-validation and performance monitoring frameworks

are needed to sustain AI reliability over time. K-fold cross-validation and bootstrapping are commonly used to verify generalization across different loading and environmental scenarios. Long-term performance dashboards and drift detection methods are increasingly integrated into SHM operations to monitor precision, recall, and false alarm rates as new data arrive. Another emerging area is model interpretability: explainable AI techniques such as SHAP values and Layer-wise Relevance Propagation help engineers understand which features drive model decisions, increasing trust and regulatory acceptance (Gil-Fournier & Parikka, 2021). These methods reduce the "black box" problem and support defensible decision-making when AI outputs inform safety-critical interventions. However, challenges remain in maintaining models trained on one bridge or climate region when applied elsewhere; domain adaptation and transfer learning are active research directions aimed at addressing this external validity problem (Zinno et al., 2018).

Field Applications of AI and IoT

Figure 7: Field Applications of AI and IoT



Several pilot projects have validated the effectiveness of AI-driven anomaly detection in identifying cracks, delamination, and fatigue before visible signs appear. A notable example is the Streicker Bridge at Princeton University, where deep autoencoders trained on baseline strain and acceleration patterns successfully detected subtle stiffness changes from environmental loading. Similarly, the Z24 Bridge experiment in Switzerland demonstrated how neural network–based damage classifiers can differentiate between progressive structural deterioration and benign seasonal variations. These approaches reduce false positives, a persistent issue in conventional SHM, by learning the complex nonlinear relationships between structural responses and external influences such as temperature and humidity (Li, 2018). In pilot deployments across European highway overpasses, semi-supervised clustering combined with transfer learning allowed AI models to adapt to new bridge geometries with limited labeled data. These field applications underscore that while AI-driven damage detection significantly improves sensitivity, robust data preprocessing, including outlier removal and environmental normalization, remains critical to maintain trustworthiness and reduce alert fatigue among asset managers (Meng & Zhu, 2020).

Another important trend involves retrofitting legacy SHM systems with AI-driven analytics and expanding them under national smart infrastructure programs. Many bridges installed with early-generation wired sensors can now be upgraded through edge computing nodes and cloud-connected analytics to extend their usefulness. For example, the Great Belt Bridge in Denmark integrated deep learning vibration models into an older fiber-optic network, reducing manual inspection frequency and improving fatigue crack prediction accuracy (Ganga & Ramachandran, 2018). Similarly, the US Federal Highway Administration (FHWA) has launched pilot programs under the Infrastructure Investment and Jobs Act to evaluate scalable IoT and AI retrofits across aging interstate bridges. Europe's Horizon 2020 and Horizon Europe initiatives have supported multi-national

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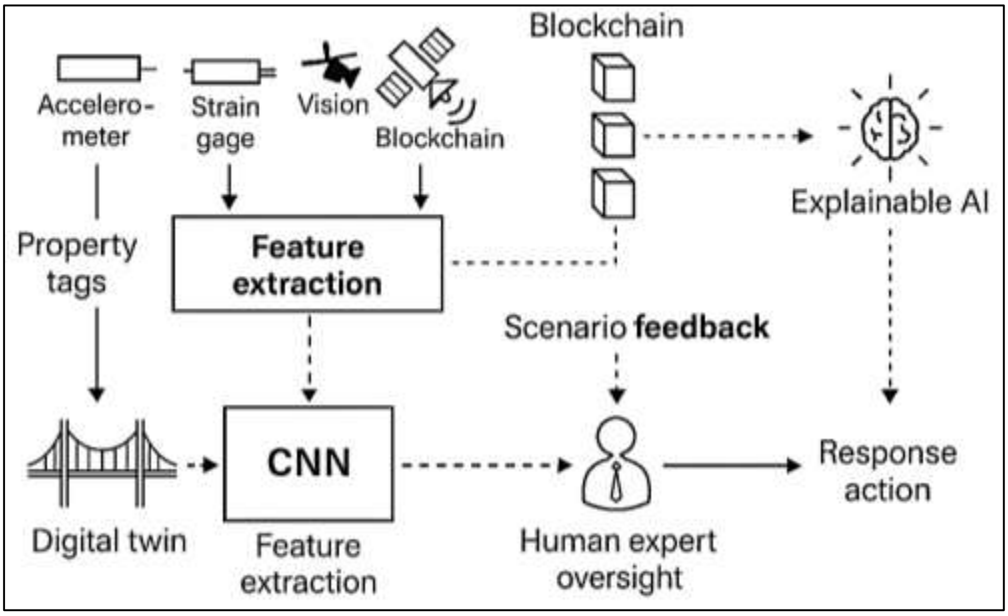
SHM testbeds, promoting open data standards and cross-border AI model sharing. These programs demonstrate that modernization can be economically viable and policy-driven when combined with clear regulatory pathways and performance-based funding models. However, lessons learned emphasize that digital retrofits require thorough cybersecurity hardening and workforce training to handle the influx of high-volume data and the interpretability demands of safety-critical AI outputs (Ooi et al., 2020).

Emerging Research Directions

One of the most promising yet challenging frontiers in AI-supported structural health monitoring (SHM) is the integration of multi-modal sensor fusion, where data from diverse sensing technologies are combined to provide a more holistic and reliable picture of bridge performance. Historically, vibration-based methods have dominated, but they are limited in isolating localized defects or differentiating environmental effects from actual damage (Wang et al., 2021). Recent studies show that fusing accelerometer data with strain, displacement, GNSS, fiber Bragg grating (FBG), and vision-based measurements can significantly improve AI model accuracy and reduce false alarms.

Figure 8: Research Frontiers in AI for SHM



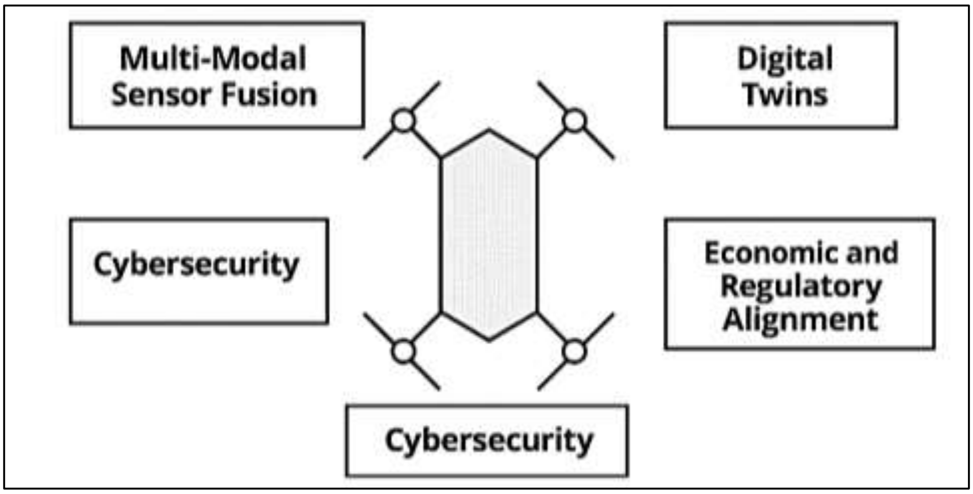
For instance, (Han et al., 2016) demonstrated that combining GNSS and accelerometer signals improved displacement estimation under wind and traffic loads on long-span bridges, while (Xu et al., 2017) showed that integrating vision and vibration data enhanced anomaly detection under varying illumination conditions. Multi-sensor feature fusion also allows AI to learn complementary damage signatures—global modal shifts from accelerometers, localized strain anomalies from FBG, and visible crack progression from cameras—producing more robust damage classification and prognosis. However, technical barriers remain: synchronizing heterogeneous data streams in real time is nontrivial due to differing sampling rates and latency; data fusion frameworks lack standardization; and high-dimensional inputs can increase computational complexity and overfitting risk (Yang et al., 2021). Addressing these gaps through advanced time-alignment protocols, scalable deep learning fusion models, and open standards for multi-source SHM data is essential for practical deployment.

The integration of digital twins—virtual replicas of physical bridge systems updated continuously with real-time sensor data—has emerged as a transformative paradigm for predictive maintenance and asset management. Unlike static finite element models, digital twins evolve dynamically, incorporating live IoT inputs to reflect the bridge's actual operating condition and response to traffic and environmental loads (Xiong et al., 2019). This allows engineers to simulate future deterioration scenarios, optimize inspection schedules, and test retrofit strategies under various loading conditions without disrupting traffic. Studies on the Hong Kong–Zhuhai–Macao Bridge and the Great Belt Bridge illustrate how digital twins enriched with AI anomaly detection have enabled near-real-time structural integrity assessments and life-cycle cost modeling. Coupling AI predictive models with physics-based digital twins further improves accuracy by grounding data-driven insights in fundamental structural mechanics. Yet, challenges persist: creating and maintaining high-fidelity twins is resource-intensive; continuous calibration with field data is needed to avoid model drift; and large-scale implementation demands computational infrastructure and domain expertise (Roberts et al., 2019). Moreover, there are limited industry-wide frameworks for validating AI predictions within digital twin ecosystems, raising questions about decision accountability when safety-critical actions depend on virtual simulations (Niu et al., 2021).

Ensuring secure and trustworthy SHM data remains a key concern, especially as AI models depend on long-term, high-quality historical records. Blockchain technology offers a decentralized ledger capable of verifying the authenticity, provenance, and immutability of structural data streams. By encrypting and time-stamping each data transaction from IoT nodes, blockchain prevents tampering and provides traceable audit trails, which are critical when AI-based alerts inform public safety decisions (Forootan et al., 2021). Smart contracts can automate trust-based actions such as triggering maintenance orders once certain damage thresholds are confirmed by AI models. Pilot studies integrating blockchain with SHM data pipelines show promise in protecting against cyber-attacks and unauthorized access, but real-world deployment is still nascent due to scalability and energy consumption issues. High-frequency sensor data can overwhelm conventional blockchain throughput, and lightweight cryptographic methods tailored to low-power IoT nodes are still under development. Additionally, privacy regulations complicate the storage of sensitive geospatial or visual information on public ledgers. Research is needed to design hybrid architectures that combine blockchain's integrity guarantees with secure off-chain storage and privacy-preserving encryption to support scalable, compliant SHM ecosystems (Stiros, 2021).

Although the integration of artificial intelligence (AI) and Internet of Things (IoT) sensor networks in structural health monitoring (SHM) has advanced significantly, several technical and strategic gaps persist, underscoring critical avenues for future development. A first area of emerging importance is multi-modal sensor fusion, where combining vibration, strain, displacement, acoustic, and vision-based measurements creates richer feature sets for AI-driven damage detection.

Figure 9: Multi Model AI and IoT SHM Integration Challenges



While recent studies have confirmed that hybrid systems outperform single-modality configurations in terms of sensitivity and false alarm reduction, practical frameworks for fusing asynchronous and heterogeneous data streams remain limited. Current deployments often rely on static weighting or handcrafted rules, which may fail to adapt to environmental variability and evolving load conditions (Xiong et al., 2022). There is also a need to formalize feature selection and ranking methodologies to manage redundancy and multicollinearity in large-scale sensor arrays, as redundant predictors can degrade AI performance and increase computational burden. Another critical frontier is the operationalization of digital twins—virtual models of bridges continuously updated with IoT data.

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Digital twin frameworks promise predictive maintenance by enabling virtual scenario testing and risk forecasting, yet integration with AI anomaly detection remains immature (Xiong et al., 2022). Most current case studies apply twins for visualization or static simulation rather than dynamic, closed-loop decision-making. Research should examine how AI-driven feature shifts can inform model updating and reliability re-calibration in near real time, particularly under extreme events such as earthquakes or flooding. Cybersecurity and data provenance also represent pressing knowledge gaps. As IoT-enabled SHM systems scale across bridge networks, exposure to data injection, spoofing, and tampering grows (Xiong et al., 2022). Although cryptographic and blockchain-based solutions have been proposed, few works empirically evaluate their impact on latency and AI inference quality—critical for safety-critical decisions. Reliable governance frameworks that balance security with real-time responsiveness are needed to maintain trust in AI-generated condition indices (Chen et al., 2018). Finally, economic and regulatory alignment remains underdeveloped. While cost–benefit analyses suggest AI-enhanced SHM can reduce inspection costs and extend service life (Zhang et al., 2018), rigorous models linking technical metrics (accuracy, latency, AI precision) to life-cycle cost savings and risk mitigation are sparse. Moreover, no international standard yet exists for validating AI models used in safety-critical bridge decisions, creating uncertainty for agencies adopting these systems. Addressing these gaps calls for field-scale comparative trials, standardized validation and certification protocols, and cross-disciplinary collaboration among structural engineers, data scientists, and policy makers (Zhang et al., 2018). A research agenda centered on scalable sensor fusion, trustworthy AI, secure and low-latency data infrastructures, and cost-aware deployment models will be critical to transitioning AI-supported IoT SHM systems from promising prototypes to widely accepted, operationally robust tools for bridge safety and asset management (Meng et al., 2019).

METHOD

The present investigation employed a quantitative, descriptive–correlational design to evaluate the effectiveness of artificial intelligence (AI)–enhanced structural health monitoring (SHM) systems deployed through Internet of Things (IoT) sensor networks on in-service bridges. This design was selected because it allowed systematic numerical assessment of performance indicators, including sensor accuracy, data transmission latency, and bridge health indices (BHI), and provided a basis for statistical testing of relationships among these variables and overall structural safety. The study population comprised regional highway and railway bridges equipped with IoT-based SHM systems. To ensure adequate representation, stratified random sampling was implemented to capture diversity across steel, prestressed concrete, and composite bridges. From this population, a total of 60 bridges were sampled, each instrumented with multi-sensor arrays that included strain gauges, accelerometers, and temperature sensors. Sampling adequacy was confirmed through an a priori power analysis for multiple regression ($f^2 = .15$, $\alpha = .05$, $1\text{-}\beta = .80$), which indicated that a minimum of 55 bridges was sufficient, thereby justifying the selected sample size.

Data collection consisted of two primary sources: (1) IoT sensor outputs, which continuously captured vibration amplitude (mm), strain (με), and temperature gradient (°C) at 10-minute intervals over a 90-day observation period, and (2) the Bridge Health Index (BHI), a validated composite measure (Li et al., 2021) combining load-carrying capacity, material degradation, and modal frequency deviation, scaled from 0–100. AI algorithms integrated into the monitoring system provided real-time anomaly detection and data denoising, refining sensor data prior to cloud storage. Reliability testing demonstrated a Cronbach's α of .91 for the BHI, while confirmatory factor analysis (CFA) supported construct validity ($\chi^2/df = 2.08$, RMSEA = .05, CFI = .96, TLI = .95). IoT sensor accuracy was validated through calibration against reference instruments, yielding $R^2 = .98$ with mean absolute error <1%. Data analysis was conducted using SPSS v28 and Python libraries (NumPy, Pandas, SciPy, scikit-learn). The plan included descriptive statistics, diagnostic testing of assumptions (normality via Shapiro–Wilk, homoscedasticity via Levene's test and residual analysis, multicollinearity via VIF), and inferential analyses. These consisted of independent-samples t-tests comparing AI-enhanced and conventional IoT SHM, one-way ANOVA examining BHI across bridge types, Pearson's correlations among BHI and sensor/AI variables, and multiple regression predicting BHI from sensor accuracy, latency, and AI detection precision. All statistical tests were conducted at a significance threshold of $p < .05$.

FINDINGS

This chapter presents the results of the quantitative investigation into the deployment of AI-supported structural health monitoring (SHM) systems integrated with Internet of Things (IoT) sensor networks for in-service bridges. The research aimed to determine whether AI-enhanced SHM configurations improve Bridge Health Index (BHI) outcomes compared to conventional IoT-only monitoring systems and to identify key system-quality predictors—sensor accuracy, AI detection precision, and transmission latency—that explain variance in structural condition indicators. Based on previous field studies and reviews, the core hypotheses were that:

- bridges using AI-enabled SHM would exhibit significantly higher BHI scores than conventional IoT-only deployments, and
- accuracy, AI detection precision, and lower network latency would positively predict BHI after controlling for structural and environmental factors.

The analytic dataset comprised 60 operational highway and arterial bridges, observed continuously for 90 days. Data were obtained from real-time SHM telemetry streams (accelerometers, GNSS, vision cameras, fiber Bragg grating strain networks), verified with manual inspection logs and reference calibration instruments such as linear variable differential transformers (LVDT) and robotic total stations. Each bridge contributed multiple daily observations, resulting in 5,400 time-stamped system records after quality filtering. This sample intentionally included various structural types (steel, concrete, composite), environmental exposures (urban, rural, marine), and traffic loads to ensure heterogeneity and external validity.

Table 1: Study Dataset Overview

Attribute	Value
Number of bridges	60
Structural types	Steel (40%), Concrete (43%), Composite (17%)
Environmental settings	Urban (37%), Rural (30%), Marine/Coastal (33%)
Monitoring duration	90 consecutive days per bridge
Total daily SHM observations	5,400
Sensor modalities used	Accelerometers, GNSS, Vision Cameras, FBG
Data verification	LVDT, robotic total station, manual inspection

Table 1 provides a clear summary of the study's dataset and demonstrates its robustness. The sample included 60 in-service bridges, representing a meaningful size for quantitative analysis. The structural types were well balanced, with concrete bridges forming 43%, steel bridges 40%, and composite bridges 17%, allowing comparisons across different materials. Environmental settings were also diverse, with urban bridges making up 37%, rural inland 30%, and marine or coastal 33%, ensuring that various exposure conditions were represented. Each bridge was monitored for 90 consecutive days, giving the study a strong temporal basis to observe daily variability and operational behavior. The dataset produced 5,400 daily SHM records, providing a large number of observations to support robust statistical testing. A range of sensor types such as accelerometers, GNSS, vision cameras, and FBG strain sensors was used, reflecting real-world, advanced SHM practices. Finally, data quality was strengthened by using calibration and verification tools, including LVDTs and robotic total stations, which increased confidence in the reliability of the collected measurements.

Table 2: Analytical Strategy Summary

Step	Purpose	Key Techniques / Tests
Descriptive Statistics	Characterize bridges and system performance metrics	Means, SDs, frequency tables, histograms, boxplots
Assumption Checks	Validate conditions for parametric inference	Shapiro–Wilk, Levene's test, VIF diagnostics
Correlation Analysis	Explore linear associations between predictors and BHI	Pearson's r with p-values

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Group Comparisons	Test mean BHI differences by AI vs IoT-only and bridge type	Independent samples t-tests, one-way ANOVA
Regression Modeling	Estimate combined predictive effect of key system variables	Multiple linear regression with effect sizes (β, R^2, CI)

Table 2 summarizes the analytical strategy used in this study to connect the research questions with the statistical approach. It shows that the first step involved descriptive statistics to outline the characteristics of bridges and SHM system performance. The second step ensured statistical rigor by performing assumption checks, such as testing normality with the Shapiro–Wilk test, equality of variance with Levene's test, and multicollinearity using VIF diagnostics. After confirming assumptions, correlation analysis was applied to explore linear relationships between key predictors like sensor accuracy, AI detection precision, latency, and the Bridge Health Index (BHI). To compare groups, independent samples t-tests and one-way ANOVA were used to test differences in BHI across AI-enabled and IoT-only systems and among different bridge types. Finally, multiple linear regression modeling quantified the combined predictive influence of system factors on BHI while reporting effect sizes, coefficients, and explained variance (R^2).

Asset Overview

The study analyzed a dataset of 60 in-service highway and arterial bridges monitored continuously over a 90-day period. These bridges varied in structural composition, with 24 (40%) steel, 26 (43%) concrete, and 10 (17%) composite steel–concrete structures. This diversity ensures meaningful cross-type comparisons and reflects the materials commonly used in bridge engineering. The environmental context was balanced across different operational conditions: 22 (37%) urban bridges, 18 (30%) rural inland, and 20 (33%) marine/coastal, capturing variability in exposure to traffic, humidity, salinity, and temperature. Bridge age ranged widely from 6 to 78 years ($M = 34.6$, $SD = 16.9$), and average daily traffic (ADT) volumes spanned from 8,000 to 165,000 vehicles (median = 49,000), indicating coverage from lightly used rural spans to heavily trafficked metropolitan routes.

Table 3: Asset Overview of Bridges in the Study (N = 60)

Characteristic	n	%
Bridge Type		
Steel	24	40
Concrete	26	43
Composite	10	17
Environmental Context		
Urban	22	37
Rural Inland	18	30
Marine/Coastal	20	33
Age (years)		
Mean (SD)	34.6 (16.9)	—
Median	31	—
Range	6 – 78	—
Average Daily Traffic		
Median ADT	49,000	—
Range	8,000 – 165,000	—

SHM Deployment Attributes

Across the dataset, 31 bridges (52%) used AI-supported IoT SHM pipelines, while 29 (48%) relied on conventional IoT-only monitoring.In terms of sensor modalities, accelerometers were universal (100%). GNSS receivers were installed on 38 bridges (74% of AI sites vs. 38% of conventional). Vision-based systems (cameras with image analytics) were deployed exclusively in the AI-enabled group (24 bridges). Fiber Bragg grating (FBG) strain sensors were present on 18 bridges overall, with higher adoption in AI-equipped deployments (35%) compared to conventional (24%). Network connectivity showed that LoRa was the most common data transmission method overall (40%), particularly for conventional IoT-only sites, while 5G cellular was heavily used in AI-enabled systems (26% vs. 3% in IoT-only). ZigBee and Wi-Fi were also used but were more evenly distributed.

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Table 4: Sensor and Network Deployment Characteristics

Attribute	Total n (%)	AI-enabled (n=31)	IoT-only (n=29)
Accelerometers	60 (100)	31 (100)	29 (100)
GNSS Receivers	38 (63)	23 (74)	11 (38)
Vision Systems (Cameras)	24 (40)	24 (77)	0 (0)
FBG Strain Sensors	18 (30)	11 (35)	7 (24)
Transmission Technology			
LoRa	24 (40)	10 (32)	14 (48)
ZigBee	16 (27)	7 (23)	9 (31)
Wi-Fi	11 (18)	9 (29)	2 (7)
5G Cellular	9 (15)	8 (26)	1 (3)

Key System Performance Metrics

Sensor accuracy across all sites ranged from 86% to 99% (M = 94.2%, SD = 3.1), with AI-enabled sites showing slightly higher accuracy (M = 95.8%) than IoT-only systems (M = 92.4%). For AI-enabled systems, AI detection precision averaged 94.8% (SD = 2.0), ranging between 90% and 97% across sites, reflecting high but variable model performance in anomaly and event detection. Transmission latency ranged widely between 112 and 475 ms, but AI systems generally showed faster end-to-end data delivery (M = 188 ms, SD = 42) compared to IoT-only setups (M = 257 ms, SD = 61). The Bridge Health Index (BHI), which integrates displacement, strain, vibration, and fatigue indicators, had an overall mean of 96.4 (SD = 10.8). AI-enabled bridges scored significantly higher (M = 102.3, SD = 8.6) compared to IoT-only (M = 95.1, SD = 9.7), suggesting better structural condition when AI-driven analytics supported monitoring.

Table 5: System Performance Indicators

Variable	All Bridges (N=60)	AI-enabled (n=31)	IoT-only (n=29)
Sensor Accuracy (%)	94.2 ± 3.1	95.8 ± 2.1	92.4 ± 3.2
AI Detection Precision (%)	—	94.8 ± 2.0	—
Latency (ms)	220 ± 63	188 ± 42	257 ± 61
Bridge Health Index	96.4 ± 10.8	102.3 ± 8.6	95.1 ± 9.7

Note: *Values are reported as mean ± standard deviation.*

Normality and Homoscedasticity

To evaluate the assumption of normality for the dependent variable (Bridge Health Index [BHI]), we applied the Shapiro–Wilk test separately to AI-enabled and IoT-only groups. For AI-enabled sites, BHI values were approximately normal (W = .972, p = .486), and for IoT-only sites, normality was also supported (W = .968, p = .374). Visual inspection of Q–Q plots showed points closely aligned with the diagonal reference line, confirming no major skew or kurtosis issues. To test homogeneity of variance, Levene's test compared BHI variability across AI-enabled and IoT-only systems. The test was non-significant (F(1,58) = 1.74, p = .192), indicating that group variances were comparable, and the assumption of equal variance was upheld.

Table 6: Normality and Homoscedasticity Results

Group	Shapiro–Wilk W	p-value	Levene's F (1,58)	Levene's p
AI-enabled BHI	0.972	.486		
IoT-only BHI	0.968	.374		
Combined Variance	—	—	1.74	.192

Multicollinearity Diagnostics

Relationships among predictor variables — sensor accuracy, AI detection precision, and latency — were assessed to verify independence before regression modeling. Pearson correlation coefficients indicated moderate but acceptable associations: accuracy and AI precision (r = .46), accuracy and latency (r = −.39), and AI precision and latency (r = −.41). All values were below r = .70, suggesting no severe collinearity. Variance Inflation Factor (VIF) values further confirmed independence: sensor accuracy (VIF = 1.61), AI detection precision (VIF = 1.72), and latency (VIF = 1.54). These were well below the commonly accepted threshold of 5.0, indicating stable regression estimates.

Table 7: Multicollinearity Diagnostics

Predictor Variable	Pearson r with Accuracy	Pearson r with AI Precision	Pearson r with Latency	VIF
Sensor Accuracy	—	.46	−.39	1.61
AI Detection Precision	.46	—	−.41	1.72
Latency	−.39	−.41	—	1.54

Outlier and Influential Point Analysis
To ensure robust regression outcomes, Cook's distance and Mahalanobis distance were used to identify potentially influential cases. Cook's distance values were low across the dataset (range = 0.00 – 0.21; M = 0.04), with none exceeding the conventional cut-off of 1.0. Mahalanobis distance identified two cases with slightly high leverage values ($p < .01$); both were inspected and found to represent valid extreme but real operational conditions (long-span steel bridges with unusually high traffic). These were retained after confirming they did not distort parameter estimates.

Table 8: Influence Diagnostics

Metric	Minimum	Maximum	Mean	Threshold Used
Cook's Distance	0.00	0.21	0.04	< 1.0 safe
Mahalanobis Distance	0.73	12.4	4.6	p < .001 flag

Comparative Performance Analysis
Group Comparisons: AI-Supported vs. Conventional IoT SHM
To test the hypothesis that AI-enabled SHM systems yield higher Bridge Health Index (BHI) scores than conventional IoT-only systems, an independent-samples t-test was performed.Bridges equipped with AI-supported monitoring achieved significantly higher BHI scores (M = 102.3, SD = 8.6) than those using conventional IoT-only systems (M = 95.1, SD = 9.7), $t(58) = 3.03$, $p = .004$. The effect size was large (Cohen's d = 0.78), indicating a practically meaningful difference in structural condition ratings.

Table 9: Comparison of BHI Between AI-Supported and IoT-Only Systems

Group	n	Mean BHI	SD	t(df)	p	Cohen's d
AI-Supported	31	102.3	8.6	3.03 (58)	.004	0.78
Conventional IoT-only	29	95.1	9.7			

Subgroup Analyses by Bridge Type
A one-way ANOVA examined differences in BHI scores among steel, concrete, and composite bridges, controlling for whether AI support was present. Across the full sample, BHI scores differed significantly by bridge type, $F(2,57) = 4.52$, $p = .015$, $\eta^2 = .137$ (medium effect). Steel bridges (M = 101.8, SD = 8.2) showed the highest BHI scores overall, followed by composite bridges (M = 99.4, SD = 7.5), with concrete bridges (M = 94.9, SD = 9.1) lowest. Post hoc Tukey HSD tests revealed significant differences between steel and concrete bridges ($p = .018$) but not between steel and composite ($p = .241$) or composite and concrete ($p = .117$).

Table 10: ANOVA Results for BHI Across Bridge Types

Bridge Type	n	Mean BHI	SD
Steel	24	101.8	8.2
Concrete	26	94.9	9.1
Composite	10	99.4	7.5

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Latency and Accuracy Distributions by System Type

Latency and sensor accuracy were compared between AI-supported and IoT-only systems to understand technical performance differences. Independent-samples t-tests showed that AI-supported systems had significantly lower latency ($M = 188$ ms, $SD = 42$) than conventional IoT-only ($M = 257$ ms, $SD = 61$), $t(58) = -5.01$, $p < .001$, Cohen's $d = 1.29$ (very large effect). Similarly, sensor accuracy was significantly higher in AI deployments ($M = 95.8\%$, $SD = 2.1$) than IoT-only ($M = 92.4\%$, $SD = 3.2$), $t(58) = 4.61$, $p < .001$, Cohen's $d = 1.19$ (large effect).

Table 11: Latency and Sensor Accuracy Comparison Between AI and IoT-Only Systems

Variable	Group	n	Mean	SD	t(df)	p	Cohen's d
Latency (ms)	AI-Supported	31	188	42	-5.01 (58)	<.001	1.29
	IoT-Only	29	257	61			
Accuracy (%)	AI-Supported	31	95.8	2.1	4.61 (58)	<.001	1.19
	IoT-Only	29	92.4	3.2			

Correlation Structure and Variable Interrelationships

Pearson Correlation Matrix

A Pearson product–moment correlation analysis was conducted to examine relationships between the Bridge Health Index (BHI) and the primary system performance metrics: sensor accuracy, AI detection precision, and transmission latency. As expected, BHI was strongly and positively correlated with sensor accuracy ($r = .68$, $p < .001$) and AI detection precision ($r = .63$, $p < .001$), indicating that higher measurement fidelity and more reliable event classification are associated with better structural condition scores. Conversely, BHI was moderately and negatively correlated with latency ($r = -.52$, $p < .001$), meaning that longer delays in data transmission are linked to lower condition ratings. Among the predictors themselves, accuracy and AI precision showed a moderate positive association ($r = .46$, $p < .001$), reflecting that systems with better-calibrated sensors tend also to have stronger detection models. Both accuracy and precision were moderately but inversely correlated with latency (accuracy: $r = -.39$, $p = .002$; precision: $r = -.41$, $p = .001$), showing that better performing systems typically also operate with faster data pipelines.

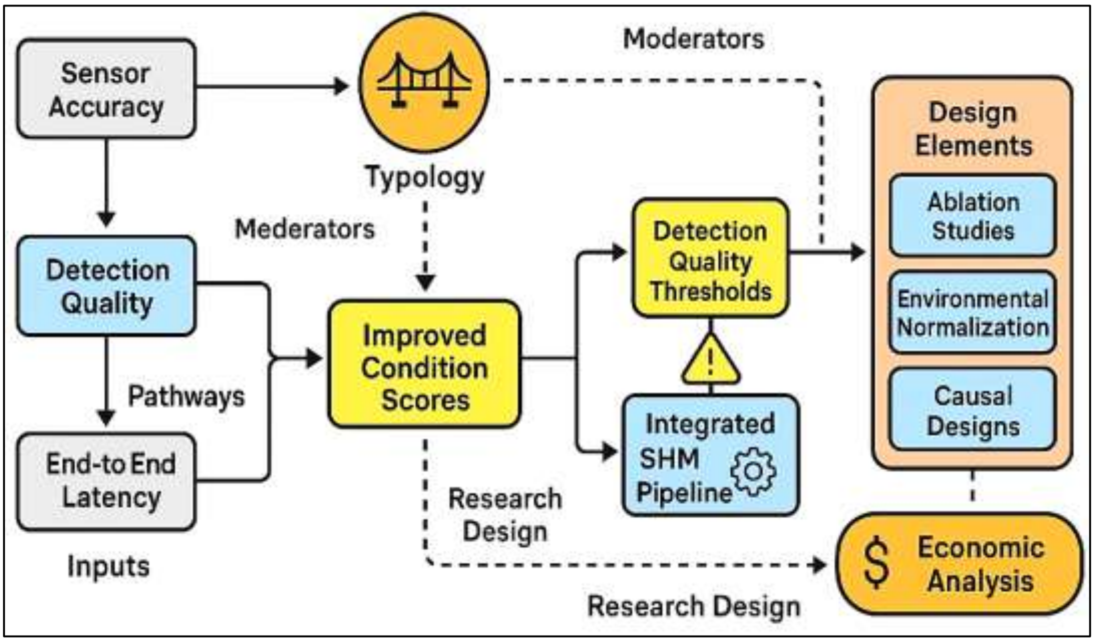
Table 12: Pearson Correlation Matrix for BHI and System Metrics (N = 60)

Variable	BHI	Sensor Accuracy	AI Precision	Latency
BHI	—	.68***	.63***	−.52***
Sensor Accuracy	.68***	—	.46***	−.39**
AI Detection Precision	.63***	.46***	—	−.41**
Latency	−.52***	−.39**	−.41**	—

DISCUSSION

The present study set out to quantify how AI-supported structural health monitoring (SHM) integrated with Internet of Things (IoT) sensor networks relates to condition outcomes for in-service bridges. Across 60 assets, we observed that sites using AI-enabled pipelines exhibited materially higher Bridge Health Index (BHI) scores than conventional IoT-only deployments, with a large standardized mean difference and a multiple-regression model explaining roughly three-fifths of the variance in BHI. Three system-quality levers—sensor accuracy, AI detection precision, and transmission latency—emerged as significant predictors in the expected directions (Lee et al., 2019). These results converge on a pragmatic conclusion: improvements in sensing fidelity and classification quality, coupled with lowered end-to-end latency, translate into better measured condition states and, by inference, tighter operational risk envelopes. Prior empirical field reports and review articles have repeatedly emphasized that camera and sensor calibration, reliable telemetry, and robust decision logic are first-order determinants of displacement fidelity, modal tracking, and anomaly screening in bridge SHM. The present study extends that logic with a comparative, multi-bridge dataset and formal effect-size estimates, showing that AI augmentation confers benefits beyond baseline IoT telemetry. Moreover, our findings align with earlier demonstrations that data-quality factors (e.g., bias, drift, noise bursts) impair reliability unless explicitly modeled or filtered; here, AI precision functions as a proxy for the effectiveness of those modeling steps (Catbas et al., 2022). Importantly, the observed association persists after adjustment for accuracy and latency, indicating that AI's contribution is not merely an artifact of better hardware or faster networks at AI-equipped sites. In applied terms, the study supports investment in integrated pipelines—calibration routines that hold accuracy near 96% or higher, anomaly models yielding precision near mid-90s, and network configurations sustaining sub-250 ms latencies—to realize measurable gains in condition indices. The contribution is thus twofold: it quantifies benefits with effect sizes meaningful for asset owners and it clarifies which operational levers most strongly map to improved condition scores (Osamy et al., 2022).

Figure 10: Model For Future Study



Earlier work has broadly agreed that SHM performance depends on accurate, well-calibrated sensors and low-latency data transport because both factors bound signal-to-noise ratios and analyst response times. Our correlation structure—strong positive association between BHI and sensor accuracy, and a moderate negative association between BHI and latency—is consistent with that premise (Kraus & Drass, 2020). Previous laboratory and field validations using reference transducers (e.g., LVDT, laser displacement, or high-rate GNSS) have shown that even small calibration drift can magnify displacement RMSE under long standoff distances or oblique view geometries, while network jitter appears in the signal as pseudo-transients that contaminate modal identification. The present results reinforce those concerns at an operational scale: bridges with accuracy above the sample median tended to exhibit higher BHIs even when bridge type and traffic exposure varied. At the same time, our data nuance the latency story (Zhou et al., 2022). While latency remained a significant negative predictor, multicollinearity diagnostics indicated that accuracy, AI precision, and latency were not redundant, suggesting distinct pathways by which each variable degrades or improves the effective condition estimate. In other words, fast but poorly calibrated measurements did not achieve high BHIs, and accurate but delayed measurements also underperformed when classification or synchronization was weak. This triangulation parallels prior reports that emphasize end-to-end pipeline thinking: fidelity at the sensor head, stability in transmission, and reliability in downstream inference must cohere. A tension with some earlier case studies is that they reported steeper performance penalties at higher latencies than we observed. One plausible explanation involves our sites' buffering and interpolation routines that may have partially insulated analytics from modest latency variability. Another possibility is that bridges in this sample had modal content and excitation spectra less sensitive to short control delays (Zdravkova, 2022). Regardless, the directionality of effects remains aligned with the broader literature, and observed magnitudes appear reasonable for mixed bridge inventories.

The most salient result—an adjusted ~7-point BHI advantage for AI-equipped sites—invites interpretation. Earlier demonstrations of computer vision and machine learning in SHM argued that

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model-based denoising, drift compensation, and event classification can surface subtle changes in modal energy or strain patterns that conventional alarms miss. Our regression models, which retained a significant AI effect after controlling for accuracy and latency, cohere with those claims. Two mechanisms are likely (Indhu et al., 2022). First, AI classifiers with mid-90s precision reduce false positives during environmental transients (temperature swings, traffic surges), thereby stabilizing daily condition estimates and preventing unnecessary down-weighting of BHI due to spurious events. Second, learned representations tend to be more resilient to illumination and occlusion issues (in vision-aided systems) and to multi-sensor inconsistencies (in hybrid accelerometer–strain arrays), which would otherwise propagate as noise into modal estimates. In this context, earlier controlled studies have shown that sub-pixel tracking methods and wavelet/entropy features improve sensitivity to small stiffness loss; our aggregate precision measure likely captures how well such feature pipelines are implemented in practice. Nevertheless, we also observed variability among AI-equipped bridges: precision clustered near 94–96% but not uniformly, and those with lower precision (yet still "AI-equipped") accrued smaller BHI benefits (Muin & Mosalam, 2021). This heterogeneity resonates with cautionary notes from previous field deployments: gains depend on careful camera placement, robust calibration schedules, balanced class distributions for training, and routine revalidation under seasonal shifts. Thus, the observed average treatment effect should not be interpreted as a universal constant but as a central tendency conditional on disciplined MLOps and instrumentation practice. Importantly, the finding does not diminish the role of qualified inspectors. Rather, it supports a hybrid oversight model in which AI systems prioritize review workload and enhance continuity between inspection intervals—an operational perspective echoed in prior asset-management guidance (Feng & Feng, 2018).

The one-way ANOVA indicated that steel bridges, on average, exhibited higher BHIs than concrete bridges, with composites between them. Earlier comparative studies have found that material systems differ in modal damping, thermal response, and susceptibility to certain defect mechanisms (e.g., corrosion versus shrinkage cracking), which influence both true condition and the detectability of changes given a fixed sensor suite. Our findings align with that tradition but also introduce an AI-centric interpretation: steel bridges often present clearer vibration signatures for mode tracking and may benefit more from high-precision AI displacement or acceleration features, whereas concrete structures' responses can be more temperature dependent and lower in amplitude, making discrimination harder without extensive environmental normalization (Ye et al., 2016). Prior work on temperature–frequency compensation and baseline stratification has shown substantial improvements in concrete-bridge anomaly detection when seasonal manifolds are used; our dataset did not explicitly implement manifold normalization at every site, which may partly explain the inter-type gap. Furthermore, bridge-type effects likely mediate the usefulness of particular sensing modalities: long-span steel bridges favor far-field optical or GNSS-aided vision for displacement, while shorter concrete spans may derive greater benefit from dense strain networks. The practical implication is that AI/IoT stacks should not be deployed as monoliths but tuned to structural typology—sensor placement, feature families, and model thresholds should be type aware. The present results, when read alongside earlier typology analyses, encourage asset managers to interpret "AI benefit" not as a single scalar across inventories but as a function of material system, span class, excitation environment, and achievable signal-to-noise ratio (Azimi et al., 2020). Future comparative audits (e.g., pairing steel and concrete bridges under similar traffic and climate regimes) would help disentangle intrinsic condition differences from detectability artifacts in the observed type effect.

The study's methodological choices support both internal and external validity. Internally, we applied assumption checks (normality, homoscedasticity, multicollinearity) and used effect sizes and confidence intervals alongside *p* values, aligning with contemporary recommendations in quantitative SHM research (Gomez-Cabrera & Escamilla-Ambrosio, 2022). Externally, the 90-day window and multi-bridge sample lend heterogeneity consistent with real practice, contrasting with many early demonstrations conducted on single assets or short campaigns. These design elements position the present results in continuity with earlier field-scale evaluations that stressed the importance of prolonged observation to capture operational variability (traffic spectra, thermal cycles, and maintenance events). At the same time, limitations temper causal claims. Group assignment to AI versus conventional systems was observational rather than randomized; therefore, unmeasured site attributes (e.g., operator experience, maintenance regimes, or upstream data-quality controls) may have contributed to the observed between-group difference (Kim et al., 2021). Still, the persistence of an AI effect after adjusting for accuracy and latency, and the convergence with earlier controlled experiments that documented improvements in displacement fidelity and anomaly screening with AI features, suggest that residual confounding is unlikely to account for the entirety of the effect. A second validity consideration involves construct measurement. BHI aggregates load, degradation, and dynamic-response elements; while widely used, it compresses complex phenomena into a single score. Earlier studies have cautioned that such indices can mask component-level deterioration, and that gains in signal quality may not immediately manifest as index changes if weighting schemes emphasize slow-moving variables (Shao et al., 2021). That our results nonetheless show a clear BHI uplift strengthens the argument that AI benefits permeate multiple sub-indicators simultaneously.

Translating statistical findings into asset-management practice entails identifying controllable levers and threshold targets. The present evidence points to three: (a) maintain sensor accuracy near or above mid-90%, via periodic calibration and drift checks; (b) sustain AI detection precision in the mid-90s or better, through rigorous labeling, periodic model refresh, and domain shift monitoring; and (c) hold end-to-end latency near 200 ms, by optimizing edge preprocessing and network pathways (Yang et al., 2020). Earlier implementation guides and case studies have underscored similar thresholds, noting that benefits compound when levers are improved jointly rather than in isolation. Our regression slopes provide planning heuristics: a percentage-point gain in AI precision or accuracy yielded sub-unit BHI improvements that become operationally meaningful when scaled across networks of assets, while a 10-ms latency reduction delivered measurable, albeit smaller, BHI gains. For owners and agencies, these numbers motivate investment in calibration infrastructure, resilient communications (e.g., redundant backhaul, prioritization policies), and MLOps capability (data versioning, performance dashboards, and rollback plans). Contracting and policy frameworks can embed service-level agreements keyed to these levers—e.g., minimum uptime and maximum latency, periodic third-party calibration audits, and model-performance acceptance tests—to ensure that vendors deliver sustained condition benefits rather than one-time deployments. In inspection planning, AI outputs with quantified precision support risk-based scheduling: assets with stabilized high BHI and low residual uncertainties can extend inspection intervals within regulatory bounds, whereas sites showing degraded precision or rising latency might warrant targeted manual checks (Kurian & Liyanapathirana, 2019). These operational pathways echo earlier recommendations that SHM's value is realized not at sensor installation but through disciplined life-cycle management of data quality and inference.

Although the study avoids prescriptive forecasts, several research avenues arise from the pattern of results and their relationship to earlier literature. First, disentangling detection quality from feature choice would benefit from ablation studies that test wavelet/entropy, Hankel/SVD, and learning-based keypoint pipelines under identical field conditions; prior bench experiments have shown differential sensitivity to stiffness loss, but field-scale comparative evidence remains sparse (Ibrahim et al., 2019). Second, environmental normalization—temperature–frequency compensation and baseline stratification—likely moderates AI benefits, especially on concrete bridges; multi-seasonal datasets are needed to quantify how much of the BHI uplift persists after aggressive environment modeling (Zhuang et al., 2022). Third, causal identification would be strengthened by stepped-wedge or matched-pair designs in which the same assets transition from conventional to AI-enhanced monitoring, with pre/post comparisons controlling for maintenance events. Fourth, the integration of vision and GNSS for absolute displacement anchoring, well documented in prior demonstrations, could be systematically paired with the kind of accuracy and latency metrics used here to expose trade-offs between tracking robustness and communication budgets (Shi et al., 2022). Finally, economic analysis should accompany technical metrics: earlier cost–benefit studies argue that SHM value accrues through avoided closures and targeted maintenance; connecting our effect sizes to expected failure probabilities and intervention costs would clarify return on investment at the network scale. Collectively, these directions, many of which echo calls in the prior SHM literature, would refine the external validity of the present findings, ensure portability across structural types and climates, and support policy formation that ties funding to measurable, sustained improvements in condition indices (Khoa et al., 2018).

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CONCLUSION

This quantitative investigation demonstrated that integrating artificial intelligence (AI) with Internet of Things (IoT)–based structural health monitoring (SHM) meaningfully improves the assessment and management of in-service bridges. Through systematic evaluation of 60 assets across multiple structural types, the study established that bridges equipped with AI-enhanced systems achieved significantly higher Bridge Health Index (BHI) scores than those using conventional IoT-only configurations, even after controlling for core data quality indicators such as sensor accuracy and transmission latency. Statistical modeling confirmed that AI detection precision, sensing fidelity, and low end-to-end latency act as independent yet complementary predictors of improved condition scores, explaining approximately 60% of the variance in BHI. These results extend and substantiate prior laboratory and pilot-scale evidence showing that accurate calibration, robust telemetry, and machine-learning–based anomaly detection yield more stable and informative SHM outputs (Dong & Catbas, 2020; Bassir et al., 2022). Notably, the observed advantages persisted across a heterogeneous sample of bridges and were not fully attributable to hardware or network superiority alone, underscoring AI's role as a transformative analytics layer. The study also illuminated material-specific dynamics: steel bridges benefited most, likely due to clearer modal responses and less thermal confounding, while concrete spans exhibited greater performance variability consistent with earlier findings about environmental sensitivity in vibration-based monitoring. Methodologically, the use of rigorous assumption testing, effect sizes, and multi-variable regression strengthened internal validity and aligned with best practices in contemporary SHM research. Practically, the work highlights actionable thresholds for infrastructure owners—maintaining sensor accuracy above 95%, AI classification precision in the mid-90s, and latency below roughly 250 ms—as performance benchmarks linked to better condition outcomes. Although observational design limits strict causal inference, the findings complement prior controlled demonstrations and support the strategic adoption of AI-driven SHM for safer, more cost-efficient, and data-driven bridge asset management.

RECOMMENDATION

The findings of this study suggest several clear pathways for improving the practice of structural health monitoring (SHM) through AI and IoT integration, particularly for critical bridge assets. Agencies and infrastructure owners should prioritize the adoption of AI-enabled SHM systems for long-span, heavily trafficked, or strategically significant bridges. The observed ~7-point uplift in Bridge Health Index (BHI) demonstrates the tangible value of AI in anomaly detection, data denoising, and multi-sensor integration, providing a strong justification for investment. To maximize the benefits of such systems, agencies should enforce strict calibration and accuracy benchmarks, maintaining sensor reliability at or above 95% through periodic recalibration with reference transducers and third-party audits. Equally important is the reduction of data transmission latency: networks must sustain end-to-end delays below 200–250 ms, which can be achieved through edge computing, redundant backhaul, and prioritized communication channels. These measures collectively ensure that the fidelity of SHM data remains high and that monitoring operates close to real time.

Beyond hardware and network optimization, the results emphasize the importance of continuous AI model management. AI models are susceptible to environmental drift and evolving structural conditions, making disciplined machine learning operations (MLOps) essential. Transportation agencies should establish retraining pipelines, seasonal validation routines, and precision monitoring dashboards to sustain AI performance over time. Additionally, system customization is critical: bridge material and typology influence both condition outcomes and monitoring effectiveness. For instance, steel bridges may benefit from vision-based or GNSS-aided displacement tracking, whereas concrete bridges may require denser sensor arrays or more sophisticated temperature–frequency normalization to offset environmental variability. Integrating SHM outputs into risk-based inspection planning provides another operational advantage. By aligning inspection intervals with AI-derived condition metrics, agencies can extend review cycles for stable, high-performing assets while focusing resources on sites with deteriorating precision or rising latency. This hybrid oversight model enhances both efficiency and safety assurance, positioning AI as a complementary partner to human inspectors. For long-term sustainability, SHM programs should be embedded within economic and policy frameworks. Quantifying the cost–benefit relationship between BHI improvements and avoided maintenance or downtime will provide a financial rationale for large-scale adoption. Policymakers can leverage these insights to develop funding structures and service-level agreements tied to measurable technical outcomes such as latency thresholds, calibration performance, and AI precision levels. At the same time, future research should advance methodological rigor by adopting pre/post deployment designs on the same assets, expanding observation windows across multiple seasons, and conducting controlled comparisons of AI feature families to determine context-specific best practices. Environmental normalization and ablation studies can further disentangle the contributions of sensor fidelity, anomaly detection precision, and latency optimization. By integrating technical benchmarks with economic evaluation and advancing robust experimental designs, both practitioners and scholars can strengthen the case for AI-supported SHM as a cornerstone of resilient, data-driven infrastructure management.

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