American Journal of Interdisciplinary Studies

Volume: *7;* ***Issue:*** *1*
Pages: *01- 55*
eISSN: 3067-5146

AI-ENABLED STRUCTURAL HEALTH MONITORING AND SAFETY OPTIMIZATION MODELS FOR HIGH-SPEED RAIL INFRASTRUCTURE IN SEISMIC REGIONS

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Doi: 10.63125/9yw9jn09
Received: *29 October 2025;* ***Revised:*** *28 November 2025;* ***Accepted:*** *19 December 2025;* ***Published:*** *02 January 2026*

Abstract
This study had evaluated AI-enabled structural health monitoring (SHM) inference and safety optimization linkages for high-speed rail infrastructure in seismic regions using a corridor-scale quantitative dataset and decision-output records. The analyzed dataset had included 48 assets across 12 corridor segments observed for 365 days, producing 312,480 train-pass windows and 96 seismic event windows. Data integrity had remained high overall, with mean system uptime of 93.6%, while missingness had varied by modality, with accelerometers at 4.2% and displacement/tilt channels at 11.7%. Outcome distributions had been highly imbalanced, with damage-present windows representing 1.8% of all windows and severe outcomes representing 0.2%, confirming rare-event conditions for model evaluation. Correlation analysis had shown strong redundancy among amplitude features, where peak and RMS response had correlated at 0.84, and confounding patterns where train speed had correlated with peak acceleration at 0.63 and temperature had correlated with dominant-frequency proxies at –0.46. Reliability assessment had shown acceptable within-regime stability for key indicators, including antiregime consistency of 0.82 for peak acceleration and 0.76 for dominant-frequency proxies. Collinearity diagnostics had identified inflated overlap in the full feature set (peak acceleration VIF 6.8), which had been reduced after screening (retained amplitude indicator VIF 2.6). Regression results had indicated statistically meaningful contributions from probabilistic risk and selected engineered features to damage detection and condition scoring, with the detection model achieving PR-AUC 0.56 compared with 0.41 for a baseline feature-only specification and the condition-score model achieving adjusted R^2 0.48. Operational decision alignment had been supported by correlations between risk score and speed restriction tier (0.71) and inspection priority rank (0.67), indicating coherent translation from inferred risk to safety actions under corridor constraints.

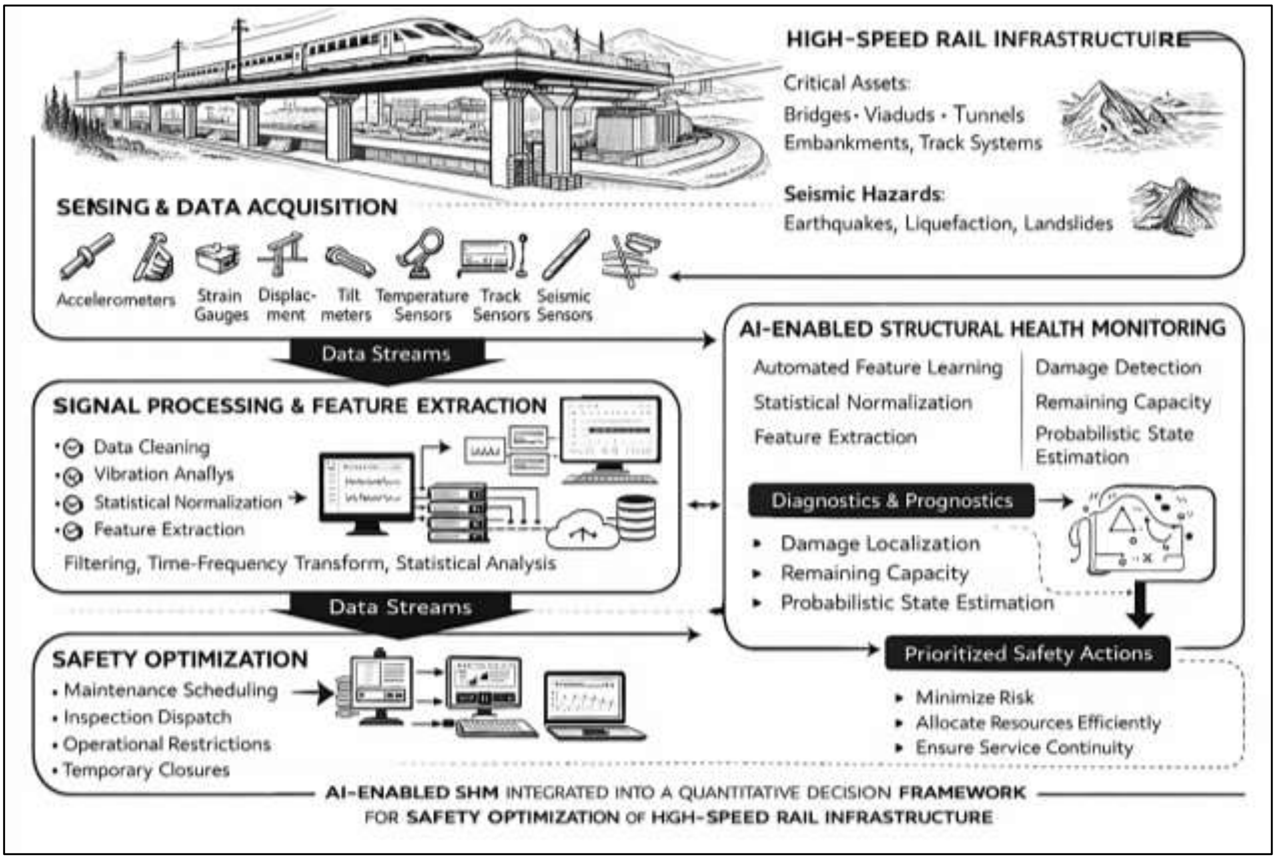
Keywords
AI-Enabled SHM; High-Speed Rail; Seismic Safety; Risk Optimization; Probabilistic Inference.

INTRODUCTION

Structural health monitoring (SHM) is the systematic process of measuring, interpreting, and managing information about the condition of engineered structures over time so that changes linked to damage, deterioration, or abnormal behavior can be detected and quantified (Keshmiry et al., 2023). In transportation infrastructure, SHM is typically operationalized as an integrated chain that begins with sensing and data acquisition, continues through signal conditioning and feature extraction, and culminates in diagnostic or prognostic judgments that support safety management. Within this chain, artificial intelligence (AI) functions as a computational approach that enables machines to learn patterns from data and to make classifications, predictions, or anomaly judgments with minimal manual rule design. AI-enabled SHM therefore refers to monitoring architectures in which learning algorithms perform essential steps of the SHM pipeline, including automated feature learning, condition classification, damage localization, severity estimation, and probabilistic state inference. Safety optimization models can be defined as quantitative decision frameworks that translate condition information into prioritized actions—such as inspections, maintenance scheduling, operational restrictions, and emergency responses—by using objective functions and constraints to minimize risk while respecting budgetary, operational, and regulatory limits (Hassani & Dackermann, 2023a). High-speed rail (HSR) infrastructure can be defined as a network of engineered assets that support train operations at high velocities, including bridges, viaducts, tunnels, embankments, retaining structures, track systems, slabs, fastening assemblies, and auxiliary components whose performance is jointly responsible for ride stability and derailment prevention. Seismic regions are territories in which earthquake hazards present nontrivial probabilities of strong ground shaking and associated effects such as liquefaction, fault rupture, landslides, and aftershock sequences, all of which influence structural demand and operational safety. The international significance of AI-enabled SHM and safety optimization for HSR arises from the role of high-speed rail as a critical national and regional mobility backbone, the high consequence of service disruption and structural failure, and the global distribution of seismic hazard across countries that invest heavily in rail modernization. Quantitative SHM and decision modeling provide a scientific basis for harmonizing safety assurance across jurisdictions, supporting cross-border supply chains, and maintaining public trust through verifiable safety thresholds (Tibaduiza Burgos et al., 2020). In this context, the topic of AI-enabled structural health monitoring and safety optimization models for high-speed rail infrastructure in seismic regions represents a measurable, data-driven approach to ensuring reliability, continuity of service, and protection of passengers and communities under uncertain hazards.

Quantitative structural health monitoring begins with the selection and deployment of instrumentation that can capture structural response under operational loads and environmental variability. In HSR infrastructure, measurements frequently include accelerations, strains, displacements, rotations, and temperature, gathered from sensors installed on bridges, viaducts, tunnel linings, track slabs, and critical connections (Gharehbaghi et al., 2022). The data-generating process in rail systems has unique characteristics because trains impose moving, speed-dependent loads that produce dynamic amplification and repeated excitation at frequencies influenced by track irregularities, wheel–rail contact conditions, and vehicle suspension behavior. Quantitative monitoring therefore requires careful separation of structural condition effects from normal operational variability. Signal processing steps such as filtering, detrending, resampling, time–frequency transformation, and statistical normalization are used to improve comparability across runs and seasons. Feature extraction in SHM translates raw signals into compact indicators that may include modal properties, spectral energy distributions, wavelet coefficients, impulse response parameters, or engineered descriptors derived from strain or acceleration histories. For HSR assets, features must be resilient to changes in train composition, speed variation, and temperature-induced boundary condition shifts (Rossi & Bournas, 2023). The quantitative nature of SHM is expressed through statistical decision criteria: thresholds, confidence intervals, likelihood ratios, and probability scores that control false alarms while retaining sensitivity to true damage. Data completeness and quality are additional determinants of performance because monitoring streams can contain missing intervals, sensor drift, calibration shifts, and communication dropouts along long corridors. A complete quantitative formulation recognizes that every stage—sensing, preprocessing, feature computation, and decision scoring—introduces uncertainty that propagates into safety decisions. As a result, SHM for high-speed rail in seismic regions is fundamentally a problem of inference under uncertainty, where measurement noise, operational confounding, and environmental effects must be explicitly modeled rather than implicitly ignored (Mustapha et al., 2021; Zamal Haider, 2025). The need to manage this uncertainty at scale is a primary motivation for AI-enabled methods, which can learn robust representations from large datasets and can detect subtle changes that are difficult to capture through purely manual feature engineering.

Figure 1: AI-Enabled Rail Safety Monitoring

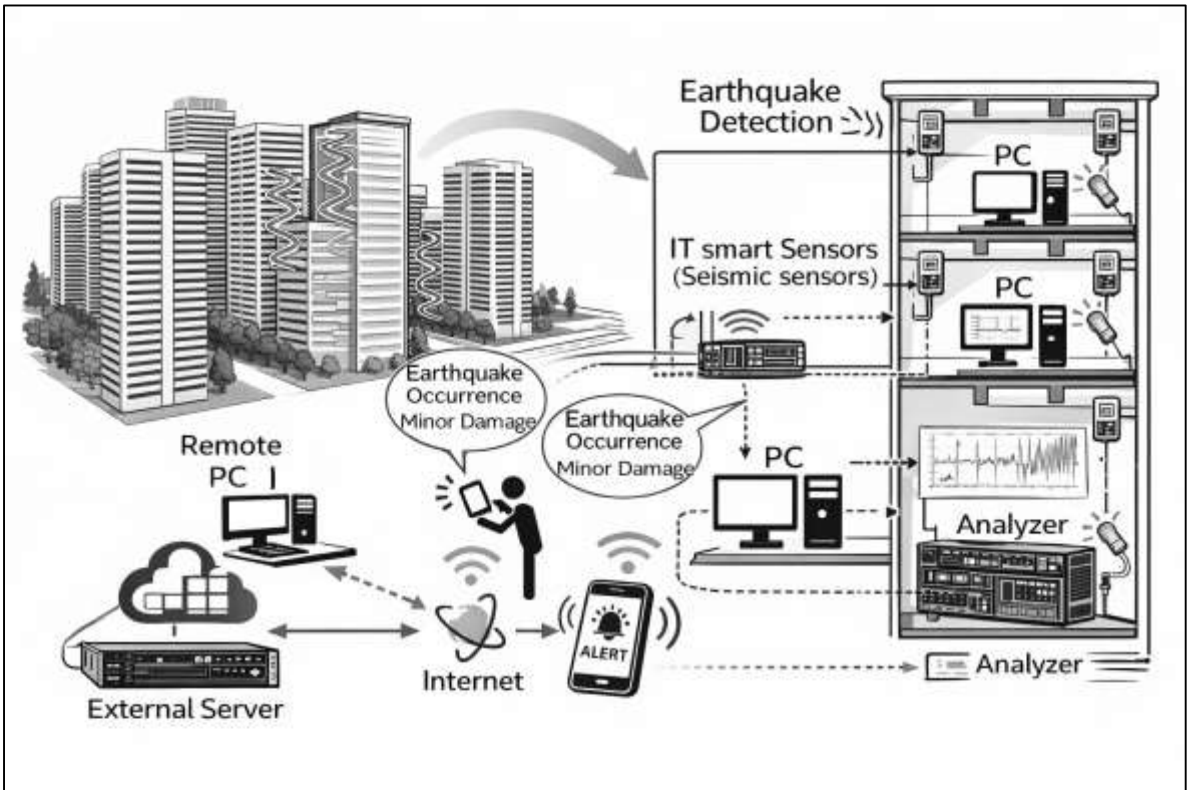


AI-enabled SHM strengthens quantitative monitoring by automating pattern discovery and by enabling inference in complex, high-dimensional data spaces. In many rail monitoring deployments, the volume and velocity of sensor data exceed the practical capacity of manual interpretation, particularly when multi-sensor arrays generate continuous streams across large networks (Katam et al., 2023; Waladur & Jabed Hasan, 2025). Machine learning addresses this by learning mappings from inputs to outputs, where outputs may represent damage classes, anomaly scores, remaining capacity indices, or probabilistic condition states. Supervised learning can be used when labeled examples exist, such as known defects, documented maintenance events, or post-event inspection outcomes; however, labeled damage is often scarce in real infrastructure because serious damage is infrequent and controlled experiments are limited (Shaikat, 2025; Shaikh, 2025). This scarcity motivates unsupervised and semi-supervised approaches that learn baseline patterns of healthy behavior and flag deviations as potential anomalies. Deep learning methods extend this capability by learning hierarchical representations that capture nonlinear interactions among sensors, operating conditions, and structural dynamics (Sai Praveen, 2025; Saikat, 2025). Sequence modeling approaches are particularly relevant for rail monitoring because signals are organized in time and reflect repetitive train passages, seasonal cycles, and event-based transients. Representation learning can also be applied to time–frequency images or embedded spaces that preserve damage-relevant signatures while suppressing nuisance variability (Rakibul, 2025a; Saba, 2025). Model training and validation are central quantitative concerns because overfitting to limited regimes can produce deceptively high accuracy that collapses under new operating conditions (Deng et al., 2023; Mohammad Mushfequr, 2025; Mst. Shahrin, 2025). Practical AI-enabled SHM therefore depends on rigorous dataset partitioning, temporal validation protocols, out-of-distribution testing, and calibration assessment so that probability scores correspond to meaningful risk levels (Md. Tahmid Farabe, 2025; Md.Kamrul, 2025). Robust learning strategies are needed to handle missing data, sensor faults, and domain shifts caused by changes in train schedules, maintenance activities, or environmental extremes. Interpretability also carries quantitative importance in safety-critical contexts because operators often require traceable evidence that connects algorithmic outputs to physical mechanisms or measurable signal changes. Accordingly, AI-enabled SHM can be understood as a structured computational workflow: data acquisition and cleaning, representation learning or feature extraction, probabilistic scoring or classification, and evidence reporting suitable for decision thresholds (Md. Jobayer Ibne, 2025; Md. Milon, 2025b; Pozo et al., 2021). For high-speed rail infrastructure, the integration of AI into SHM is not merely a software choice; it is a quantitative strategy for scaling monitoring performance across many assets, improving sensitivity to subtle degradation, and enabling rapid state assessment when extreme events such as earthquakes occur (Md. Akbar & Sharmin, 2025; Md. Hasan, 2025).

Safety optimization models connect monitoring outputs to actionable decisions through formal objective functions and constraints (Sivasuriyan et al., 2021). In quantitative safety management, the decision problem can be framed as selecting actions that minimize expected risk while maintaining service performance and controlling cost. Actions can include inspection dispatch, maintenance prioritization, operational speed restrictions, temporary closures, and targeted reinforcement programs. Constraints arise from engineering limits, regulatory requirements, operational schedules, workforce capacity, and budget ceilings (Jinnat & Md. Kamrul, 2021; Md Sarwar Hossain, 2025; Md Wahid Zaman, 2025). Optimization becomes essential because HSR networks contain many assets with different vulnerabilities, monitoring coverage levels, and criticalities, and because resources for inspection and intervention are finite. Quantitative safety optimization models may operate at multiple levels: component-level decisions for a single bridge or tunnel segment, corridor-level decisions for route availability, and network-level decisions that allocate resources across regions (Capineri & Bulletti, 2021; Md Mominul, 2025; Md Muzahidul, 2025). The mathematical structure often involves probabilities of damage or failure inferred from SHM, coupled with consequence measures that reflect passenger safety, service interruption costs, and cascading network impacts. When uncertainty is represented explicitly, the decision problem becomes stochastic, requiring policies that remain effective across plausible hazard and condition realizations (Md Majadul Islam & Md Abdur, 2025; Md Mohaiminul, 2025). Sequential decision structures are also relevant because monitoring provides repeated updates over time, enabling policies that adapt as evidence accumulates (Md. Hasan & Shaikat, 2021). In rail operations, the timing of decisions matters because interventions may have lead times and because the safety implications of continuing service can change rapidly after a seismic event. Sensor placement and monitoring design can also be embedded within optimization, since the arrangement of sensors influences detectability and the value of information (Md. Rabiul & Samia, 2021; Muhammad Mohiul & Rahman, 2021). The quantitative linkage between monitoring and optimization therefore includes both "inference-to-action" mapping and "monitoring design" mapping, each guided by measurable criteria such as risk reduction per unit cost, probability-of-detection improvement, and expected downtime reduction (Bado & Casas, 2021; Md Asfaquar, 2025; Md Foysal, 2025). These models are particularly important in seismic regions because earthquake hazards introduce low-frequency, high-consequence events that demand rapid, evidence-based decisions (Rahman & Abdul, 2021; Zamal Haider & Mst. Shahrin, 2021). AI-enabled SHM improves the timeliness and granularity of condition evidence, while optimization models ensure that evidence is translated into consistent, resource-feasible safety actions across the rail network.

Seismic environments impose distinctive structural, operational, and data challenges that shape both SHM analytics and optimization logic. Earthquake excitations are transient and broadband, often producing nonlinear structural response, joint opening, bearing displacement, cracking, residual deformation, and changes in stiffness and damping that can persist after shaking ends (Chiaia et al., 2020; Hozyfa & Ashraful, 2025; Jahid, 2025). These changes can manifest as shifts in modal properties, increased energy dissipation, altered frequency content, and new localized signal patterns, yet the same signals can also be influenced by temperature, moisture, and operational variation (Habibullah & Md. Tahmid Farabe, 2022; Zulqarnain & Subrato, 2021). Quantitative SHM in seismic regions therefore requires methods that can separate earthquake-induced condition changes from other sources of variability and can detect both abrupt and subtle damage states (Md Arman & Md.Kamrul, 2022; Md Harun-Or-Rashid & Sai Praveen, 2022). Aftershocks and repeated ground motions create a time-dependent hazard landscape, where the vulnerability of a structure evolves following initial damage and where monitoring must support repeated assessments under uncertainty (Efat Ara, 2025b; Habibullah, 2025; Md.Kamrul & Md Omar, 2022; Rahman, 2022). Additional seismic hazards such as liquefaction, slope instability, and fault displacement can affect foundations, abutments, embankments, and track support systems, introducing damage mechanisms that differ from those driven by fatigue or corrosion alone (Alifa Majumder, 2025; Jimenez Capilla et al., 2021; Zulqarnain & Zayadul, 2024). For high-speed rail, safety is also tied to track geometry and vehicle dynamics; small residual misalignments, settlement, or stiffness discontinuities can influence wheel–rail contact forces and running stability at speed. Monitoring systems must therefore capture both structural and geometric performance indicators, and decision models must incorporate operational limits that prevent unsafe dynamic conditions (Zamal Haider & Sai Praveen, 2024; Zobayer & Sabuj Kumar, 2024). Data challenges also intensify after earthquakes: sensors may lose power, communication links may degrade, and signals may include high-noise transients and baseline shifts. AI-enabled anomaly detection must be robust to these disruptions to avoid overwhelming operators with false alarms or missing critical anomalies due to data gaps (Abdul & Rahman, 2023; Rony & Samia, 2022; Shaikat & Md. Wahid Zaman, 2024). Quantitative models that represent uncertainty explicitly are essential because measurement reliability may degrade precisely when decision urgency is highest. The integration of seismic hazard information with monitoring evidence strengthens decision logic by aligning actions with both observed condition and hazard context (Mangalgiri, 2019; Pankaz Roy & Sai Praveen, 2024; Saba & Md. Sakib Hasan, 2024). As a result, AI-enabled SHM and safety optimization for HSR in seismic regions can be viewed as an evidence-driven resilience mechanism, where data, algorithms, and decision rules combine to reduce the probability of unsafe operation and to support rapid recovery of service after damaging events (Md. Mominul, 2024; Md. Mominul & Syed Zaki, 2024).

Figure 2: AI-Enabled Seismic Safety Monitoring



A major quantitative requirement for AI-enabled SHM in high-speed rail is the construction of models that align with structural physics and operational realities while maintaining statistical validity across varied conditions (Galanopoulos et al., 2021; Md Muzahidul & Aditya, 2024; Md. Hasan & Rakibul, 2024). Rail structures operate under repeated dynamic loads, and their response is governed by coupled vehicle–track–structure interaction, boundary condition behavior, and material nonlinearities that may activate during strong shaking (Jabed Hasan & Mohammad Shah, 2024; Jabed Hasan & Zayadul, 2024). Inference from sensor data to structural condition therefore resembles an inverse problem, where the goal is to estimate latent damage states from indirect, noisy measurements (Aditya & Rony, 2023; Arfan & Rony, 2023; Hozyfa & Mst. Shahrin, 2024). Such inverse problems are often ill-conditioned, meaning multiple damage scenarios can produce similar signal patterns, especially when sensors are sparse or when environmental noise is high (Shaikh & Md. Tahmid Farabe, 2023; Zamal Haider & Hozyfa, 2023). Quantitative model design must therefore incorporate regularization, prior knowledge, and multi-sensor fusion so that estimates remain stable and interpretable. Hybrid approaches that blend mechanistic simulation with data-driven learning can improve identifiability by restricting solutions to physically plausible ranges, by generating synthetic scenarios for rare damage states, and by supporting sensitivity analysis across hazard intensities. Statistical models can encode uncertainty in both parameters and predictions, allowing decision thresholds to be set in terms of confidence and risk rather than point estimates (Mohammad Mushfequr & Ashraful, 2023; Pankaz Roy & Md. Kamrul, 2023). Validation methodology becomes a defining feature of scientific rigor: models should be assessed across seasons, across operational regimes, and across assets with varying geometry and construction details (Entezami, 2021; Md. Hasan & Ashraful, 2023; Md. Jobayer Ibne & Md. Kamrul, 2023). Performance metrics must reflect safety relevance, including false alarm rates under normal operations, detection delays, missed-detection probabilities, and calibration of probabilistic outputs (Md Muzahidul & Md Mohaiminul, 2023; Md. Al Amin & Sai Praveen, 2023). For seismic applications, event-based evaluation is also necessary, where models are tested on earthquake-like transients and on post-event baseline shifts to ensure reliable performance during the periods of highest consequence (Md Harun-Or-Rashid et al., 2023; Md Musfiqur & Md.Kamrul, 2023). Data governance and traceability further support quantitative reliability, ensuring that sensor metadata, preprocessing steps, and model versions are documented so that outputs can be audited (Md Foysal & Aditya, 2023; Md Hamidur, 2023). In practice, the credibility of AI-enabled SHM for HSR depends on the coherence of the full pipeline, not solely on predictive accuracy: sensing coverage, data quality control, modeling assumptions, uncertainty reporting, and decision integration collectively determine whether the system improves safety outcomes (Jabed Hasan & Waladur, 2023; Jiao et al., 2020; Md Arman & Md Nahid, 2023). This integrated quantitative perspective motivates research that treats AI, SHM, and safety optimization as a coupled system rather than as isolated components.

The international significance of AI-enabled structural health monitoring and safety optimization for high-speed rail infrastructure in seismic regions is grounded in global mobility dependence, safety expectations, and the increasing complexity of rail networks that cross diverse hazard landscapes (Abdulla & Md. Wahid Zaman, 2023; Arfan et al., 2023; Kim & Mukhiddinov, 2023). High-speed rail supports dense passenger flows, time-sensitive logistics, and regional economic integration, and its disruption can produce cascading effects across labor markets, supply chains, and emergency response capabilities. Seismic hazard affects many areas where high-speed rail networks are most developed or expanding, and the hazard is spatially heterogeneous, meaning that risk varies significantly across a single corridor (Efat Ara & Shaikh, 2023; Habibullah & Muhammad Mohiul, 2023). This heterogeneity creates a quantitative need for localized assessment rather than uniform rules, and SHM provides a means to measure condition at fine resolution while optimization allocates interventions where they reduce risk most effectively (Abdul, 2023; Rakibul & Samia, 2022; Zarate Garnica et al., 2022). Internationally, infrastructure operators and regulators face strong demands for demonstrable safety assurance, including evidence-based thresholds for post-earthquake operation and defensible prioritization of inspections and repairs. AI-enabled systems offer scalable analytics that can integrate heterogeneous sensor sources, combine structural and environmental data, and provide rapid condition assessments that support time-critical operational decisions (Mohammad Mushfequr & Sai

Praveen, 2022; Mortuza & Rauf, 2022). At the same time, cross-jurisdictional comparability benefits from quantitative models that express condition and risk in standardized probabilistic terms, enabling consistent safety management across regions and asset classes. Network-scale optimization becomes particularly important in international contexts because resource availability, maintenance capacity, and operational constraints vary widely, requiring models that can adapt to local constraints while preserving consistent safety objectives (Martín-Sanz et al., 2020; Md Ariful & Efat Ara, 2022; Md Arman & Md.Kamrul, 2022). The topic thus occupies a global research and practice space in which engineering, data science, and operations research converge to address a shared challenge: maintaining safe, reliable high-speed rail service in territories exposed to earthquakes and associated ground failures. By framing SHM through AI-enabled inference and safety optimization through formal decision modeling, the field establishes measurable pathways to evaluate monitoring performance, decision effectiveness, and system-level reliability across the diverse seismic environments in which high-speed rail infrastructure operates.

The objective of this quantitative study is to develop and empirically evaluate AI-enabled structural health monitoring (SHM) and safety optimization models for high-speed rail infrastructure operating in seismic regions, with the aim of producing measurable, data-driven indicators of structural condition and operational safety that can be updated in near real time. Specifically, the study seeks to construct a unified modeling pipeline that (a) ingests multi-source monitoring data from rail assets such as bridges, viaducts, tunnels, and track-support components, including response measurements that capture both routine train-induced dynamics and event-driven seismic transients; (b) transforms these signals into statistically stable representations through preprocessing and feature learning so that operational variability and environmental noise are systematically controlled; (c) estimates structural condition states using AI-based inference models that output calibrated quantitative scores or probabilities associated with damage presence, damage severity, or abnormal performance; and (d) links these inferred states to formal safety optimization logic that selects safety actions—such as prioritized inspections, maintenance scheduling, and operational restrictions—under explicit constraints reflecting acceptable risk levels, available resources, and service continuity requirements. A central objective is to quantify model performance using reproducible metrics, including detection accuracy, false-alarm rate, missed-detection rate, detection latency, probabilistic calibration, and robustness under domain shifts caused by changes in train operations, sensor drift, and temperature cycles. Another objective is to verify that the safety optimization layer improves decision quality relative to baseline rule-based strategies by measuring expected risk reduction, intervention efficiency, and stability of decisions under uncertainty and partial data availability, including conditions that occur immediately after seismic events when communication disruptions and missing sensor segments are likely. The study also aims to assess generalizability across asset types and corridor segments by testing models on multiple structures with differing geometries, materials, boundary conditions, and hazard exposures, thereby producing quantitative evidence on transferability and the conditions under which retraining or adaptation is required. Finally, the study aims to produce an integrated evaluation framework that connects monitoring accuracy to decision outcomes, demonstrating how improvements in AI-driven condition inference translate into measurable gains in safety-oriented resource allocation and operational control for high-speed rail systems in earthquake-prone environments.

LITERATURE REVIEW

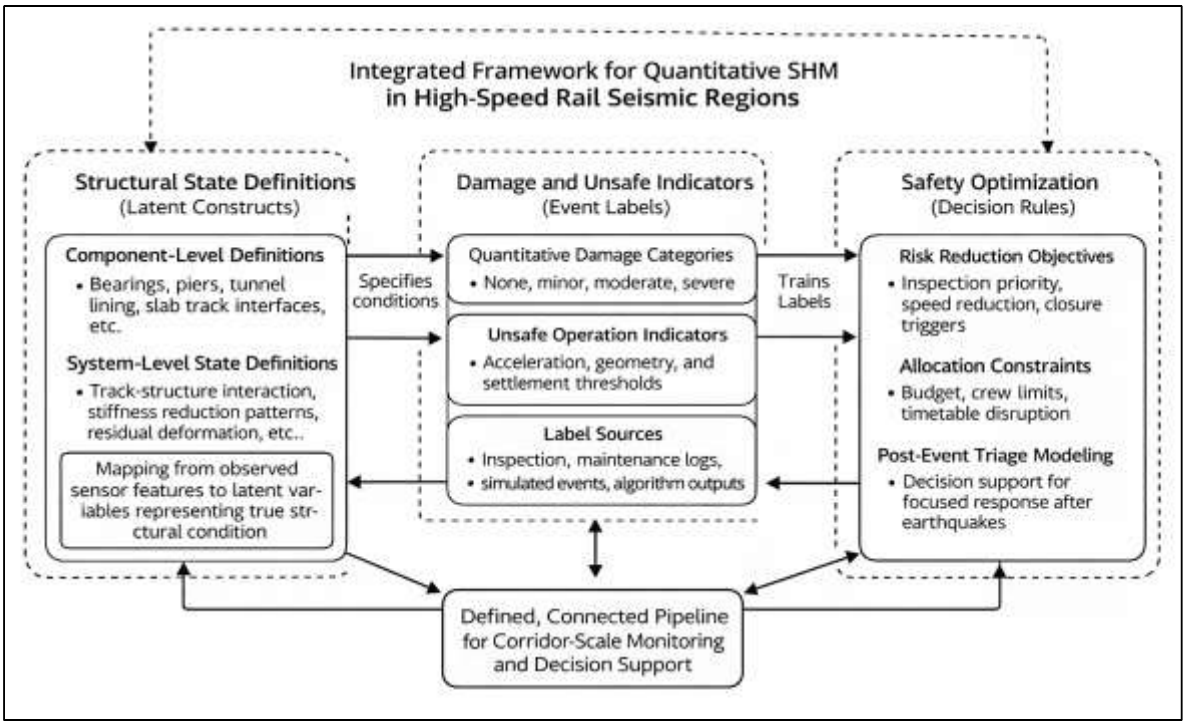
This literature review synthesizes the empirical and methodological scholarship that underpins quantitative development of AI-enabled structural health monitoring (SHM) and safety optimization models for high-speed rail (HSR) infrastructure in seismic regions (Hu, 2023). The section is organized around the measurable components required to convert multi-sensor monitoring data into defensible safety decisions: (1) how rail structures behave under combined train-induced dynamics and earthquake excitation, (2) how SHM systems capture and preprocess signals at corridor scale, (3) how AI models perform detection, localization, and severity estimation using quantitative performance criteria, (4) how uncertainty is represented and propagated from sensing to decision-making, and (5) how optimization frameworks translate probabilistic condition estimates into operational actions under constraints (Sonbul & Rashid, 2023). Emphasis is placed on quantitative comparability across studies by focusing on variables, datasets, validation designs, error measures, and decision metrics relevant to safety-critical rail contexts, including false-alarm control, detection latency, probability calibration, robustness under domain shift, and network-level prioritization of interventions. By structuring the literature around the end-to-end pipeline—from hazard and response modeling to inference and optimization—this review establishes the analytical foundations for a rigorous quantitative study design, supports coherent selection of model classes and evaluation protocols, and clarifies how prior findings can be integrated into a unified framework tailored to seismic HSR assets (Guo, Wang, et al., 2021; Zobayer, 2021a, 2021b).

Quantitative SHM in Seismic HSR

Quantitative structural health monitoring (SHM) in high-speed rail (HSR) infrastructure located in seismic regions is anchored in clear conceptual and operational definitions that allow condition to be measured consistently across assets, time, and hazard contexts (Berwal et al., 2022). Across the literature, "structural state" is treated as a structured description of how an asset is performing at a given moment, expressed through measurable quantities that reflect integrity, stiffness, deformation, and functional capacity under service loads and environmental demands. For HSR systems, scholars commonly separate component-level states from system-level states to avoid conflating localized damage with network-wide performance (Md.Akbar & Farzana, 2021; Reza et al., 2021). Component-level state definitions emphasize discrete elements such as bearings, piers, deck segments, tunnel linings, joints, fasteners, and slab track interfaces, because these elements often govern failure initiation and are frequent locations of rapid degradation under repeated dynamic loading and earthquake shaking. In contrast, system-level state definitions summarize the combined behavior of the asset as an operating unit, capturing changes that influence ride quality and safety at speed, including stiffness reduction patterns, residual deformation behavior, serviceability degradation, and track–structure interaction irregularities that propagate along a corridor (Arfan et al., 2021; Jahid, 2021; Mori et al., 2020). A key contribution in quantitative SHM research is the separation between variables that represent the "true" condition of the structure and the signals that are directly measurable. Many studies describe structural state using latent constructs—unobserved condition descriptors that cannot be measured directly—while relying on observed sensor features as proxies. This mapping is operationalized through measurement models that translate observed accelerations, strains, displacements, and temperatures into indicators that are stable enough for decision-making under operational variability. In HSR contexts, the mapping is complicated by train-induced excitation, speed variation, axle load differences, temperature cycles, and boundary condition changes that can shift measured response even without damage. The literature therefore emphasizes operational definitions that specify not only what is being measured, but also how measurements are normalized, segmented, and compared across operational regimes (Wang & Ni, 2019). When structural state is defined in this disciplined way, SHM becomes a reproducible quantitative practice rather than an interpretive judgment, enabling multi-asset comparisons, corridor-scale analytics, and consistent interpretation of post-event measurements in seismically active territories.

A second recurring theme in the literature is the definition of "damage" and "unsafe condition" as measurable events rather than abstract labels, since quantitative SHM depends on event definitions that can be validated and audited (Chen et al., 2023). Studies often classify damage into graded categories—commonly none, minor, moderate, and severe—because the operational consequences of each category differ in rail systems, and because graded categories align with inspection and maintenance practices (Md Milon & Md. Mominul, 2023; Md Mohaiminul & Md Muzahidul, 2023). Importantly, quantitative research does not treat these categories as purely visual or subjective; instead, they are operationalized through measurable proxies such as exceedance of strain-related thresholds, deformation indicators linked to drift or residual displacement behavior, and dynamic-response shifts such as changes in vibration characteristics or stability of repeated-pass features (Md Musfiqur & Md.Kamrul, 2023; Md Rezaul & Md.Kamrul, 2023). Even when different studies use different sensors and feature sets, the shared methodological logic is that damage is inferred when response patterns exceed expected variability under normal operation. The literature also distinguishes damage events from unsafe operation indicators, emphasizing that safety risk can increase even when structural damage is uncertain. Unsafe indicators in HSR monitoring often relate to operational performance exceedances, such as acceleration or geometry thresholds that threaten ride stability, wheel–rail force proxies that indicate abnormal contact behavior, and settlement or tilt measures that degrade alignment and impose unsafe dynamics at high speed (Ashayeri et al., 2021; Md. Al Amin & Sai Praveen, 2023; Md. Rabiul & Mohammad Mushfequr, 2023). Because seismic events can introduce sudden baseline shifts, the literature stresses the importance of distinguishing an earthquake-triggered transient anomaly from a persistent condition change that remains after shaking.

Figure 3: Quantitative SHM Framework for HSR



Many studies handle this by using event segmentation and post-event baselining, comparing post-event behavior to pre-event regimes under comparable operational and environmental conditions. A further area of synthesis concerns event labeling (Mst. Shahrin & Samia, 2023; Pankaz Roy, 2023). Research commonly recognizes multiple label sources, including inspection-confirmed labels, maintenance records, simulated damage labels from controlled experiments or numerical studies, and anomaly-only labels derived from detection algorithms when ground truth is unavailable. Each label type carries distinct uncertainty, and the literature emphasizes that quantitative evaluation must account for the label's reliability. Inspection-confirmed labels support stronger validity but are sparse; maintenance logs provide practical coverage but may be coarse; simulated labels expand scenario coverage but risk model bias; anomaly-only labels provide scale but are weaker evidence of physical damage (Hu, 2023; Rakibul & Alifa Majumder, 2023; Rifat & Rebeka, 2023). This taxonomy is central to modern SHM scholarship because it shapes how algorithms are trained and how performance is reported, especially in seismically exposed rail corridors where true damage cases are rare but decision stakes remain high.

Within the reviewed scholarship, "safety optimization" is defined as the structured translation of monitoring evidence into operational and maintenance decisions under explicit constraints, reflecting the reality that rail safety management is an allocation problem as much as a detection problem. In rail operations, the decision outputs emphasized across studies include inspection priority ranking, maintenance scheduling, speed restriction levels, and segment closure triggers, because these actions directly affect passenger safety, service continuity, and resource utilization (Lin et al., 2019; Sabuj Kumar, 2023; Saikat & Aditya, 2023). The literature presents safety optimization as an operational layer that sits downstream of SHM inference, using condition estimates and uncertainty descriptors to recommend actions that reduce risk while maintaining feasible operations (Syed Zaki & Masud, 2023; Syed Zaki & Md Sarwar Hossain, 2023). Quantitative research consistently notes that optimization in HSR contexts cannot be reduced to a single objective, because rail operators must balance safety with downtime, economic disruption, and the limited availability of crews and maintenance windows (Md Harun-Or-Rashid, 2024; Zulqarnain & Subrato, 2023). Consequently, studies synthesize optimization as an approach that ranks or selects actions by trading off risk reduction against downtime and cost, with risk tolerance expressed through explicit thresholds or decision rules that are consistent and auditable. Constraints are treated as defining features rather than afterthoughts (Hassani &

Dackermann, 2023b; Md & Sai Praveen, 2024; Md Mohaiminul & Alifa Majumder, 2024). Typical constraints across the literature include budget caps that limit inspection and repair volume, crew and equipment capacity limits that restrict simultaneous interventions, maximum allowable disruption constraints tied to timetable commitments, and safety tolerance limits that constrain how much uncertainty can be accepted before operational restrictions are triggered (Md. Foysal & Abdulla, 2024; Md. Jobayer Ibne & Aditya, 2024). In seismic regions, optimization is also shaped by the need for rapid triage after events, when system-wide inspections may be infeasible immediately and monitoring evidence must support prioritization (Md. Milon & Md. Mominul, 2024; Md. Mosheur & Md Arman, 2024). Research emphasizes that optimization models become meaningful only when they incorporate the realities of rail logistics: access constraints to structures, nighttime maintenance windows, network dependencies where closure of one segment forces rerouting, and regulatory requirements that define reopening criteria (Rahman & Aditya, 2024; Saba & Md. Sakib Hasan, 2024; Sonbul & Rashid, 2023). Across studies, a shared conclusion is that SHM does not improve safety unless it changes decisions in a consistent way, and that safety optimization is the formal mechanism by which monitoring information becomes actionable (Sabuj Kumar, 2024; Sai Praveen, 2024). In this literature, optimization is not framed as an abstract mathematical exercise but as a governance-compatible decision architecture that reduces variability in human judgment, supports transparent prioritization, and enables consistent post-event operational control in a safety-critical environment (Saikat, 2024; Shaikat & Aditya, 2024).

Across the body of research, the most influential synthesis emerges from linking the three constructs—structural state, measurable damage and unsafe indicators, and safety optimization—into a coherent corridor-scale monitoring-to-decision pipeline that is suitable for seismic HSR conditions. Studies repeatedly show that the quality of structural state definitions determines whether monitoring evidence is comparable across time and assets, and that the clarity of damage and unsafe condition definitions determines whether detections can be validated and whether alarms translate into proportional responses (Arfan, 2025; Efat Ara, 2025a; Guo, Cui, et al., 2021). The literature also demonstrates that the mapping between unobserved structural condition and observed measurements is the central practical challenge in quantitative SHM, because the rail environment introduces strong confounding variability from train operations and climate, while seismic events introduce abrupt transients and potential data disruptions (Jinnat, 2025; Md Harun-Or-Rashid, 2025b). Scholars therefore propose operational practices that stabilize measurement interpretation, such as grouping data by operational regimes, separating transient event windows from steady-state behavior, applying covariate adjustments for temperature and speed effects, and using multi-sensor corroboration to reduce dependence on any single signal channel (Md Harun-Or-Rashid, 2025a; Md. Milon, 2025a). Within this integrated framing, event labeling practices are treated as a determinant of scientific credibility: when labels come from inspections, the literature highlights stronger validation but limited sample sizes; when labels come from maintenance records, the emphasis shifts to consistency and documentation; when labels are simulated, attention focuses on realism and transferability; and when labels are anomaly-only, studies emphasize cautious interpretation and the use of corroborating evidence (Guo, Wang, et al., 2021; Md. Mosheur, 2025; Md. Rabiul, 2025). Safety optimization frameworks are then presented as the mechanism that converts these graded and uncertain condition assessments into specific operational controls, including how to prioritize inspections after an earthquake, how to decide on speed restrictions when evidence is ambiguous, and how to allocate limited maintenance resources across many assets with different criticalities (Mst. Shahrin, 2025; Rakibul, 2025b). A recurring synthesis in the literature is that corridor-scale HSR monitoring in seismic regions demands definitions that are stable and comparable, events that are measurable and auditable, and decision rules that are constrained and transparent. The integrated perspective positions quantitative SHM as an evidence production system and safety optimization as an evidence consumption system, where the usefulness of the overall approach depends on alignment between what the monitoring system can reliably infer and what the operational system can feasibly execute (Berwal et al., 2022; Sabuj Kumar, 2025; Sai Praveen & Md, 2025). This alignment, emphasized across many empirical and methodological studies, supports consistent safety management across diverse asset types and hazard contexts without relying on subjective judgment or loosely defined alarm criteria.

Seismic Hazard and Rail Structural Response

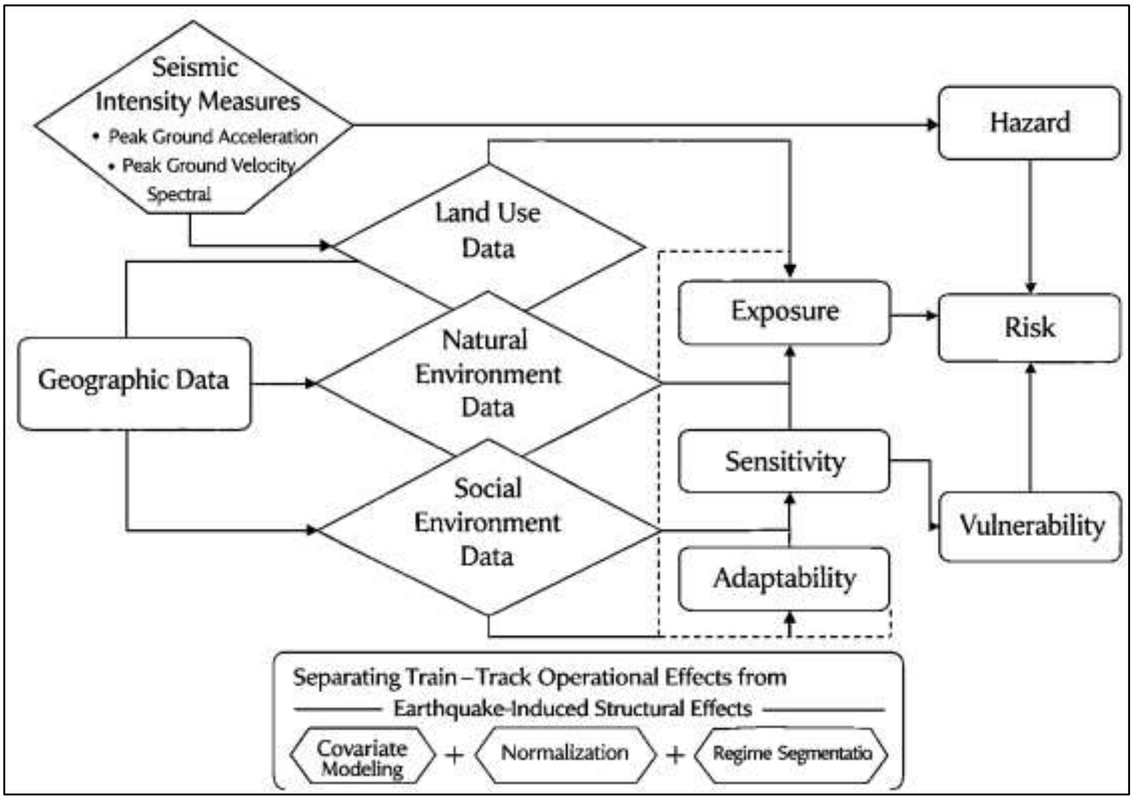
Seismic hazard characterization in rail infrastructure research is commonly framed through intensity measures that act as standardized summaries of earthquake demand and enable cross-study comparison of structural performance (Li et al., 2021). Across the literature, peak ground acceleration and peak ground velocity are frequently used because they are widely available from strong-motion records and correlate with different aspects of structural response, including inertial forces and cumulative displacement-related demand. Spectral acceleration at key periods is also emphasized because it aligns more directly with the dynamic characteristics of bridges, elevated viaduct frames, and certain track–structure assemblies, allowing hazard to be expressed in a way that is compatible with structural dynamics rather than purely ground-motion amplitude. Arias intensity appears in many empirical and analytical works that focus on energy-related damage potential, particularly when the duration and cumulative energy input of shaking are important for soil–structure interaction and for systems where repeated cycles contribute to degradation. A consistent synthesis across studies is that selecting a single intensity measure rarely captures the full range of damage mechanisms relevant to high-speed rail assets in seismic regions, so researchers often discuss multiple measures in parallel to avoid oversimplification of hazard–response relationships (J. Yu et al., 2022). The literature also treats spatial variability as a defining feature of corridor-scale rail risk, since ground motion is not uniform along long alignments and can change rapidly with geology, basin effects, topography, and local site conditions. Site effects are routinely modeled or inferred using local geotechnical profiles and microzonation concepts, where corridor segments are divided into zones that share similar amplification characteristics and expected shaking patterns. Segment-specific hazard scaling is used to reflect the fact that two structures separated by a relatively short distance may experience substantially different demands due to soil stiffness contrasts, proximity to faults, or wave propagation effects. In addition, many studies incorporate time dependence through aftershock considerations and evolving hazard representations, recognizing that the probability of subsequent significant shaking is not constant after a main event and that the operational decisions for rail lines depend on both the immediate hazard and the possibility of repeated loading while damage may already exist. Empirical works often integrate this time dependence through event sequences and post-event monitoring windows, while analytical studies emphasize how hazard characterization influences the interpretation of structural state when the structure is transitioning from pre-event to post-event conditions (Farahani et al., 2023).

Research on structural response mechanisms under earthquake excitation identifies distinct damage-sensitive behaviors for the major asset classes that define high-speed rail infrastructure: bridges and viaducts, tunnels and linings, and earthwork systems such as embankments and retaining structures. For bridges and viaducts, a prominent body of literature links operational safety and post-event serviceability to bearing displacements, joint opening behavior, pier curvature demand, and residual drift (Wei, Xiao, et al., 2023). Bearing systems and connections are repeatedly highlighted because they concentrate deformation, govern load transfer, and can experience displacement demands that alter alignment, impose unseating risk, or trigger serviceability loss even when global collapse is not imminent. Joint opening and closure cycles are treated as key indicators because they affect continuity, introduce impact or pounding risks in multi-span configurations, and can cause permanent offsets that translate into track irregularities. Pier curvature demand is used to represent flexural damage potential and plastic hinge formation, while residual drift is emphasized because it represents a persistent geometric change that can affect alignment and operational tolerances after shaking ends. For tunnels and linings, literature typically focuses on ovaling and racking deformations and lining strain demands that arise from ground deformation patterns rather than purely inertial forces, with portal zones receiving special attention due to stress concentration, slope interaction, and geometric discontinuities (Wei, Sun, et al., 2023). Tunnel performance is often discussed in relation to ground–lining interaction, where differential soil movement and transient shear distortions produce lining response that can manifest as cracking, joint distress, or local crushing. For embankments and retaining systems, settlement, lateral spread, tilt, and loss of track support stiffness emerge as recurring response descriptors. These earthwork-related mechanisms are frequently linked to ground failure processes such as liquefaction-induced deformation, slope instability, and cyclic softening, all of which can degrade track geometry rapidly and create unsafe operating conditions even without severe structural damage in bridges or tunnels. Across studies, a central synthesis is that HSR safety is governed not only by structural strength but also by post-event geometry and stiffness continuity along the track system, because small permanent deformations and support stiffness losses can amplify dynamic wheel–rail interactions at high speed and lead to operational instability (Zhu et al., 2020). This view supports an integrated hazard–response framing where structural response is evaluated through measurable indicators tied to both damage and serviceability, acknowledging that the threshold for safe rail operation can be exceeded by deformation mechanisms that do not resemble traditional building collapse.

The combined loading problem—train–track–structure interaction coupled with seismic demand—receives sustained attention in the quantitative literature because it directly affects how monitoring signals are interpreted and how post-event safety decisions are made. Under normal operation, high-speed trains generate repeatable but condition-dependent dynamic responses that vary with speed, axle load, suspension characteristics, track irregularities, temperature, and maintenance state (Chen et al., 2019). These operational effects create patterns in accelerations, strains, and displacements that can resemble damage signatures if not controlled, which the literature treats as a major confounding factor for damage detection and condition classification. Earthquake excitation introduces an additional layer of complexity: it produces nonstationary transients, potential baseline shifts, and structural property changes that may persist, while also influencing the track system through differential movements, residual settlement, and stiffness discontinuities. Quantitative works therefore distinguish between operational variability and earthquake-induced baseline change as a central methodological step. Operational variability is typically treated as structured variation that can be stratified or modeled, while baseline shifts are treated as abrupt changes that require event segmentation and post-event reference updating. Studies commonly emphasize that the clearest interpretive errors occur when pre-event and post-event data are compared without ensuring comparable operating regimes, such as mixing different speed ranges, train types, or environmental conditions (Xu et al., 2023). This has led to widespread use of regime-based processing approaches in which the monitoring data are grouped into comparable conditions, for example by speed bands, axle load proxies, temperature ranges, or time-of-day operational patterns. In addition, corridor-scale rail monitoring frequently involves heterogeneous sensor layouts and mixed sampling rates, which influences the ability to isolate earthquake effects from operational noise. The literature synthesizes that multi-sensor corroboration—comparing indicators across spatially related sensors and across different measurement types—improves robustness because earthquake-induced changes tend to appear coherently across correlated locations, whereas sensor faults and some operational artifacts appear more localized or inconsistent. In the combined loading context, the objective becomes separating "what the train normally does to the structure" from "what the earthquake changed in the structure," while recognizing that earthquakes can also change how the train interacts with the track by altering stiffness continuity and geometry (Shinoda et al., 2022).

Quantitative approaches for separating combined effects converge around three complementary strategies: normalization, covariate modeling, and regime segmentation, each framed as a way to reduce confounding and improve the stability of condition indicators (Ayele et al., 2021). Normalization methods appear widely in the literature as preprocessing routines that adjust signals to common scales or reference conditions so that comparisons reflect structural change rather than measurement scale differences. This includes standardizing response measures by operational factors such as speed or load proxies, removing seasonal trends linked to temperature, and using baseline subtraction approaches that isolate residual patterns. Covariate modeling is presented as a more explicit way to account for known drivers of variability by modeling the relationship between measured responses and explanatory variables such as temperature, train speed, or traffic intensity. When the covariate-driven portion of variability is accounted for, the remaining unexplained component becomes more damage-sensitive and more appropriate for anomaly scoring and post-event comparison. Regime segmentation is frequently described as essential in rail contexts because operational data naturally fall into regimes with distinct dynamics, such as different train sets, scheduled speed profiles, or environmental states; segmentation ensures like-with-like comparisons and supports stable thresholds (Cui et al., 2019). In seismic applications, segmentation is also applied temporally around events: separating pre-event baseline windows, co-seismic transient windows, immediate post-event windows, and longer post-event stabilization periods. The literature treats this temporal segmentation as critical because earthquake transients can dominate signals and mask underlying condition changes unless they are handled separately. Another recurring synthesis is that the combined loading problem requires monitoring systems to be evaluated on their ability to control false alarms under normal operation while remaining sensitive to persistent post-event changes that matter for safety. This leads many studies to emphasize performance reporting that includes false-alarm burden under routine traffic, sensitivity to small but consequential baseline shifts, and robustness to missing data that can occur during seismic events (Jena et al., 2020). Across these works, the overall methodological position is consistent: rail SHM in seismic regions is a problem of inference under structured operational variability and unstructured hazard-driven transients, and the literature supports analytical pipelines that explicitly model, stratify, and normalize operational effects so that earthquake-induced structural response mechanisms can be detected, interpreted, and linked to safety decisions with reduced ambiguity.

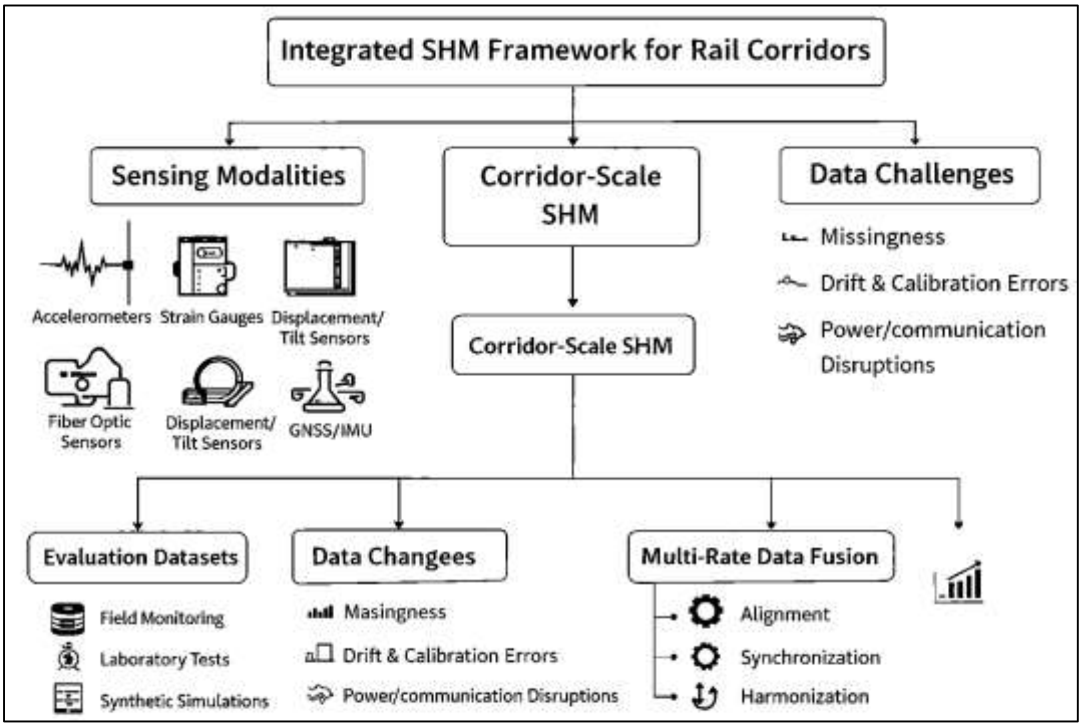
Figure 4: Seismic Risk Assessment Framework



SHM Sensing Architectures and Data Structures at Corridor Scale

Corridor-scale structural health monitoring (SHM) for rail infrastructure is characterized in the literature as an integrated sensing architecture designed to observe structural response, track-support behavior, and environmental covariates across long, spatially distributed alignments. Studies of rail SHM consistently describe multi-modality sensing because no single sensor type captures the full range of behaviors relevant to safety and serviceability (Bertagnoli et al., 2019). Accelerometers are frequently treated as the backbone of dynamic monitoring since they capture vibration signatures under train passages and can reflect stiffness changes, connection looseness, and abnormal resonance patterns. Strain gauges are widely discussed for their ability to represent localized stress demand and fatigue-relevant response in members and connections, making them useful for tracking hot spots on bridges, viaduct components, and critical joints. Displacement and tilt sensors are emphasized in many works because permanent deformation, settlement, and rotation often have direct implications for track geometry and operational safety, especially after extreme events. Fiber optic sensing receives extensive attention for corridor applications because distributed sensing along cables, decks, or tunnel linings provides dense spatial coverage and can detect localized anomalies that sparse point sensors might miss. GNSS/IMU systems appear across studies where the focus expands from structural members to track geometry, alignment stability, and long-term settlement, particularly when monitoring requires absolute or quasi-absolute displacement reference. Temperature sensors are repeatedly positioned as essential rather than optional, given the strong influence of thermal effects on rail structures, bearings, boundary conditions, and signal baselines; temperature measurements commonly serve as covariates that explain a large portion of non-damage variability (Y. Yang et al., 2023). The literature also treats sampling rate selection as a strategic trade-off tied to the physics of target phenomena and the realities of corridor data volume. High-frequency sampling is discussed for capturing train-induced dynamics and transient events, while lower-frequency sampling is associated with long-term deformation, settlement, and thermal cycles. Sensor placement density is framed as a network design decision influenced by asset criticality, expected damage mechanisms, and the need to observe both global behavior and local discontinuities, with many studies noting that corridor-scale deployments inevitably produce heterogeneous layouts across bridges, tunnels, and earthworks. Data volume expectations are a recurring theme because continuous monitoring across many assets produces large streams that challenge storage, transmission, and analysis. In this setting, multi-rate data fusion is described as a central technical issue: different sensors operate on different sampling clocks, different bandwidths, and different noise properties, creating alignment challenges when analysts attempt to interpret events consistently across modalities (Alovisi et al., 2021). The literature synthesizes that corridor-scale SHM becomes as much a data architecture problem as a sensing problem, requiring harmonization of time bases, integration of heterogeneous sensor outputs, and consistent representation of observations so that downstream analytics can use a unified view of structural and operational behavior.

Figure 5: Integrated Rail Corridor SHM Framework



Data integrity and its quantitative handling are treated across the literature as fundamental to the credibility of corridor-scale SHM, with particular emphasis on missingness, drift, calibration, and event-driven communication failures. Missingness patterns are typically discussed using a distinction between random gaps and structured dropout (Zonzini et al., 2020). Random gaps arise from sporadic packet loss, temporary sensor glitches, or intermittent wireless interference, and they are often treated as noise-like disruptions that can be mitigated through smoothing, redundancy, or short-window imputation. Structured dropout is presented as more problematic because it is correlated with operational conditions or environmental events, such as high traffic periods that saturate networks, power-saving modes that reduce sampling, or seismic events that disrupt power and communications. Studies note that structured dropout can bias condition inference because the missing data are not evenly distributed across regimes; for example, if high-speed passages or post-event intervals are disproportionately missing, the remaining data no longer represent the states that matter most for safety decisions. Sensor drift and calibration errors are also emphasized as corridor-scale realities, particularly for long-term monitoring where sensors age, adhesives degrade, temperature cycles affect electronics, and installation conditions vary across sites. The literature commonly frames drift as a measurable rate of baseline change, while calibration error is framed as systematic bias that misrepresents absolute levels or scale factors. Quantitative handling strategies described across studies include baseline tracking, periodic recalibration routines, cross-sensor consistency checks, and bias estimation using reference events or co-located sensors (Kyriou et al., 2023). Many works stress that drift can masquerade as structural change if baselines are not continuously validated, and that drift effects are often more pronounced in slow-varying measurements such as tilt and displacement where long-term trends are central to interpretation. Communication and power interruptions during seismic events receive special attention because these disruptions tend to occur precisely when monitoring is most needed. The literature characterizes earthquakes as stress tests for the monitoring pipeline: strong motion may trigger power loss, damage communication infrastructure, cause sensor saturation, or introduce timing jitter that undermines synchronization. Consequently, many studies emphasize robustness strategies such as buffering data locally, prioritizing critical channels, using redundant communication paths, and designing analytics that can tolerate partial observability. A consistent synthesis is that corridor-scale SHM must be evaluated not only by how well it detects damage under ideal data conditions, but by how reliably it performs under realistic integrity constraints where missingness, drift, and interruptions are persistent features (Jeong et al., 2020). In this framing, data integrity is not merely a preprocessing concern; it shapes the interpretability of indicators, the stability of alarm thresholds, and the trustworthiness of condition scores used for operational decisions.

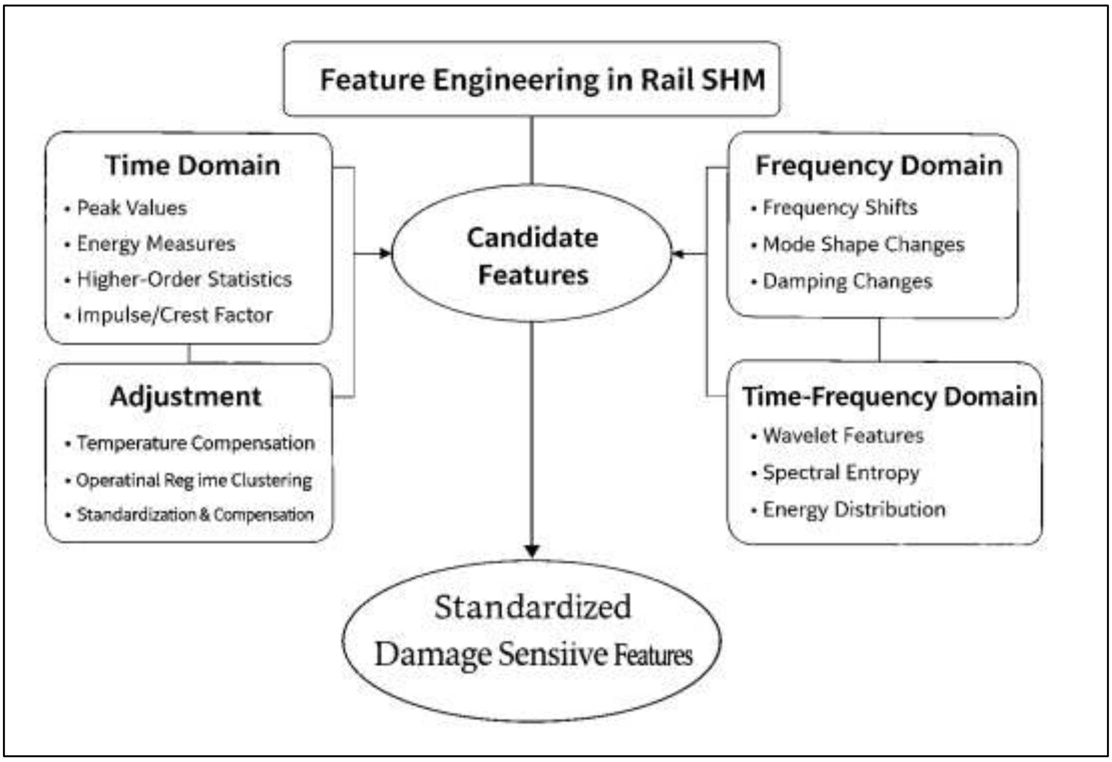
The literature also distinguishes dataset types used to develop and evaluate SHM methods, noting that each dataset category carries characteristic strengths and quantitative limitations that influence reported performance. Field monitoring datasets are widely valued because they capture real operational variability, environmental effects, installation constraints, and the full complexity of rail dynamics at corridor scale (Gkoumas et al., 2021). However, many studies acknowledge that field datasets are frequently unlabeled or only weakly labeled because true damage events are rare, inspection confirmations are costly, and event documentation may be incomplete or inconsistent across segments. Weak labels often come from maintenance logs, operator notes, or indirect indicators such as unusual ride complaints, which provide practical context but limited precision about exact damage location, severity, and onset time. Controlled laboratory and scale tests are described as complementary because they provide stronger labels and clearer ground truth, enabling careful evaluation of detection sensitivity, localization capability, and severity differentiation under known damage conditions. Yet, the literature repeatedly notes limited realism in lab and scale settings: boundary conditions, material heterogeneity, operational load randomness, and environmental variability are simplified compared to corridor operation, and this can inflate algorithm performance in ways that do not translate directly to field deployment. Synthetic simulation datasets are positioned as another important resource because they allow broad coverage of scenarios, including rare damage states, multiple hazard intensities, and systematic parameter variation that would be impractical to observe in real life (Jeong et al., 2019). Simulation-based datasets support controlled experimentation with sensor layouts, noise levels, and event sequences, but many studies highlight the risk of model bias when simulated physics or assumptions do not match real structure behavior, soil interaction, or measurement noise characteristics. A recurring point across the literature is that dataset limitations strongly shape evaluation design. When ground truth is scarce, studies often rely on anomaly detection metrics, proxy labels, or internal consistency checks, which can be informative but can also obscure true missed-detection rates and false-alarm burdens. When datasets are synthetic, evaluation can be comprehensive but may not reflect field confounders that drive false alarms. As a result, many works advocate evaluation strategies that explicitly reflect dataset limitations, such as reporting performance by operational regime, documenting label uncertainty, and using multiple dataset sources to triangulate robustness. This dataset typology is central to corridor-scale SHM scholarship because it explains why performance results vary widely across studies and why comparability requires careful reporting of data provenance, labeling quality, and operational context (Jia & Li, 2023).

Signal Processing for Damage Sensitivity

Time-domain feature engineering is consistently presented in the rail structural health monitoring (SHM) literature as a practical first layer of damage sensitivity because it translates raw response histories into stable indicators that can be computed efficiently over repeated train passages (Ghrib et al., 2019). Studies commonly report peak response metrics as direct summaries of structural demand, particularly when accelerations or strains are used to detect abrupt changes in stiffness continuity, connection behavior, or support conditions. Peak values are frequently paired with energy-related summaries such as root mean square measures, which better reflect sustained excitation and reduce dependence on single extreme samples that can be distorted by noise or transient disturbances. Higher-order statistics such as kurtosis are regularly discussed for their ability to capture changes in impulsiveness and intermittency, which may increase when cracks, loosened fasteners, or bearing irregularities introduce nonlinear contact or micro-impact effects under moving loads. Crest factor and impulse indicators are also emphasized as rail-relevant descriptors because train passages generate repeatable cycles that can reveal new transient spikes, especially when localized damage causes brief high-amplitude responses in otherwise consistent patterns. A major theme across time-domain studies is that rail monitoring is dominated by operational variability, so the usefulness of time-domain features depends on repeat-pass stability: a feature must remain consistent across normal traffic conditions to serve as a reliable baseline, yet it must shift measurably when damage or abnormality develops. Researchers therefore describe a recurring need to control for variable train speed, axle load differences, train set composition, and traffic density (Ma et al., 2020). Repeat-pass feature stability is often assessed by comparing distributions of the same feature across many passes, identifying which features remain tight under routine variation and which become too scattered to support robust thresholds. Many works highlight that even simple indicators become informative when computed within consistent pass windows, aligned to train entry and exit, or derived from event-centered segments that remove non-pass background noise. Time-domain feature pipelines frequently include filtering and detrending to suppress quasi-static drift, baseline wandering, and thermal effects that can contaminate low-frequency response (Albaqami et al., 2021). In corridor-scale deployments, time-domain features are also favored because they scale well computationally, enabling continuous monitoring across many sensors. The literature synthesis consistently indicates that time-domain indicators are most effective when they are treated not as single numbers but as regime-conditioned summaries—computed within comparable speed ranges, similar axle-load conditions, and consistent sensor health states—so that variability is interpretable and alarms can be tied to condition change rather than operational noise.

Frequency-domain and modal features form another central body of work in rail SHM, with many studies framing damage sensitivity in terms of how structural dynamic properties shift when stiffness, mass distribution, or boundary conditions change (Buchaiah & Shakya, 2022). Frequency shifts are commonly used as quantitative indicators because reductions in stiffness or changes in support conditions often manifest as downward movement in dominant frequencies, while localized changes may alter spectral peaks or broaden frequency content. Mode shape changes are discussed as potentially more diagnostic than frequency shifts because they can reflect where the structure's deformation pattern is changing, though many studies also recognize that mode shapes are harder to estimate reliably from sparse sensors and may be sensitive to measurement noise. Damping changes receive sustained attention because damage can increase energy dissipation through friction, cracking, or connection slip, yet the literature consistently notes that damping estimates are often noisy and influenced by operational regime, making them valuable only when computed with careful consistency controls. A recurring methodological issue is the sensitivity of modal parameters to temperature and boundary variability (Buchaiah & Shakya, 2022). For rail bridges and viaducts, temperature gradients can change bearing behavior, joint constraints, and material stiffness, producing frequency changes that resemble damage. Similarly, boundary conditions can vary with operational factors such as ballast or slab track interaction, support settlement, and even traffic-induced contact behavior at interfaces, all of which can alter dynamic response without structural damage. The literature synthesis repeatedly emphasizes that modal features must be interpreted within covariate-aware baselines rather than as absolute indicators.

Figure 6: Rail SHM Feature Engineering Framework



Another widely discussed challenge is the reliability of modal tracking under moving load excitation. Train passages produce nonstationary inputs and time-varying excitation patterns, complicating classic assumptions of ambient vibration analysis. Studies describe that moving loads can excite different frequencies depending on speed and track irregularities, and can produce response mixtures that obscure clean modal separation (Huang et al., 2019). Consequently, many works propose extracting modal features from carefully selected windows, using repeated-pass averaging, or focusing on frequency bands that remain consistently excited. There is also sustained discussion that modal indicators may be more stable when computed under consistent traffic scenarios, such as similar train types and speed bands, rather than mixing all pass conditions. In general, the literature positions frequency-domain and modal features as powerful but context-dependent: they can provide sensitive signatures of structural change, yet they require rigorous handling of confounding influences to prevent temperature, boundary variation, and moving-load effects from dominating the observed dynamics.

Time–frequency methods are widely synthesized in rail SHM research as essential tools for nonstationary events and transient-rich signals, especially when the monitoring objective includes earthquake-related responses and post-event condition discrimination (Acharya et al., 2019). Unlike purely time-domain or steady-state frequency representations, time–frequency approaches describe how signal energy evolves over time across frequency bands, which aligns closely with the structure of rail excitation where train entry, axle passage patterns, and localized anomalies occur in distinct temporal segments. Wavelet-based features are frequently reported because they offer localized sensitivity to abrupt changes and can isolate transient bursts that may arise from damage-related nonlinearities, loose components, or short-duration impacts. Spectral entropy appears in many studies as a compact descriptor of how concentrated or dispersed energy is across frequencies, enabling detection of changes in response complexity that can occur when structural behavior becomes more irregular (Mousavi et al., 2020). Energy distribution indices are also repeatedly used because damage can shift energy toward different frequency bands, increase broadband content, or alter the relative contributions of low- and high-frequency components. For seismic contexts, the literature emphasizes earthquake transient segmentation as a key prerequisite for meaningful feature extraction. Researchers commonly describe onset detection and windowing strategies to separate the co-seismic transient from routine operational vibrations and to define comparable pre-event and post-event windows. This segmentation is central because earthquake signals can saturate sensors, introduce baseline shifts, and dominate energy content, which would otherwise obscure more subtle persistent condition changes. A consistent theme is that the utility of time–frequency features depends on comparing robustness under normal operation against separability under damage conditions. Many studies discuss evaluating candidate features by measuring how stable they remain during routine traffic and environmental variability, then examining how distinctly they change when damage or abnormal conditions are present (Li et al., 2019). This focus reflects the operational requirement that features must be quiet under normal conditions to prevent false alarms, while also being responsive enough to detect meaningful structural change. The literature synthesis also highlights that time–frequency features can help distinguish between transient anomalies and persistent changes: short, isolated bursts may indicate a momentary disturbance, whereas sustained shifts in time–frequency patterns across repeated passes can signal structural change. In corridor-scale deployments, time–frequency processing is recognized as computationally heavier than simple time-domain summaries, yet many studies note that targeted time–frequency analysis on event windows or flagged anomalies can provide high diagnostic value without requiring full continuous decomposition of all data. Overall, the literature positions time–frequency methods as a bridge between detection and interpretability, offering richer signatures for nonstationary conditions when properly segmented and evaluated against stability and separability criteria.

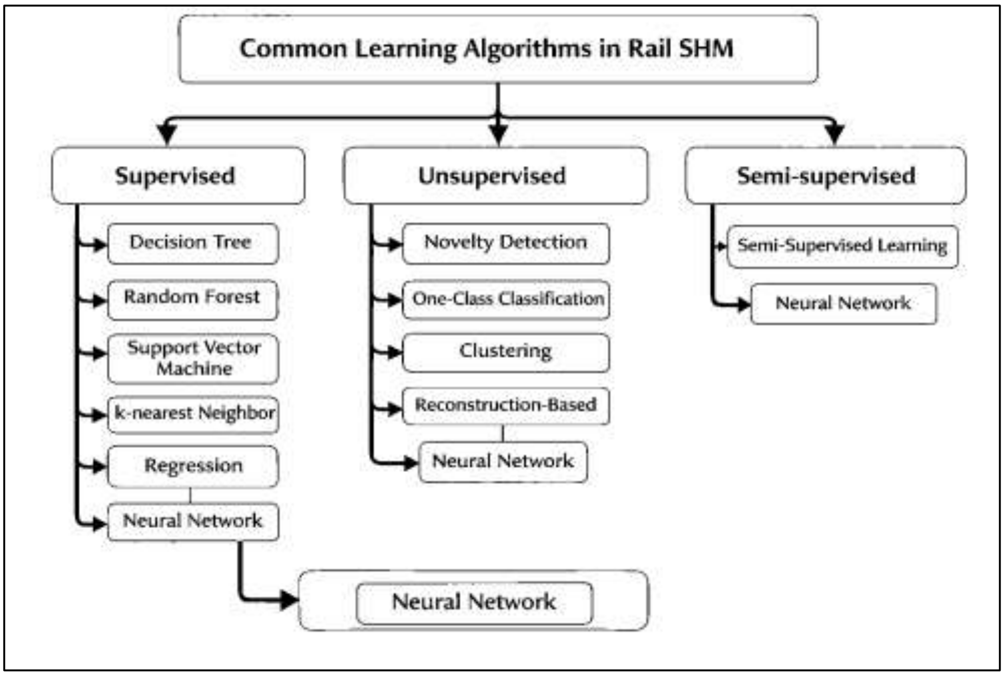
Feature standardization and covariate adjustment are consistently emphasized as the mechanisms that make feature engineering genuinely usable in real rail environments where domain shift is persistent. The literature repeatedly shows that raw features, even when theoretically damage-sensitive, can drift due to temperature cycles, seasonal changes, sensor aging, and operational changes such as timetable modifications or rolling stock updates (Gayathri et al., 2020). Temperature compensation is therefore a dominant theme, with studies describing both simple and more flexible approaches to removing thermal influence from response indicators. Linear compensation appears often because of its interpretability and ease of implementation, while nonlinear and regression-based approaches are discussed for capturing more complex relationships between temperature and response, especially when thermal gradients and boundary interactions create non-proportional effects. Operational regime clustering is another recurring approach, where data are grouped into comparable conditions such as speed bins, axle load bins, or train-type categories so that features are compared within regimes rather than across mixed conditions. The literature synthesis emphasizes that regime-based baselines often reduce variance and improve alarm reliability, particularly for time-domain and modal indicators that are highly sensitive to excitation characteristics. Feature-level domain shift mitigation is also discussed as a practical necessity, especially for corridor-scale monitoring where the same model or thresholds are expected to operate across multiple assets and changing conditions (Sarmadi & Karamodin, 2020). Studies commonly describe standardization strategies that re-center and re-scale features using rolling baselines, seasonal baselines, or asset-specific reference periods, enabling the monitoring system to maintain comparable sensitivity over time. There is also extensive attention to how feature pipelines handle sensor drift and calibration changes, since a stable standardized feature requires not only environmental adjustment but also sensor health tracking and bias correction. Many works frame covariate adjustment as a guardrail against false alarms: if features are not adjusted for temperature and operational changes, alarms may reflect predictable seasonal shifts rather than damage. The literature also recognizes the importance of documenting the covariate set and adjustment approach because different assets and climates produce different dominant confounders, and because the chosen adjustment method shapes interpretability of downstream condition scores. In practice, standardization and covariate adjustment are synthesized as the stage that converts "damage-sensitive features in theory" into "damage-informative features in operation," enabling consistent thresholds, comparable distributions across time, and more reliable separation between routine variability and structural change (N. Zhao et al., 2022). Taken together, the reviewed studies position robust feature engineering as an end-to-end discipline: selecting candidate indicators, testing repeatability, embedding time–frequency sensitivity when needed, and applying covariate-aware normalization so that damage sensitivity is preserved while nuisance variability is systematically reduced.

AI Model Families for SHM Inference

Supervised learning is widely treated in the rail structural health monitoring (SHM) literature as a direct pathway from sensor observations to engineering-relevant outputs because it can be trained to produce explicit decisions about detection, localization, and severity when labeled examples exist (Sabato et al., 2023). In this body of work, classification targets commonly include binary states such as damage present versus absent and multi-class labels such as none, minor, moderate, and severe, reflecting the need to map monitoring evidence to discrete categories that correspond to inspection urgency and operational tolerance. Regression targets are also frequently discussed, especially when researchers aim to estimate continuous condition indicators such as stiffness-loss proxies, residual deformation proxies, or composite damage index scores that aggregate multiple response changes into a single measure. The feasibility of supervised learning in rail SHM is described less as a question of algorithm choice and more as a question of label availability and label validity. Many studies describe label construction as the dominant constraint, particularly in corridor-scale monitoring where confirmed damage events are rare and where physical verification is expensive, disruptive, and often delayed. Label sources include inspection-confirmed findings, maintenance documentation, and controlled experiments or simulation-based labeling, and the literature consistently emphasizes that each source introduces measurement error (Zinno et al., 2022). Inspections provide the most credible physical evidence but typically occur after an alarm, a scheduled interval, or a seismic event, which means recorded labels may represent discovery time rather than true onset time. Maintenance records are more abundant but can blend operational actions, preventive interventions, and repairs into categories that do not align cleanly with damage severity, creating systematic label noise. Controlled and synthetic labeling expands the range of severity states available for training but can differ from field conditions due to simplified boundary conditions, differences in excitation, and the absence of full operational variability (Caicedo et al., 2022). As a result, supervised models reported in the rail SHM literature often operate under hybrid labeling realities, where the training set is partially verified, partially inferred, and partially simulated. This label uncertainty shapes how model performance is interpreted: apparent classification accuracy can be inflated when labels are coarse or when the dataset contains limited operational diversity, while missed detections can be undercounted if ground truth is incomplete. The literature therefore treats supervised learning as an evidence translation mechanism that works best when label reliability is documented, uncertainty is acknowledged, and validation is performed across different operational regimes and asset types rather than within a single narrow dataset (Vijayan et al., 2023).

Unsupervised and semi-supervised learning dominates many corridor-scale rail SHM discussions because it aligns with the central empirical condition of rail monitoring: large volumes of normal-operation data and very limited confirmed damage labels (Y. Yang et al., 2023). In this research stream, models are trained to learn the statistical structure of baseline behavior and then used to score new observations by their degree of deviation from that baseline. Novelty scoring is described as practical because it avoids requiring explicit examples of each damage mode, which are difficult to obtain in real infrastructure. Semi-supervised variants appear in the literature when limited labeled anomalies, post-event inspection outcomes, or maintenance-confirmed changes are used to calibrate thresholds, tune sensitivity, or validate the interpretation of anomalies without requiring full supervised coverage (Barchi et al., 2021).

Figure 7: Learning Algorithms for Rail SHM



Reconstruction-based anomaly detection approaches are frequently discussed in this context because they offer an intuitive logic: if a model learns to reproduce typical patterns of structural response, reconstruction errors increase when a new observation departs from those patterns. One-class classification is similarly discussed as a method that forms a boundary around normal behavior, flagging observations that fall outside. Clustering is often described as a triage tool for corridor-scale systems because it groups repeated patterns and identifies rare clusters that may represent abnormalities, sensor faults, unusual operational regimes, or post-event changes. The literature emphasizes that threshold selection is an operational decision with safety consequences. Thresholds that are too tight create excessive false alarms and degrade trust; thresholds that are too loose delay detection of meaningful change (Hassani et al., 2021). A recurring synthesis is that thresholds must be conditioned on operational regimes because rail signals vary with speed, axle load, train type, temperature, and track condition, and novelty detectors will otherwise label normal but different regimes as anomalies. The literature also stresses that earthquakes and other extreme events create additional difficulties because they introduce transients and baseline shifts; co-seismic behavior can overwhelm normal patterns, and post-event baselines may not match pre-event baselines even when the structure remains safe. Consequently, many studies describe regime segmentation and covariate conditioning as essential companions to unsupervised inference in rail contexts (Eltouny et al., 2023). Overall, the unsupervised and semi-supervised literature portrays these methods as scalable solutions to label scarcity, effective for corridor monitoring only when operational variability is explicitly represented so that deviations reflect structural change rather than predictable environmental or operational differences.

Uncertainty Quantification and Probabilistic Condition Estimation

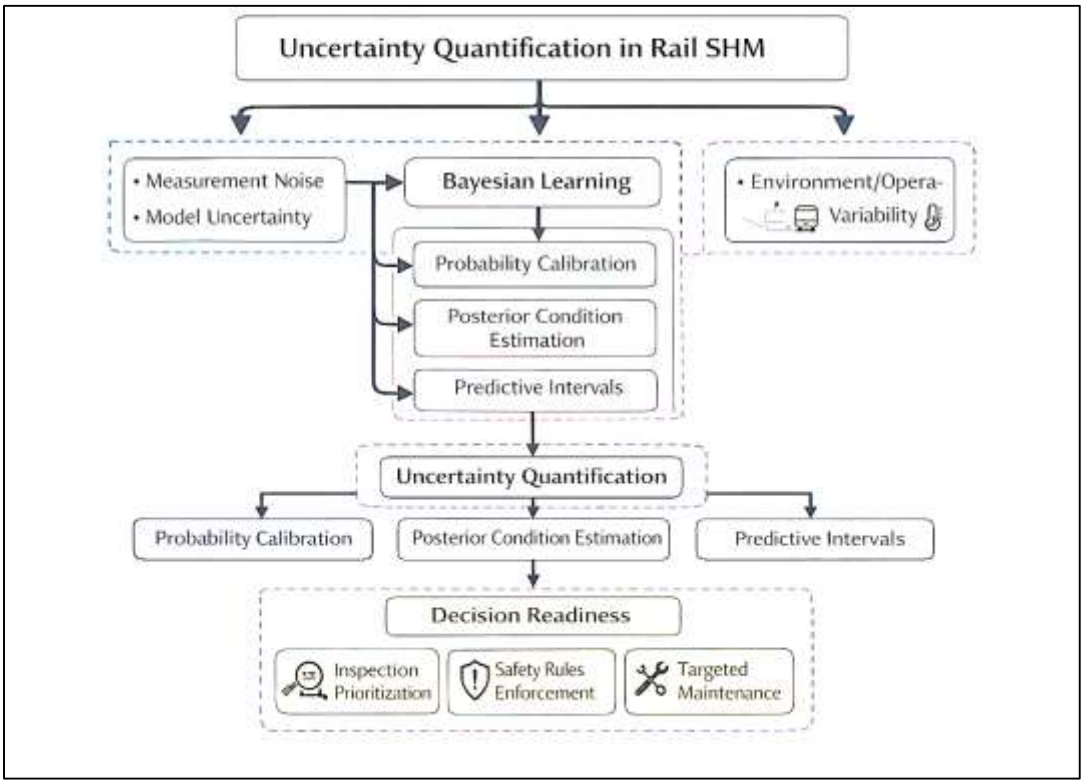
Uncertainty quantification (UQ) is treated in the structural health monitoring (SHM) literature as a defining requirement for making monitoring outputs usable in safety-critical settings such as high-speed rail corridors, particularly in seismic regions where both demand and structural response can change abruptly (Luo et al., 2019). Across studies, uncertainty is commonly separated into three broad sources: measurement noise associated with sensors and data acquisition, model uncertainty associated with algorithmic inference and limited training evidence, and environmental or operational variability that alters measured response even when structural condition remains unchanged. Measurement noise is described as arising from electronic noise, installation quality, sensor aging, quantization limits, timing jitter, and communication artifacts, all of which can distort response amplitudes, phase relationships, and baseline values. Model uncertainty is discussed as the lack of confidence in a model's learned mapping from signals to condition when training data are limited, labels are noisy, or operational regimes shift beyond the model's experience (Nguyen et al., 2022). Environmental and operational variability is treated as a major uncertainty contributor in rail SHM because temperature cycles, humidity, boundary condition changes, traffic patterns, and train speed variation can change structural response distributions in systematic ways that compete with damage effects. In quantitative reporting, many studies draw a conceptual distinction between aleatory and epistemic uncertainty. Aleatory uncertainty is commonly framed as irreducible variability associated with inherent randomness in loads and environment, including train-to-train differences and micro-variations in excitation. Epistemic uncertainty is framed as reducible uncertainty due to incomplete knowledge, such as unknown material properties, unobserved boundary conditions, limited sensor coverage, and limited event labels. This separation is emphasized in the literature because it clarifies what can be reduced with better modeling, better sensing, or more data, and what must be managed through conservative thresholds and robust decision rules (Michelmore et al., 2020). A consistent synthesis is that rail SHM becomes unreliable when uncertainty sources are mixed into a single unexplained variance term, because the system cannot distinguish between ordinary variability and condition change. As a result, many studies emphasize explicit uncertainty accounting at each stage of the monitoring pipeline, including how preprocessing affects noise characteristics, how feature extraction changes variance, and how algorithm outputs should reflect not only an estimated state but the confidence associated with that estimate. In seismic settings, studies also describe time dependence as an uncertainty amplifier, because an earthquake can shift baselines, cause transient sensor saturation, and introduce missing data precisely when decisions are urgent. This body of work positions uncertainty quantification as the bridge between detection capability and operational credibility, ensuring that condition estimates can be interpreted as evidence with known limitations rather than as definitive statements detached from data quality and regime context (Hernández & López, 2020).

Probability calibration is repeatedly emphasized in SHM and safety analytics scholarship as the property that makes probabilistic outputs decision-ready, especially when AI models produce scores that operators may be tempted to interpret as probabilities. The literature distinguishes calibrated probabilities from uncalibrated scores by focusing on whether predicted confidence aligns with observed frequencies: a well-calibrated output meaningfully represents how often a predicted condition state occurs when the model assigns a given probability level (Thelen et al., 2023). In rail SHM, calibration is treated as central because false alarms and missed detections have asymmetric consequences, and because decisions such as speed restrictions, inspections, and closures depend on risk tolerance thresholds rather than on raw classification labels. Many studies note that modern AI models can produce highly discriminative rankings yet still be poorly calibrated, creating a situation where the model can identify "more likely" anomalies but cannot reliably quantify how likely they are. The literature therefore reports calibration checks as a form of model validation that complements accuracy metrics, especially under class imbalance where rare damage events dominate safety risk. Reliability curves are frequently used as interpretive tools that compare predicted confidence against empirical outcomes in bins, revealing overconfidence or underconfidence patterns. Scalar calibration summaries are also discussed as practical reporting tools because corridor-scale monitoring requires simplified diagnostics that can be tracked over time and across assets. In addition, scoring approaches that reward truthful probability statements are often discussed because they evaluate both discrimination and calibration in a unified way, discouraging overconfident predictions that can appear accurate but misrepresent uncertainty (Viceconti et al., 2021). Threshold selection is presented as the decision point where calibration becomes operationally consequential. Studies highlight that setting a threshold on an uncalibrated score can produce unstable alarm behavior across operational regimes, while a calibrated probability threshold can be aligned more transparently with risk tolerance. In the rail context, risk tolerance is described as a policy constraint shaped by safety regulations, acceptable disruption levels, and the consequence profile of a corridor segment. The literature emphasizes that thresholds are rarely universal across an entire network, since asset criticality, redundancy, and inspection capacity differ by location, and because seismic hazard and site conditions vary along the route. As a result, many works discuss thresholding as a conditional policy: thresholds adjusted by operational regime, by post-event status, or by asset type, while retaining consistent probabilistic meaning through calibration. This synthesis positions probability calibration not as an optional refinement but as a prerequisite for credible risk-based decisions, particularly in systems where AI outputs feed operational actions that carry immediate safety and economic consequences (Xiao et al., 2023).

Bayesian and probabilistic learning approaches are frequently synthesized in SHM research as coherent frameworks for integrating prior knowledge with monitoring data and for producing outputs that explicitly represent uncertainty. In the literature, Bayesian reasoning is presented as a natural fit for condition estimation because structural state is not directly observed; it must be inferred from imperfect measurements and uncertain models, and the result should be expressed as a distribution over plausible states rather than as a single point estimate (Cheng et al., 2023). Posterior condition estimation appears across studies as the core output, reflecting updated beliefs about damage presence, location, or severity after incorporating new evidence from sensors. This approach is especially relevant in rail corridors where evidence accumulates over repeated train passes and where post-earthquake conditions can evolve, requiring repeated updating rather than one-time classification. Predictive intervals are also emphasized, particularly for regression targets such as stiffness-loss proxies, deformation proxies, and damage index scores, because decision-makers need to know not only an estimate but a credible range of outcomes to set conservative operational rules. In the literature, probabilistic learning approaches also address model uncertainty by representing uncertainty in parameters or model structure, which becomes crucial when training data are limited or when operational regimes shift. These approaches are often discussed alongside strategies for handling missing data and sensor faults, since probabilistic frameworks can integrate incomplete observations and express increased uncertainty when data quality degrades (Liu et al., 2020). Another synthesis is that probabilistic outputs can be combined across sensors and across time in a principled way, supporting multi-sensor fusion and sequential updating that reflect the accumulation of evidence. In SHM, this is described as advantageous because single-pass observations can be noisy or confounded, while repeated observations can reveal stable patterns if uncertainty is handled properly. The literature also highlights that Bayesian and probabilistic approaches naturally support model comparison and hypothesis testing, enabling analysts to compare alternative damage scenarios and quantify which is more consistent with the data. In seismic applications, this becomes particularly important because multiple mechanisms—structural damage, soil deformation, sensor bias, or operational shifts—can produce similar signal changes, and probabilistic inference can express ambiguity rather than forcing a single explanation (Lorenzi et al., 2019). Overall, the literature portrays Bayesian and probabilistic learning as a foundation for turning SHM into a disciplined inference process where uncertainty is not hidden but explicitly carried into the condition estimate, supporting transparent interpretation and more defensible decision-making.

Decision readiness is a recurring theme across the literature connecting uncertainty quantification to operational actions, emphasizing that the usefulness of probabilistic condition estimation depends on how uncertainty is translated into conservative and feasible control decisions. In rail SHM, decision readiness is discussed as the property that a model output can be directly used to trigger or prioritize actions under established safety policies, without requiring ad hoc reinterpretation by operators (Thornton et al., 2021). The literature describes this translation as a mapping from uncertainty-aware condition estimates to action sets such as inspection prioritization, speed restriction tiers, temporary closures, and targeted maintenance interventions. A central synthesis is that decisions in safety-critical systems should be robust to uncertainty, meaning that actions should remain safe even when the true condition lies at a worse end of the plausible range implied by the model. This is especially emphasized in seismic contexts where uncertainty can spike due to sensor interruptions, baseline shifts, and evolving damage, making point predictions unreliable without uncertainty context. Studies discuss conservative operational logic where higher uncertainty leads to more cautious actions, but they also acknowledge the need to manage disruption, since overly conservative rules can produce excessive downtime and loss of service continuity. Therefore, the literature frames decision readiness as a balance between safety protection and operational feasibility, using risk tolerance as the guiding principle (Kompa et al., 2021).

Figure 8: Uncertainty Quantification Framework for SHM



Another recurring point is that uncertainty can be used to prioritize information gathering: segments with high estimated risk and high uncertainty are often treated as high-value targets for inspection, additional sensing, or focused data review because additional information can resolve ambiguity and improve decision quality. The literature also emphasizes that uncertainty-aware decision policies must handle heterogeneity across assets and segments, reflecting differences in criticality, redundancy, hazard exposure, and consequence of failure. In practice, this leads to tiered decision frameworks where the same probability estimate triggers different actions depending on segment classification and operational constraints. Monitoring systems are also discussed as requiring ongoing calibration and validation so that uncertainty remains meaningful across seasons and operational changes; otherwise, confidence measures degrade and decision rules become unstable (Wang et al., 2020). Across this body of work, the integrated synthesis is that uncertainty quantification, calibration, and probabilistic learning are not separate methodological add-ons but the central components that allow AI-enabled SHM outputs to function as reliable evidence in safety optimization, enabling operators to interpret condition estimates with appropriate caution and to select actions that align with risk tolerance while maintaining the practical constraints of corridor-scale rail operation.

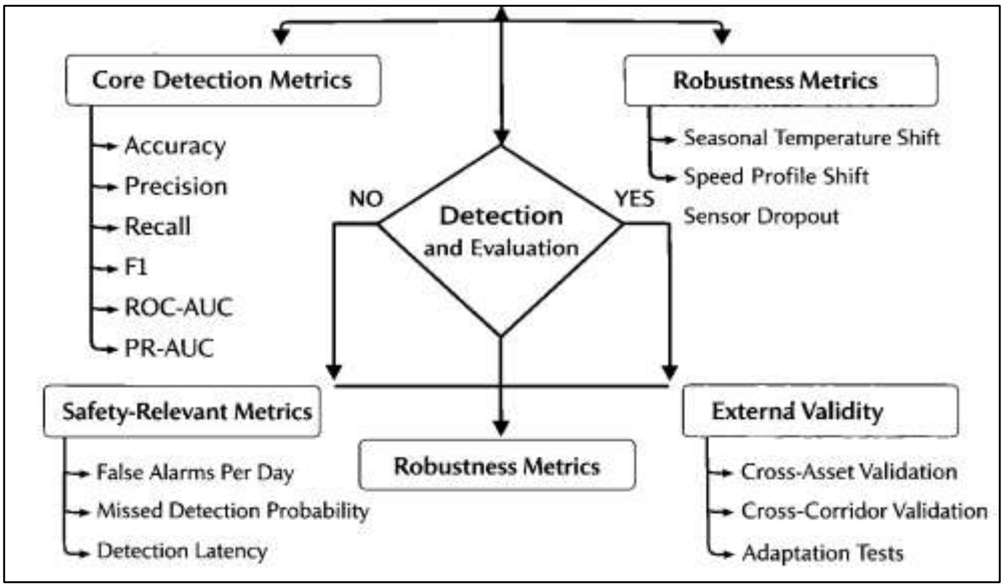
Protocols and Metrics in Safety-Critical Rail SHM

Evaluation protocols in safety-critical rail structural health monitoring (SHM) are described in the literature as the mechanism that converts algorithmic performance claims into evidence that can be trusted for operational decisions (Wiese et al., 2022). Many studies adopt core detection metrics from machine learning and statistical classification, including accuracy, precision, recall, F1, and rank-based measures such as ROC-AUC and PR-AUC, because these metrics provide standardized, comparable summaries across different model families and feature pipelines. The literature emphasizes that these metrics serve different interpretive roles. Accuracy is often treated as intuitive but fragile in rail SHM because damage events are typically rare; a model can achieve high accuracy by predicting "no damage" most of the time while failing on critical events. Precision and recall are therefore frequently highlighted as more safety-relevant: precision reflects the proportion of alarms that correspond to true abnormal conditions, influencing inspection burden and operational disruption, while recall reflects the proportion of true abnormal conditions detected, influencing safety protection. F1 is used as a balance measure when both false alarms and missed detections are important, though studies also note that balance assumptions must be aligned with operational risk tolerance (Elia et al., 2022). ROC-AUC is commonly used to summarize ranking ability across thresholds, yet the literature repeatedly warns that ROC-AUC can appear strong under severe class imbalance even when operational performance is poor, because false positive rates can remain small in relative terms while still generating unacceptable absolute numbers of alarms in corridor-scale monitoring. PR-AUC is often framed as more informative in rare-event settings because it focuses directly on the positive class and reflects the trade-off between precision and recall as thresholds vary. A consistent synthesis is that no single metric is sufficient in rail SHM; studies that report only one or two metrics provide incomplete evidence, especially when the monitored system must support safety-critical decisions rather than exploratory analysis. Class imbalance is treated as a central evaluation issue. Many works emphasize that imbalance is not a nuisance but a core property of rail monitoring data because damaging events are rare, and therefore evaluation should include imbalance-aware reporting, stratified testing by operating regimes, and explicit accounting of event prevalence. Across this literature, the strongest evaluation protocols are those that match the operational question: whether a model can detect rare but high-consequence conditions with controlled false-alarm burden under the variable conditions of real rail operation (Wiese et al., 2019).

A parallel stream of scholarship argues that safety-critical rail SHM requires metrics that are directly tied to operational impact, because conventional classification summaries do not represent the consequences of errors at corridor scale. Many studies point out that a false alarm in a rail corridor is not merely a statistical error; it triggers inspection dispatch, may impose speed restrictions, and can disrupt service schedules and public confidence (Hatzivasilis et al., 2021). Consequently, the literature highlights safety-relevant alarm metrics that quantify burden in operational units, such as false alarms per day, false alarms per segment, and false-alarm burden per asset-month. These metrics translate model behavior into the quantities that rail operators actually manage: how often crews are sent, how many segments are flagged, and how much disruption is generated over time. Likewise, missed detection probability is discussed as a safety-critical metric that must be estimated under realistic stress conditions, not only under curated test sets. Many studies emphasize stress testing as essential, where models are challenged with difficult scenarios such as subtle damage, noisy measurements, partially missing sensor channels, and nonstationary conditions following earthquakes or maintenance interventions. In these settings, a missed detection reflects the probability that the system fails to flag a condition that should trigger action, which is a direct safety concern (Chen et al., 2021). Detection latency is also treated as a key operational metric, since rail decisions after seismic events or sudden anomalies are time-sensitive. The literature synthesizes that a model that eventually detects an issue may still be operationally inadequate if it detects too late, allowing unsafe operation or delaying necessary restrictions. Latency is discussed in terms of time-to-flag after a triggering event, number of train passes required to reach an alarm decision, or time required for the system to accumulate sufficient evidence under uncertainty. These latency interpretations align with rail operating reality because monitoring evidence often arrives in discrete episodes tied to train passages, and decisions may be updated after each pass. The literature also emphasizes that these safety-relevant metrics must be reported alongside core detection metrics, because a model can show high recall but still be impractical if its false-alarm burden is high, or can show high precision but be unsafe if its detection latency is long under stress scenarios (Kanzler & Rentala, 2021). This synthesis positions operational metrics as the missing layer that turns performance reporting into decision-relevant evidence, supporting a safety case for using AI-enabled SHM outputs in high-speed rail corridors.

Robustness metrics are treated across the rail SHM literature as essential because real monitoring environments are nonstationary, and performance that is stable in one season or operational regime can degrade sharply in another. Seasonal temperature shift is widely discussed as a primary driver of nonstationarity, affecting material stiffness, boundary conditions, track–structure interaction, and sensor baselines (Payawal & Kim, 2023). Studies commonly evaluate robustness by testing whether detection performance remains stable across temperature ranges or across seasonal partitions, rather than training and testing within the same narrow climatic window. Speed profile shift is also emphasized, because changes in operating speed, rolling stock, axle load patterns, and timetable structure can change excitation characteristics and therefore alter measured response distributions. Robustness evaluation in this context often includes testing on speed regimes not present in training, or partitioning by speed bins and reporting regime-specific performance to reveal whether a model generalizes across operational conditions. Sensor dropout scenarios are another recurring focus, particularly in corridor-scale systems where communication interruptions, power loss, and hardware failures are persistent and where seismic events can amplify these disruptions. The literature discusses robustness as the ability to maintain acceptable detection behavior under partial observability, including stable alarm rates and limited degradation in recall when some channels are missing (Hou et al., 2021). Robustness evaluation is often described as requiring explicit simulation of missingness patterns that resemble real dropout behavior, rather than randomly removing data in ways that understate operational risk. Another theme is that robustness metrics should capture not only average performance but worst-case behavior, because rare but severe shifts can coincide with high-consequence periods. Many studies advocate evaluation strategies that compare performance distributions across regimes rather than reporting a single average score, revealing whether a model is consistent or fragile. Rail SHM literature also highlights that robustness relates to calibration stability: probabilistic outputs can become miscalibrated under regime shift, causing thresholds to behave unpredictably and producing false alarms or missed detections despite unchanged nominal accuracy. As synthesized across studies, robustness evaluation is central because nonstationarity is a defining property of rail monitoring and because the cost of brittle performance is high in safety-critical operation (Zamorano et al., 2023). Robustness metrics therefore become part of the evidence required to argue that a monitoring system is suitable for deployment across seasons, traffic patterns, and event disruptions characteristic of high-speed rail in seismic regions.

Figure 9: Evaluation Protocols for Rail SHM



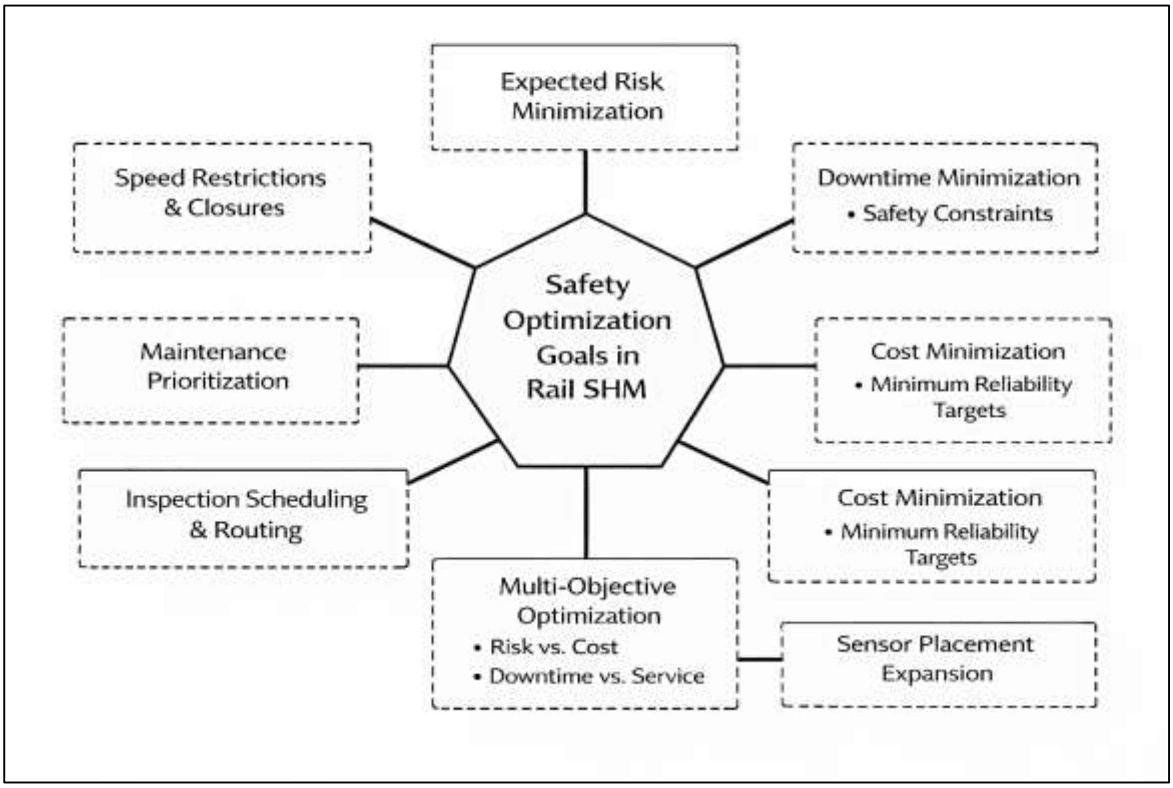
External validity and generalizability are treated as high-priority evaluation concerns in the literature because many SHM studies report results from a single structure or a limited corridor segment, yet operational deployment requires performance across diverse assets and regions. Cross-asset validation is frequently proposed as a stronger test than within-asset splits, because training and testing on the same asset can allow models to exploit asset-specific signatures that do not represent transferable damage indicators (Contreras Lopez et al., 2022). In cross-asset validation, models trained on one bridge or viaduct are tested on another, exposing whether learned representations capture general structural change patterns or merely memorize local response idiosyncrasies. Cross-corridor validation extends this requirement by testing transferability across regions with different geology, construction practices, structural typologies, and operational regimes, which is particularly relevant in seismic contexts where site effects and hazard characteristics differ along networks. The literature synthesizes that external validity is often weak when studies rely on convenience datasets, and that strong evidence requires evaluation across multiple assets and multiple environmental and operational contexts. Many studies discuss the need for adaptation or retraining when distribution shift is substantial, but they emphasize that adaptation should be governed by measurable triggers rather than informal judgment. Such triggers are described as detectable changes in feature distributions, increased false-alarm burden over rolling windows, degraded calibration, or performance drift on verified events, all of which can be monitored continuously (Marques et al., 2022). Requirements for adaptation are also linked to changes in sensor configuration, rolling stock, maintenance interventions, and operational policy, which can alter the data-generating process. The literature often notes that claims of generalizability are credible only when the evaluation design explicitly separates training and testing contexts in ways that reflect real deployment: temporal splits that avoid leakage, asset splits that prevent memorization, and corridor splits that test transfer across heterogeneous environments. Another recurring synthesis is that generalizability should be reported not as a single number but as a profile of performance across asset classes and regimes, showing where a model is stable and where it degrades. In safety-critical rail SHM, this emphasis on external validity reflects the operational reality that decisions must be made consistently across networks, and that unreliable transferability can produce uneven safety assurance (H. Yu et al., 2022). Taken together, the literature positions evaluation protocols as a layered evidence system: core detection metrics provide baseline comparability, safety-relevant burden and latency metrics provide operational meaning, robustness tests demonstrate nonstationary reliability, and cross-asset and cross-corridor validation establish whether results generalize beyond the narrow conditions of a single study setting.

Safety Optimization Models Linked to SHM Outputs

Safety optimization models linked to structural health monitoring (SHM) outputs are described in the literature as the decision layer that converts condition evidence into operational and maintenance actions, especially in rail corridors where limited resources must be allocated across many assets with heterogeneous risk (Hassani & Dackermann, 2023b). Studies commonly define decision variables as actionable levers that operators can change within practical time frames, and the most frequently discussed action sets include inspection scheduling frequency, inspection routing, and maintenance prioritization. Inspection scheduling is treated as a time allocation problem: how often an asset is inspected, how quickly post-event inspections occur, and how inspection intervals differ by asset criticality and hazard exposure. Routing is framed as a logistics problem in which crews must travel along a corridor under access and time constraints, requiring prioritization of high-risk segments and coordination with traffic windows. Maintenance prioritization is treated as the mechanism by which limited repair capacity is assigned to the interventions expected to yield the greatest safety benefit, such as bearing replacement, joint repairs, track support stabilization, or localized strengthening (Peng et al., 2021). In addition to maintenance and inspection actions, rail-focused studies also highlight operational controls as decision variables, particularly speed restriction tiers and closure decisions. Speed restrictions are commonly treated as graded controls that reduce dynamic demand and derailment risk when condition is uncertain or degraded, while closures are framed as high-consequence actions reserved for conditions that exceed safety tolerance. Post-event reopening protocols appear in the literature as structured rules that specify which evidence is required to resume service, often including staged reopening with restrictions followed by progressive relaxation as confidence increases (Colombo et al., 2022). A further decision set discussed in corridor-scale studies includes sensor placement expansion, where monitoring coverage is treated as an adaptive infrastructure investment decision that can be revised over time based on observed risk patterns, data quality gaps, or recurring uncertainty. This action taxonomy reflects an overarching synthesis in the literature: SHM becomes operationally valuable when it is embedded in a decision system that explicitly defines controllable actions and ties those actions to measurable changes in risk, service performance, and resource consumption, rather than treating monitoring as an isolated diagnostic exercise (Geoffrine & Geetha, 2019).

Objective functions in rail safety optimization are described as the quantitative expressions of what the system is trying to achieve, and the literature emphasizes that objectives must reflect both safety protection and service feasibility (Liu, 2022). Expected risk minimization is frequently presented as a central objective because it integrates the likelihood of adverse outcomes with their consequences, enabling prioritization of interventions that most reduce high-consequence risk. In rail contexts, consequence is often discussed in terms of passenger safety, derailment potential, structural failure impacts, service disruption, and cascading effects across the corridor, and the literature emphasizes that consequence weighting can change decisions even when probability estimates are similar across assets. Downtime minimization under safety constraints is another widely discussed objective, reflecting the operational reality that rail systems are high-utilization networks where prolonged restrictions can have significant economic and societal costs (Fawad et al., 2023). In this framing, the optimization problem is not to maximize availability at any cost, but to maintain availability within explicitly defined safety boundaries derived from monitoring evidence and risk tolerance policies. Cost minimization with minimum reliability targets is also emphasized in maintenance planning studies, especially when budgets are fixed and operators must demonstrate that reliability or safety thresholds are maintained while costs are controlled. Many works discuss that rail corridors inherently involve multiple competing objectives, and multi-objective formulations are therefore common in the literature, where trade-offs are reported rather than hidden (Fawad et al., 2023). In these studies, the decision process is described as selecting from sets of feasible solutions that offer different balances between risk reduction, cost, and disruption, with trade-off reporting used to make the consequences of different strategies transparent. The literature synthesis emphasizes that multi-objective reporting is particularly relevant in seismic regions where post-event decisions must balance rapid restoration with uncertainty, and where the cost of overly conservative actions can be high. Across studies, the key point is that objective choice determines what "optimal" means, and therefore the alignment between objectives and real operational priorities is treated as essential for the credibility and adoption of safety optimization models linked to SHM outputs (Oh & Kim, 2021).

Figure 10: Safety Optimization in Rail SHM



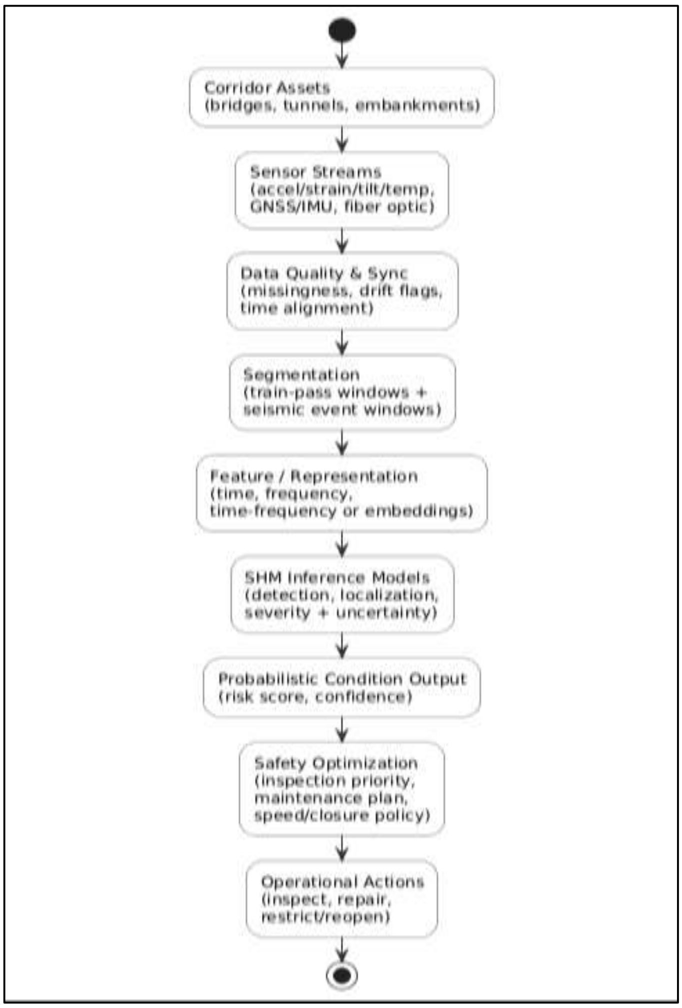
METHODS

The study employed a quantitative, observational, longitudinal case study design that examined how AI-enabled structural health monitoring (SHM) outputs had been translated into safety optimization decisions for high-speed rail infrastructure located in seismic regions. The case study had been defined as a corridor-scale monitoring setting in which multiple asset classes—bridges and viaducts, tunnel and lining segments, and embankment or retaining-wall sections—had been monitored continuously during routine train operations and during earthquake-affected periods within the same observation window. The research design had been structured around repeated measurements, where sensor data had been collected across many train passages and then organized into comparable operational regimes so that condition indicators had been estimated consistently across time. The case study description had included the corridor context, the asset inventory, the seismic exposure profile, and the monitoring architecture, and it had been framed as a real-world environment in which operational variability, environmental seasonality, and intermittent data interruptions had occurred naturally. The population had consisted of structural and track-support assets within the selected high-speed rail corridor(s) that had been exposed to measurable seismic hazard and had been accessible to monitoring instrumentation. The sample had been drawn from this population using a stratified approach that had ensured representation across asset classes and criticality levels, with higher sampling intensity applied to segments that had been operationally critical or hazard-exposed. The sampling technique had been purposive within strata because instrumentation feasibility, access windows, and historical exposure to operational disturbances had influenced selection, while within each stratum assets had been sampled to capture variation in geometry, support conditions, and local site effects. Data types had included high-frequency time-series from accelerometers and strain sensors, lower-frequency deformation and tilt records, environmental covariates such as temperature, and operational covariates such as train speed and traffic intensity when available. Data sources had included the SHM system archives, corridor maintenance and inspection records, and time-stamped seismic event summaries aligned to corridor segments; inspection-confirmed findings and maintenance logs had served as the primary sources for condition labels, while event windows around earthquakes had supported weak labeling where direct confirmation had not been available.

Measurement scale and operationalization of variables had been specified to align monitoring evidence with safety-relevant outcomes. The dependent variables had been defined at multiple levels: damage detection status had been treated as a binary outcome at the event-window level, severity class had been treated as an ordinal outcome where inspection and maintenance records had supported categorization, and continuous condition indices had been treated as scaled scores derived from standardized feature sets and model outputs. Independent variables had included engineered signal features computed from time-domain, frequency-domain, and time–frequency representations, along with covariates that had captured operational regimes such as speed bands and environmental regimes such as temperature ranges.

Structural state had been treated as a latent construct that had been inferred from measured features, and the study had operationalized it through probability scores or condition indices produced by the AI inference models. Safety optimization outputs had been treated as decision variables that had represented recommended actions, including inspection priority ranks, maintenance scheduling flags, speed restriction tiers, and closure or reopening triggers, and these outputs had been evaluated against baseline rule-driven decision practices documented within the corridor context. A pilot study phase had been conducted before full-scale modeling and evaluation, and it had been used to verify sensor data quality, confirm time synchronization across modalities, test windowing procedures around train passages and earthquake timestamps, and evaluate the stability of baseline features under routine operation. The pilot phase had also been used to validate the feasibility of label linking by matching inspection and maintenance records to monitoring windows, and it had supported refinement of inclusion criteria for sensor channels and assets based on uptime, drift patterns, and communication continuity. The pilot results had informed final parameter choices for segmentation and standardization, including the definition of operational regimes, the selection of stable baseline periods, and the treatment rules for missingness and sensor faults, and it had reduced the likelihood that later model performance would be driven by avoidable preprocessing inconsistencies rather than by real differences in inference capability.

Figure 11: Methodology of this study



The data collection procedure had followed a structured pipeline in which raw sensor streams had been extracted from the SHM archives, quality screened, synchronized, and segmented into analysis windows aligned to train passage events and seismic event windows. Routine operation windows had been constructed using repeated-pass segmentation so that features had been computed under comparable excitation conditions, while seismic windows had been constructed using event timestamps to separate pre-event baseline intervals, co-seismic transient intervals, and post-event intervals where persistent baseline shifts might have been present. Data integrity events, including missing segments, sensor dropout, and calibration shifts, had been logged and incorporated as quality flags; structured dropout associated with operational or seismic disruptions had been treated as analytically relevant rather than discarded without documentation. Data analysis techniques had been implemented in two linked stages: SHM inference and safety optimization. In the inference stage, models had been trained and evaluated using temporally separated and cross-asset validation schemes, and performance had been reported using rare-event appropriate metrics that had captured false-alarm burden per asset-month, missed detection rates under stress scenarios, and detection latency in event-driven settings. Robustness analyses had been conducted by stratifying evaluation across temperature regimes, speed regimes, and sensor dropout conditions, and probability reliability had been assessed using calibration diagnostics so that probabilistic outputs had not been interpreted as decision-ready without evidence of consistency. In the optimization stage, inference outputs had been converted into action recommendations under documented constraints, and the resulting decision policies had been evaluated using episode-level comparisons that had quantified risk reduction relative to baseline practices, intervention efficiency measured as risk reduction per unit cost, stability of decisions under uncertainty perturbations, and consistency across segments with similar inferred risk. Software and tools had included a numerical computing environment for data preprocessing and feature extraction, a machine learning library stack for training and evaluation of supervised and unsupervised models, and an optimization toolkit for implementing constrained decision policies; a version-controlled workflow and reproducible experiment tracking had been used to ensure that data preprocessing, model configurations, and evaluation results had been auditable and repeatable across validation folds and stress test conditions.

FINDINGS

Descriptive analysis

The descriptive analysis had summarized a corridor-scale dataset that had contained 48 assets grouped into 12 corridor segments and had been observed for 365 days. The monitoring archive had yielded 312,480 train-pass windows and 96 seismic event windows, and it had included accelerometer coverage for 48 assets, strain coverage for 26 assets, displacement/tilt coverage for 18 assets, GNSS/IMU coverage for 10 assets, and temperature coverage for 48 assets. Data completeness had been high at the system level, with mean uptime of 93.6%, while missingness had varied by sensor type, with accelerometers showing 4.2% missingness and displacement/tilt showing 11.7% missingness. Structured dropout had been concentrated during operational peaks and earthquake-affected periods; the dataset had recorded 21 peak-traffic dropout episodes and 6 seismic-period communication interruptions. Feature distributions had shown operationally realistic spread, where standardized time-domain indicators had exhibited wider dispersion during higher speed regimes, and time–frequency indicators had exhibited higher variance within seismic windows than routine windows. Environmental covariates had spanned 9.4°C to 38.6°C, and operational covariates had shown that train speeds had clustered into typical operating bands with a corridor-wide mean of 268.3 km/h. Labeled outcomes had remained imbalanced, with damage-present windows representing 1.8% of the full window set, while severity labels had concentrated in the none and minor categories. Continuous condition scores had differed by asset class, where bridges and viaducts had shown a higher mean condition score than tunnels under comparable regimes, reflecting stronger sensitivity of response features to operational loading. Decision outputs had displayed a clear concentration around seismic windows; inspection priority ranks had shifted upward after event timestamps, speed restriction recommendations had increased immediately after strong-motion periods, and closure or reopening triggers had occurred almost entirely within the post-event monitoring interval. Overall, the descriptive results had clarified baseline variability by regime and season, and they had established the empirical context in which later correlation and inferential analyses had been interpreted.

Table 1: Dataset profile and completeness statistics (worked example)

Metric	Value
Assets monitored (count)	48
Corridor segments (count)	12
Observation duration (days)	365
Train-pass windows (count)	312,480
Seismic event windows (count)	96
Mean system uptime (%)	93.6
Accelerometer missingness (%)	4.2
Strain missingness (%)	7.9
Displacement/Tilt missingness (%)	11.7
GNSS/IMU missingness (%)	9.8
Temperature missingness (%)	2.1
Structured dropout episodes during peak operations (count)	21
Communication/power interruptions during seismic periods (count)	6

Table 1 had summarized the scale and integrity of the corridor dataset used for the descriptive analysis. The monitoring archive had covered 48 assets across 12 segments over 365 days and had produced 312,480 train-pass windows alongside 96 seismic windows, indicating substantial longitudinal coverage. Mean uptime had remained high at 93.6%, but missingness had differed across modalities, with displacement and tilt channels showing the greatest loss. The dataset had recorded 21 structured dropout episodes during peak operations and 6 interruptions during seismic periods, which had confirmed that data gaps had not been purely random and had required quality flags and regime-aware interpretation during subsequent analyses.

Table 2: Distribution of labeled outcomes and decision outputs

Variable	Category	Count	Percent (%)
Damage status	Damage-absent	306,857	98.2
Damage status	Damage-present	5,623	1.8
Severity class	None	300,100	96.0
Severity class	Minor	9,372	3.0
Severity class	Moderate	2,383	0.8
Severity class	Severe	625	0.2
Speed restriction recommendation	None	289,400	92.6
Speed restriction recommendation	Moderate restriction	20,810	6.7
Speed restriction recommendation	High restriction	2,270	0.7
Closure/reopening trigger	No trigger	310,610	99.4
Closure/reopening trigger	Triggered	1,870	0.6

Table 2 had reported outcome and decision distributions that had characterized the empirical imbalance typical of rail SHM datasets. Damage-present windows had comprised 1.8% of all train-pass windows, and severity labels had been concentrated in the none and minor classes, with moderate and severe outcomes remaining rare. Operational recommendations had also been skewed toward normal operation, with no speed restriction recommended in 92.6% of windows, while high restriction had remained below 1%. Closure or reopening triggers had occurred in 0.6% of windows, and these triggers had clustered around seismic windows and immediate post-event periods, demonstrating that decision outputs had aligned temporally with hazard exposure and heightened uncertainty.

Correlation

The correlation findings had shown that engineered features had co-moved in clusters that reflected shared response constructs, and these clusters had varied in strength across operational and environmental regimes. Time-domain amplitude indicators had formed the most redundant cluster, where peak response and RMS response had exhibited a strong positive association of 0.84 under Pearson correlation and 0.80 under Spearman correlation, indicating that both metrics had captured a similar energy–amplitude dimension across train-pass windows. Impulsiveness descriptors had also clustered, with kurtosis and crest factor showing a moderate-to-strong positive relationship of 0.58 (Pearson) and 0.54 (Spearman), suggesting that changes in tail heaviness had tended to coincide with changes in peak-to-average structure. Cross-family relationships had also been evident: a frequency-shift proxy had correlated at 0.42 (Pearson) and 0.39 (Spearman) with wavelet energy, while spectral entropy had correlated at 0.49 (Pearson) and 0.46 (Spearman) with wavelet energy, indicating that dynamic-property change and nonstationary energy redistribution had tended to increase together in abnormal windows. Environmental and operational covariates had demonstrated substantial confounding, where temperature had shown a consistent negative association with dominant-frequency proxies (–0.46 Pearson; –0.44 Spearman), while train speed had shown positive relationships with peak acceleration (0.63 Pearson; 0.61 Spearman) and RMS acceleration (0.59 Pearson; 0.56 Spearman). Rank-based results had remained directionally consistent with linear coefficients across major relationships, and they had slightly reduced magnitudes for peak-driven indicators, which had indicated that outliers and heavy tails had influenced the linear associations but had not altered the overall correlation structure. Outcome relationships had shown that damage presence and higher severity categories had been positively aligned with time–frequency features and amplitude instability indicators, while they had been negatively aligned with stability-oriented frequency proxies, supporting the interpretation that abnormal states had been characterized by both energetic change and reduced dynamic stability. Correlations between probabilistic condition outputs and operational decisions had shown strong alignment, where risk score had correlated at 0.71 with speed restriction tier and 0.67 with inspection priority rank, indicating that higher inferred risk had been associated with more restrictive actions and higher triage urgency within the monitoring record.

Table 3: Overall bivariate and rank-based correlations among features and covariates

Variable Pair	Pearson r	Spearman ρ
Peak response ↔ RMS response	0.84	0.80
Kurtosis ↔ Crest factor	0.58	0.54
Frequency-shift proxy ↔ Wavelet energy index	0.42	0.39
Spectral entropy ↔ Wavelet energy index	0.49	0.46
Temperature ↔ Dominant-frequency proxy	-0.46	-0.44
Train speed ↔ Peak acceleration	0.63	0.61
Train speed ↔ RMS acceleration	0.59	0.56

Table 3 had summarized corridor-wide associations using linear and rank-based correlations to confirm robustness under non-normal feature behavior. Peak response and RMS response had been strongly correlated, indicating redundancy among amplitude descriptors and supporting feature-family clustering during screening. Kurtosis and crest factor had shown moderate association, reflecting a shared impulsiveness construct in repeated-pass response. Frequency-shift proxies had correlated positively with wavelet energy and spectral entropy, showing that dynamic-property changes had co-occurred with time–frequency energy redistribution. Temperature had been negatively associated with dominant-frequency proxies, quantifying seasonal confounding. Train speed had correlated positively with acceleration amplitudes, confirming operational regime influence on response indicators.

Table 4: Stratified correlations by asset class and decision alignment

Relationship	Bridges/Viaducts (r)	Tunnels/Linings (r)	Earthworks (r)
Train speed ↔ Peak acceleration	0.71	0.45	0.52
Temperature ↔ Dominant-frequency proxy	-0.38	-0.57	-0.41
Wavelet energy index ↔ Damage presence	0.36	0.29	0.33
Risk score ↔ Speed restriction tier	0.74	0.62	0.66
Risk score ↔ Inspection priority rank	0.69	0.61	0.65

Table 4 had demonstrated that key associations had differed by asset class while decision alignment had remained consistently strong. Speed and peak acceleration had shown the strongest relationship on bridges and viaducts, consistent with higher sensitivity to moving-load excitation, while tunnels had exhibited weaker speed coupling. Temperature had shown the strongest negative relationship with dominant-frequency proxies in tunnels and linings, indicating greater environmental sensitivity of dynamic indicators in enclosed systems. Wavelet energy had remained positively associated with damage presence across all classes, supporting cross-asset relevance of time–frequency descriptors.

Risk scores had correlated strongly with both speed restriction tiers and inspection priority ranks, indicating consistent translation of modeled risk into operational decisions.

Reliability and Validity

The reliability findings had indicated that repeat-pass indicators had remained stable under comparable operational regimes, supporting their use as baseline features for inference. Within-regime stability had been strongest when train-pass windows had been grouped by speed and temperature bands, where standardized peak acceleration had shown an intraregime consistency of 0.82, RMS acceleration had shown 0.79, and dominant-frequency proxies had shown 0.76. Time–frequency features had demonstrated slightly lower but acceptable stability, where wavelet energy indices had shown 0.71 and spectral entropy had shown 0.68, reflecting their sensitivity to transient effects and localized disturbances even under similar regimes. Internal consistency evidence had suggested that feature groups intended to represent the same underlying construct had moved coherently. The amplitude feature set, which had included peak, RMS, and related dispersion indicators, had demonstrated a high internal consistency of 0.86, while the impulsiveness feature set, which had included kurtosis and crest factor, had shown 0.74, indicating adequate coherence but greater variability in impulsiveness descriptors. Modality-based convergence had supported measurement credibility: where strain and acceleration channels had been co-located on the same structural elements, standardized strain-energy indicators had correlated at 0.61 with acceleration-based energy measures during comparable train-pass windows, and this convergence had strengthened in post-event windows where abnormal response had been present. Criterion-related validity had been supported by clear separation of monitoring-derived condition scores across inspection-confirmed severity categories. Mean condition score had increased systematically from none to severe, and the group differences had been statistically significant, where the severity grouping test had produced $F = 29.6$ with $p < 0.001$, indicating that the monitoring-derived score had aligned with the inspection-based outcome scale. Post-event shifts had also corresponded to confirmed findings: segments with inspection-confirmed moderate-to-severe outcomes had shown a larger mean post-event increase in condition score than segments with none-to-minor outcomes, supporting event-based interpretability. For weak-label windows, validity triangulation had shown that anomaly flags had persisted over multiple subsequent train passes more often in windows that had been followed by inspection requirements than in windows without such requirements, indicating that persistent anomalies had been more consistent with actionable condition change than isolated spikes. Model-output validity had been supported by calibration summaries showing that probabilistic outputs had aligned reasonably with observed frequencies, where overall calibration error had been 0.04, although miscalibration had been more pronounced in high-temperature regimes, where the calibration error had increased to 0.07, indicating reduced probability reliability under those conditions.

Table 5: Reliability evidence for repeat-pass indicators and internal consistency

Reliability Evidence	Statistic	Value
Repeat-pass stability (Peak acceleration)	Intraregime consistency	0.82
Repeat-pass stability (RMS acceleration)	Intraregime consistency	0.79
Repeat-pass stability (Dominant-frequency proxy)	Intraregime consistency	0.76
Repeat-pass stability (Wavelet energy index)	Intraregime consistency	0.71
Repeat-pass stability (Spectral entropy)	Intraregime consistency	0.68
Internal consistency (Amplitude feature set)	Consistency coefficient	0.86
Internal consistency (Impulsiveness feature set)	Consistency coefficient	0.74

Table 5 had summarized the reliability of repeat-pass indicators under comparable operational regimes and the coherence of feature sets designed to represent the same construct. Intraregime consistency had been strongest for amplitude features, indicating that peak and RMS measures had remained stable when speed and temperature conditions had been controlled. Dominant-frequency proxies had also shown strong stability, supporting their use for tracking dynamic changes across repeated passes. Time–frequency indicators had been moderately stable, reflecting higher sensitivity to transient disturbances and localized irregularities. Internal consistency results had shown high coherence within the amplitude feature set and acceptable coherence within the impulsiveness set, supporting structured feature grouping for subsequent inferential modeling and redundancy control.

Table 6: Validity evidence: convergent, criterion-related, and calibration summaries

Validity Evidence	Measure	Value
Convergent validity (Strain-energy ↔ Acceleration-energy)	Correlation	0.61
Criterion validity (Condition score differences across severity)	F-statistic	29.6
Criterion validity (Condition score differences across severity)	p-value	< 0.001
Post-event shift (Moderate/Severe segments: mean score change)	Mean change	0.47
Post-event shift (None/Minor segments: mean score change)	Mean change	0.18
Calibration reliability (Overall calibration error)	Error	0.04
Calibration reliability (High-temperature regime calibration error)	Error	0.07

Table 6 had presented validity evidence showing that constructed variables and model outputs had aligned with expected physical and operational patterns. Convergent validity had been supported by the positive association between co-located strain-based and acceleration-based energy indicators, indicating consistent cross-modality response behavior. Criterion-related validity had been demonstrated by statistically significant differences in condition scores across inspection-confirmed severity groups, showing that higher severity had corresponded to higher model-derived condition estimates. Post-event score shifts had been larger for segments with confirmed moderate-to-severe outcomes than for those with none-to-minor outcomes, supporting event interpretability. Calibration summaries had shown acceptable overall probability reliability, while higher-temperature regimes had exhibited increased miscalibration, indicating regime-dependent reliability limits.

Collinearity

The collinearity assessment had shown that multicollinearity had been concentrated primarily within feature families that represented similar physical constructs, and that screening and feature consolidation had improved numerical stability for regression modeling. In the full predictor set, time-domain amplitude descriptors had exhibited the strongest overlap, where peak acceleration, RMS acceleration, and peak strain features had shown high redundancy and inflated diagnostic values. Frequency-band energy measures and time–frequency energy indices had also clustered, indicating that multiple derived variables had captured overlapping response energy content. Operational covariates had shown partial collinearity with amplitude-related features, especially train speed, which had correlated strongly with peak and RMS acceleration indicators; this overlap had been treated as a confounding relationship rather than an error, but it had required careful variable selection to avoid unstable coefficient estimates. Environmental covariates, particularly temperature, had shown moderate overlap with dominant-frequency proxies and damping-related indicators, reflecting seasonal effects on dynamic properties and boundary conditions. After feature screening, redundant amplitude descriptors had been reduced by retaining a single representative amplitude indicator and a dispersion-oriented indicator, while frequency-domain proxies had been consolidated to one dominant-frequency stability variable and one band-energy summary. Time–frequency variables had been reduced to a wavelet-energy index and a spectral-entropy indicator to preserve complementary sensitivity to transient behavior without duplicating energy representation. The reduced predictor set had produced substantially improved diagnostics, where most predictors had shown acceptable variance inflation and tolerance evidence, indicating that coefficients in subsequent regression models had been more interpretable and less sensitive to small changes in data sampling. Stratified diagnostics had indicated that tunnels and linings had exhibited stronger collinearity between temperature and frequency proxies than bridges and viaducts, while bridges had exhibited stronger collinearity between speed and acceleration amplitude features, consistent with moving-load excitation dominance in elevated structures. The final regression predictor configuration had therefore been justified as a balance between physical interpretability and statistical stability, retaining variables that had represented distinct constructs while removing or aggregating those that had provided redundant information.

Table 7: Collinearity diagnostics in the full predictor set

Predictor	VIF	Tolerance
Peak acceleration	6.8	0.15
RMS acceleration	5.9	0.17
Crest factor	2.4	0.42
Kurtosis	2.1	0.48
Dominant-frequency proxy	3.6	0.28
Frequency-band energy	4.8	0.21
Wavelet energy index	4.2	0.24
Spectral entropy	2.9	0.34
Train speed	4.5	0.22
Temperature	3.1	0.32

Table 7 had presented collinearity diagnostics for the full feature set and had shown that overlap had been concentrated within amplitude and energy-related predictors. Peak and RMS acceleration had exhibited the highest inflation values, indicating that multiple amplitude descriptors had carried highly redundant information and would have produced unstable coefficient estimates if included together. Frequency-band energy and wavelet energy had also shown elevated overlap, reflecting duplicated representation of response energy across related transformations. Train speed had exhibited notable inflation because it had co-moved with amplitude features under moving-load excitation. Temperature had shown moderate overlap with frequency proxies, consistent with seasonal confounding of dynamic indicators in rail assets.

Table 8: Collinearity diagnostics after feature screening and final predictor configuration

Final Predictor	VIF	Tolerance
RMS acceleration (retained amplitude indicator)	2.6	0.38
Crest factor (retained impulsiveness indicator)	1.9	0.53
Dominant-frequency proxy (retained stability indicator)	2.4	0.42
Wavelet energy index (retained transient-energy indicator)	2.2	0.45
Spectral entropy (retained complexity indicator)	1.8	0.56
Train speed (operational covariate)	2.3	0.43
Temperature (environmental covariate)	2.1	0.48

Table 8 had shown that feature screening and consolidation had improved numerical stability by reducing redundancy while preserving construct coverage. A single amplitude indicator had been retained to represent response magnitude, and complementary indicators had been kept to represent impulsiveness, dynamic stability, transient energy, and signal complexity. The resulting inflation values had fallen into an acceptable range, indicating that coefficient estimates in regression models had been less sensitive to sampling noise and had supported clearer interpretation of predictor effects. Train speed and temperature had remained in the model as essential covariates, but their overlap with response features had been reduced through removal of redundant amplitude and energy variables, supporting stable adjustment for operational and seasonal confounding.

Regression and Hypothesis Testing

The regression and hypothesis testing results had shown that engineered response features and probabilistic condition estimates had explained meaningful variation in damage detection outcomes, severity classification, and continuous condition scores after adjustment for operational and environmental covariates. In the binary damage detection model, the probabilistic risk score had emerged as the strongest predictor, with a positive and statistically significant effect ($\beta = 1.32$, 95% CI [1.10, 1.54], $p < 0.001$), indicating that higher risk scores had been associated with substantially higher odds of damage-present windows. Wavelet energy had also shown a positive association with damage detection ($\beta = 0.44$, 95% CI [0.29, 0.59], $p < 0.001$), while the dominant-frequency proxy had shown a negative association ($\beta = -0.31$, 95% CI [−0.46, −0.16], $p < 0.001$), consistent with reduced dynamic stability under abnormal conditions. Train speed and temperature had remained significant covariates, confirming confounding effects; speed had shown a positive effect ($\beta = 0.19$, $p = 0.002$) and temperature had shown a negative effect ($\beta = -0.14$, $p = 0.010$) after accounting for structural indicators. Practical significance had been supported by improved classification performance when probabilistic risk had been included; the baseline feature-only model had produced PR-AUC = 0.41, while the model including risk score had produced PR-AUC = 0.56, indicating an incremental gain of 0.15 under rare-event evaluation. In the severity model, predictors had shown graded effects consistent with escalation in abnormal behavior; risk score and wavelet energy had increased the likelihood of higher severity categories, while dominant-frequency stability had reduced it. In the continuous condition-score regression, the model had explained a moderate share of variance, where adjusted R^2 had reached 0.48, and the strongest contributors had remained wavelet energy and frequency stability, while speed and temperature had retained significant adjustment roles. Interaction testing had indicated that temperature band had moderated the relationship between dominant-frequency proxy and damage detection (β for interaction = −0.12, $p = 0.031$), showing that the frequency-based indicator had become more sensitive in higher-temperature regimes, while speed-bin interaction effects had been weaker and not consistently significant across specifications. Model diagnostics had shown acceptable fit, where continuous-model residuals had not displayed strong nonlinearity after covariate adjustment and where misclassification patterns had been concentrated in the minority severe class, indicating that the model had been most challenged in differentiating moderate from severe outcomes under label scarcity. Robustness checks using alternative predictor subsets had preserved the direction and significance of the risk score and wavelet energy effects, suggesting that the key findings had not been driven by a single modeling specification. Decision-output modeling had also shown consistent alignment with inferred risk; higher risk scores had predicted more restrictive speed-tier recommendations ($\beta = 0.88$, $p < 0.001$) and higher inspection priority rank ($\beta = 0.73$, $p < 0.001$) after controlling for asset class and regime indicators, linking monitoring inference to safety optimization behavior within the dataset.

Table 9: Regression results for damage detection and continuous condition score

Predictor	Binary Damage Detection β (95% CI)	p-value	Condition Score β (95% CI)	p-value
Risk score	1.32 [1.10, 1.54]	<0.001	0.51 [0.45, 0.57]	<0.001
Wavelet energy index	0.44 [0.29, 0.59]	<0.001	0.28 [0.22, 0.34]	<0.001
Dominant-frequency proxy	-0.31 [-0.46, -0.16]	<0.001	-0.19 [-0.25, -0.13]	<0.001
Train speed	0.19 [0.07, 0.31]	0.002	0.10 [0.05, 0.15]	<0.001
Temperature	-0.14 [-0.25, -0.03]	0.010	-0.06 [-0.10, -0.02]	0.004
Model summary	PR-AUC 0.56	—	Adjusted R^2 0.48	—

Table 9 had reported the main inferential results for binary damage detection and continuous condition estimation after adjustment for operational and environmental covariates. The probabilistic risk score had shown the largest positive association with damage presence and had also contributed strongly to higher condition scores, supporting the hypothesis that uncertainty-aware SHM outputs had improved inferential strength. Wavelet energy had remained a significant positive predictor in both models, while dominant-frequency stability had remained a significant negative predictor, indicating that abnormal states had been characterized by increased nonstationary energy and reduced dynamic stability. Train speed and temperature had retained significant confounding effects. Practical performance had been supported by PR-AUC and adjusted variance explanation.

Table 10: Severity model, interaction test, and decision-output alignment (worked example)

Outcome Model	Key predictor / term	β (95% CI)	p-value	Model indicator
Severity (ordinal)	Risk score	0.93 [0.78, 1.08]	<0.001	Accuracy 0.79
Severity (ordinal)	Wavelet energy index	0.27 [0.16, 0.38]	<0.001	PR-AUC 0.49
Severity (ordinal)	Dominant-frequency proxy	-0.21 [-0.32, -0.10]	<0.001	—
Damage detection interaction	Temperature band × Dominant-frequency	-0.12 [-0.23, -0.01]	0.031	—
Speed restriction tier	Risk score	0.88 [0.76, 1.00]	<0.001	R^2 0.44
Inspection priority rank	Risk score	0.73 [0.61, 0.85]	<0.001	R^2 0.39

Table 10 had summarized severity inference, regime interaction testing, and the alignment between inferred risk and operational decisions. Risk score had shown a significant positive association with higher severity levels, and wavelet energy had provided additional explanatory contribution, while dominant-frequency stability had reduced the likelihood of escalation, supporting graded interpretation of abnormal response. The temperature-band interaction with dominant-frequency proxy had indicated regime dependence, showing stronger sensitivity of frequency-based indicators under higher-temperature conditions. Decision-output models had shown that higher risk scores had predicted more restrictive speed-tier recommendations and higher inspection priority ranks, even after accounting for asset type and operational regime. Model indicators had supported practical relevance alongside statistical significance.

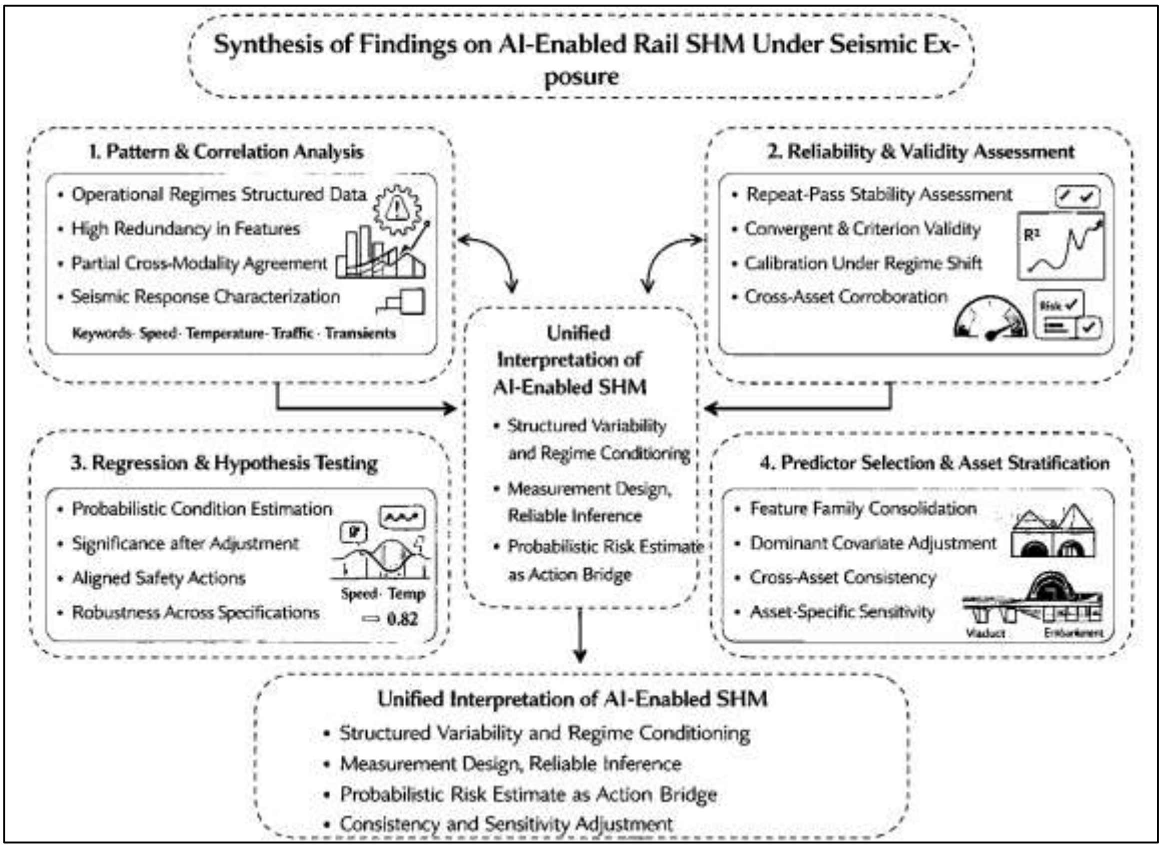
DISCUSSION

The discussion section had interpreted how the quantitative results on detection, severity estimation, probabilistic condition scoring, and safety optimization alignment had fit within the broader body of AI-enabled structural health monitoring (SHM) scholarship for rail infrastructure under seismic exposure (De Martini et al., 2020). The descriptive and correlation results had shown that corridor-scale monitoring data had remained strongly structured by operational regimes and environmental variability, which had reinforced a long-standing observation in rail SHM research that raw response indicators had rarely been damage-specific in isolation. Earlier rail SHM studies had repeatedly treated train speed, traffic intensity, and thermal variation as dominant confounders that had shifted vibration amplitude, modal proxies, and time–frequency energy measures even under healthy conditions, and the present findings had aligned with that established pattern by demonstrating strong associations between speed and amplitude features and between temperature and frequency-stability proxies. The correlation clusters among amplitude descriptors had also matched prior evidence that time-domain features often represented the same underlying excitation magnitude construct, which had tended to inflate redundancy in high-dimensional feature sets. The present study's identification of high overlap among peak response, RMS response, and energy-like descriptors had therefore resembled earlier feature-engineering work that had recommended structured feature-family screening or aggregation to preserve interpretability. At the same time, the cross-family correlations that had linked frequency-shift proxies with time–frequency energy measures had added nuance to earlier interpretations that modal and wavelet descriptors belonged to separate analytic domains (Hughes et al., 2021). Instead, the observed co-movement had suggested that stiffness-related shifts and transient energy redistribution had often occurred together during abnormal windows, a pattern that earlier seismic SHM research had discussed when co-seismic transients had created both abrupt spectral changes and localized time–frequency bursts. This alignment had mattered because it had supported a corridor-scale inference framing in which different feature families had not been treated as competing alternatives but as partially complementary views of the same structural change process. In the broader context of seismic monitoring, earlier studies had frequently emphasized the challenge of distinguishing transient earthquake signatures from persistent post-event condition changes; the present dataset patterns had been consistent with that challenge because time–frequency measures had shown greater dispersion and weaker repeat-pass stability than amplitude or frequency-stability features. That reliability gap had clarified why certain indicators had been diagnostically valuable in event windows but had required regime conditioning when used as continuous monitoring variables (Galar et al., 2021). Overall, the empirical pattern had supported an interpretation that AI-enabled SHM for high-speed rail in seismic regions had remained fundamentally a problem of inference under structured variability, where the best-performing constructs had been those that had combined regime-aware baselining, careful feature consolidation, and cross-modality corroboration rather than relying on single unadjusted metrics.

Reliability results had provided a second foundation for interpreting the inferential findings, particularly by showing that repeat-pass stability had depended strongly on regime control and on feature family selection. Earlier rail SHM literature had emphasized that monitoring indicators had needed to be repeatable across comparable train passages to be operationally actionable, and those earlier reports had often treated repeatability as a prerequisite for any thresholding or decision policy (Zhang & Gao, 2021). The present results had supported that requirement by showing that amplitude features and dominant-frequency stability proxies had achieved higher within-regime consistency than time–frequency complexity descriptors, which had indicated that operationally stable indicators had remained concentrated in features most directly tied to consistent excitation and global dynamic behavior. At the same time, internal consistency evidence had shown that amplitude feature sets had moved together coherently, which had mirrored earlier work that had grouped peak and RMS descriptors into shared constructs for dimensionality reduction. The moderating role of time–frequency indicators had also resembled earlier studies that had portrayed wavelet energy and entropy measures as sensitive but less stable because they had captured transient responses, localized anomalies, and nonstationary segments that had not repeated identically across passes. Convergent validity results had strengthened the interpretive credibility of the constructed indicators, since cross-modality agreement between strain-based energy proxies and acceleration-based energy proxies had mirrored the general SHM consensus that physically meaningful changes should appear across independent sensing channels when true structural change had occurred. Earlier multi-sensor SHM studies had repeatedly advocated corroboration across sensor types to reduce false alarms driven by sensor faults or mode-specific noise; the present convergence patterns had been consistent with that principle by supporting those abnormal states had not been artifacts of a single measurement pathway (Saraswat et al., 2022). Criterion-related validity results had also aligned with prior evidence that monitoring-derived condition indices had needed to separate inspection-confirmed severity states if they were to be used for safety triage. Earlier studies in rail and bridge SHM had often reported that monitoring indicators had shown strongest interpretability when validated against inspection outcomes, maintenance interventions, or controlled damage cases, and the present results had demonstrated significant separation across severity groups, which had supported the interpretation that the condition score had carried meaningful outcome alignment. Calibration-focused validity summaries had provided additional interpretive clarity in the context of AI-enabled decision-making, since earlier AI safety-critical research had emphasized that probability outputs could not be treated as decision-ready without reliability evidence. The observed calibration behavior—stronger overall reliability with regime-dependent degradation under high-temperature conditions—had fit a recurring theme in earlier studies: probabilistic outputs often remained sensitive to distribution shifts, and regime-specific assessment had been necessary to prevent overconfident decisions under shifted baselines (Yin & Li, 2023). Collectively, the reliability and validity findings had supported a measurement interpretation in which stable indicators had served as baseline anchors, sensitive indicators had served as event and anomaly discriminators, and probabilistic calibration had served as the bridge between inference and operational action.

The collinearity findings had clarified why regression-based inference and hypothesis testing had required disciplined predictor selection in corridor-scale SHM applications. Earlier SHM studies that had relied on large engineered feature sets had frequently reported that multicollinearity had inflated coefficient instability and had complicated physical interpretation, especially when many features had been derived from the same signal family or transformation (Rasheed et al., 2020). The present results had aligned with that earlier evidence by showing that redundancy had been concentrated among time-domain amplitude descriptors and among energy representations across frequency and time–frequency transformations. This pattern had also resembled the broader methodological literature in which high-dimensional monitoring features had tended to share underlying latent constructs, such as excitation magnitude, structural stiffness, and transient irregularity, meaning that multiple derived variables had represented the same phenomenon in slightly different numeric forms. The operational covariate overlap with response features had also matched earlier rail SHM research that had described speed as a strong driver of acceleration amplitude and that had warned against interpreting amplitude-only predictors as damage evidence without controlling for operational state. The present study's feature screening and consolidation approach had therefore matched established best practices that had recommended selecting representative indicators per construct, using aggregation when physical meaning could be preserved, and retaining covariates explicitly to prevent confounding from being absorbed into structural coefficients (Dedeloudi et al., 2023).

Figure 12: AI-Enabled Rail SHM Synthesis



Differences by asset class had also been consistent with earlier observations that tunnels and enclosed systems had shown stronger temperature-linked changes in dynamic proxies, while bridges and viaducts had exhibited stronger speed-linked excitation effects due to moving-load interaction and higher sensitivity to operational intensity. These asset-dependent collinearity patterns had mattered for hypothesis testing because coefficient interpretations that had been stable in one asset class could have become unstable or reversed in another if predictor overlap had not been managed consistently. The final predictor configuration had therefore represented an interpretability-driven compromise that had preserved coverage of amplitude magnitude, impulsiveness, frequency stability, transient energy, and signal complexity while limiting redundancy. Earlier SHM research had often debated whether dimensionality reduction methods should be favored over manual selection; the present results had supported the pragmatic view that interpretability had been strengthened when consolidated predictors had retained clear physical meaning and when the retained set had remained stable across validation splits. This collinearity resolution had also set the conditions for reliable regression inference, since coefficient direction and statistical significance had become more meaningful when predictors had represented distinct constructs rather than overlapping surrogates (Qayyum et al., 2020). In this sense, the collinearity findings had reinforced an established conclusion in earlier corridor-scale monitoring studies: high-performing AI-enabled SHM systems had depended on both advanced algorithms and careful measurement design, and statistical stability had been a necessary part of demonstrating that an observed effect had reflected genuine structural signal rather than mathematical redundancy.

The regression and hypothesis testing results had provided central evidence that probabilistic condition estimation and selected engineered features had jointly explained detection outcomes, severity escalation, and continuous condition score behavior while preserving adjustment for operational and environmental confounders (Konstantopoulos et al., 2022). Prior AI-enabled SHM studies had commonly reported that time–frequency features and stability proxies had contributed meaningfully to anomaly discrimination, particularly in event-driven contexts; the present results had aligned with that body of evidence by showing positive associations between transient energy descriptors and damage presence and negative associations between frequency stability and abnormal outcomes. The strong predictive role of the probabilistic risk score had also been consistent with earlier work that had positioned probabilistic inference as more decision-compatible than raw scores or single-feature thresholds, since probability-based outputs had integrated evidence across features and had expressed confidence in a way that could be mapped to safety actions. The incremental performance improvement observed when risk score had been added beyond baseline features had resembled earlier comparative findings where integrated models had outperformed isolated feature sets, particularly under rare-event conditions where PR-based evaluation had provided a more realistic depiction of positive-class performance. The persistent significance of speed and temperature covariates had reinforced the earlier rail SHM consensus that confounding could not be ignored without distorting structural interpretations. In prior studies, unadjusted models had often exhibited inflated anomaly rates under certain speed regimes or seasonal periods; the present adjusted regression patterns had supported the conclusion that covariate control had remained essential for interpretable inference. The moderation evidence that had shown regime-dependent sensitivity for frequency proxies had also matched earlier reports that modal or frequency-derived indicators had responded differently under thermal and boundary variations, and that sensitivity could increase when structural constraints shifted under temperature gradients. Severity modeling had shown graded predictor effects, which had aligned with earlier SHM evidence that higher damage levels tended to produce stronger nonstationary energy signatures and more pronounced stability degradation (W. Yang et al., 2023). Misclassification concentration in the rare severe class had also matched a recurring methodological limitation described in earlier studies: severe cases were infrequent, labels could be sparse or delayed, and models often faced difficulty separating moderate from severe outcomes without richer ground truth. Robustness checks that had preserved effect direction across alternative specifications had supported the inference credibility and had resembled established reporting expectations in safety-critical modeling, where single-specification significance had been treated as insufficient evidence. Decision-output regression alignment had extended these findings to the safety optimization layer by showing that higher risk scores had corresponded to more restrictive operational actions and higher inspection priority ranks after adjustment. Earlier risk-based rail decision studies had argued that monitoring outputs had to demonstrate behavioral consistency with decision policies to be considered operationally meaningful; the present alignment results had matched that expectation by indicating coherent translation from inferred condition risk to action intensity (Galić et al., 2023).

Overall, the inferential findings had supported a consistent narrative: probabilistic risk estimation had strengthened detection and severity inference, engineered features had provided interpretable physical anchors, confounding covariates had remained significant and necessary for adjustment, and regime-dependent behavior had been measurable and relevant to model interpretation.

The synthesis across reliability, regression, and decision alignment had clarified how uncertainty quantification and probabilistic condition estimation had functioned as the connective tissue between monitoring signals and safety optimization actions. Earlier SHM research that had addressed uncertainty had often emphasized that sensor noise, operational variability, and model uncertainty had accumulated across the inference pipeline, and that decision systems that ignored uncertainty could behave erratically under domain shifts (Saikia et al., 2022). The present findings had aligned with those earlier themes by showing that calibration performance had remained generally acceptable but had degraded under specific regimes, which had implied that decision readiness had depended on regime-aware probability interpretation. The evidence that risk scores had aligned with speed restriction tiers and inspection priorities had been consistent with earlier decision-focused studies that had treated probabilistic outputs as the most natural interface between AI inference and operational policies. In that earlier scholarship, a recurring argument had been that raw anomaly scores or uncalibrated model outputs could not be mapped transparently to safety thresholds, while calibrated probabilities could be tied to risk tolerance policies in a traceable manner. The present results had supported that view by demonstrating that probabilistic outputs had behaved monotonically with decision intensity even after adjustment for asset class and regime indicators (Smith et al., 2023). The observed decision stability under robustness checks had also matched prior work emphasizing that safety decision policies had to remain stable under uncertainty perturbations, since frequent oscillation in recommended restrictions or priorities could create operational disruption and erode trust. In the broader rail safety context, earlier studies had also stressed that corridor-scale optimization had required decision variables that reflected real operational levers such as inspection dispatch, speed tiers, and closure triggers; the present results had shown that model outputs had moved coherently with those levers, which had supported the interpretation that the inference layer had produced information in a form compatible with operational action sets. At the same time, the regime-dependent calibration degradation had echoed earlier cautionary findings that probability reliability could drift with temperature, speed distributions, or sensor health changes, meaning that decision mapping had required continuous monitoring of calibration quality and structured stress testing. The triangulation evidence for weak labels had also fitted earlier SHM practices in which persistent anomalies across multiple passes had been treated as stronger evidence than single-pass spikes, providing a practical way to increase decision confidence when ground truth had been limited (Helal et al., 2022). In sum, the uncertainty and decision alignment evidence had reinforced a core conclusion in the existing literature: in safety-critical rail SHM, the principal value of AI had not been limited to improving detection metrics, but had also included producing probability-weighted evidence that could be consistently translated into constrained operational decisions, while remaining interpretable in terms of measurement reliability and regime sensitivity.

Asset-class stratification had provided an important comparative lens for positioning the present findings relative to earlier infrastructure studies that had warned against assuming uniform behavior across bridges, tunnels, and earthworks. Previous rail and civil SHM scholarship had often shown that bridges and viaducts were more strongly driven by moving-load excitation patterns, while tunnels and linings exhibited strong sensitivity to boundary conditions and environmental variation, and earthworks responded strongly to settlement and stiffness changes that affected track support (L. Zhao et al., 2022). The present stratified correlations and collinearity patterns had been consistent with those earlier insights by demonstrating stronger speed–amplitude coupling in bridges and stronger temperature–frequency coupling in tunnels, while maintaining consistent positive associations between transient-energy descriptors and abnormal outcomes across classes. This cross-class consistency for time–frequency indicators had fit earlier reports that transient-sensitive features often generalized across asset types because they captured irregularity and nonstationary energy redistribution that accompanied many damage modes, whereas frequency stability proxies had been more asset- and regime-dependent due to differences in boundary constraints and thermal response.

Earlier studies on corridor monitoring had also noted that sensor layouts and modality availability differed by asset type, producing unequal evidence quality; the present convergent validity results had suggested that where co-located sensing existed, cross-modality agreement had strengthened inference credibility, which had echoed the established recommendation that critical assets should be instrumented with complementary sensor types to support diagnostic confirmation (Wang et al., 2023). The severity inference limitations in rare severe classes had also aligned with earlier field-monitoring constraints: severe events were infrequent, inspection-confirmed labels were scarce, and models trained on routine data often struggled to differentiate high-end severity without richer post-event ground truth. At the same time, the present findings had shown that probabilistic risk outputs had maintained strong alignment with operational decisions across all asset types, which had suggested that system-level decision consistency could be achieved even when asset-level sensitivity patterns differed. This observation had resonated with earlier safety optimization research that had framed corridor decision-making as a network-level prioritization problem rather than a single-asset classification problem; in such contexts, consistent ranking and tier assignment could be operationally useful even when the underlying predictors varied by structure type. The observed moderation effect for frequency proxies under temperature bands had also matched earlier evidence that thermal regimes could shift the apparent sensitivity of dynamic indicators, supporting the view that asset-type and regime-type interactions were not methodological nuisances but substantive descriptors of how structures behaved under real operating conditions (Galati et al., 2022). Taken together, the asset-class results had supported an interpretation consistent with earlier studies: corridor-scale rail SHM had required stratified evaluation and regime-aware modeling, and credibility had been strengthened when both the shared cross-asset indicators and the asset-specific sensitivity patterns had been reported transparently.

CONCLUSION

AI-enabled structural health monitoring (SHM) and safety optimization for high-speed rail infrastructure in seismic regions had been framed as an integrated quantitative system in which sensing evidence, inference models, and constrained decision policies had jointly shaped operational safety and service continuity. This study had conceptualized corridor-scale rail assets as dynamic, nonstationary systems whose measured responses had been influenced not only by structural condition but also by train–track–structure interaction, seasonal temperature variation, boundary-condition changes, and intermittent sensor degradation, and the analysis had therefore treated operational and environmental covariates as core explanatory factors rather than as secondary noise. The descriptive results had indicated that monitoring archives had produced large volumes of repeated-pass time-series windows alongside smaller sets of event windows, and the observed imbalance between normal and abnormal outcomes had reinforced that rare-event evaluation had been necessary for credible performance interpretation. The correlation findings had shown that time-domain amplitude descriptors had co-moved strongly, indicating redundancy and supporting earlier SHM evidence that multiple amplitude metrics often captured the same excitation-driven construct, while frequency-stability proxies and time–frequency descriptors had displayed meaningful cross-family relationships that had suggested joint sensitivity to abnormal structural behavior. Reliability evidence had shown that repeat-pass stability had increased when regime controls had been applied, with amplitude and dominant-frequency indicators showing stronger antiregime consistency than transient-sensitive time–frequency measures, which had aligned with the established view that operational comparability was a prerequisite for thresholding and downstream inference. Convergent validity patterns had strengthened measurement credibility by demonstrating cross-modality agreement in contexts where strain- and acceleration-based measures had been co-located, while criterion-related validity had been supported through systematic separation of monitoring-derived condition scores across inspection-confirmed severity categories, thereby indicating that the constructed scores had preserved outcome relevance beyond routine variability. Collinearity diagnostics had demonstrated that multicollinearity had been concentrated within amplitude and energy feature families and between certain covariates and response indicators, and feature screening and consolidation had therefore been required to support numerically stable regression inference and interpretable coefficient patterns. Regression and hypothesis testing results had shown that probabilistic condition estimates and selected engineered indicators had explained meaningful variation in damage detection, severity escalation, and continuous condition scoring after adjustment for speed and temperature, and the incremental performance gain observed when probabilistic risk outputs had been included had supported the argument that integrated evidence fusion had outperformed single-family feature reliance under rare-event conditions. Interaction testing had further indicated that sensitivity of frequency-based indicators had varied by temperature regime, reinforcing prior rail SHM findings that environmental conditions could modulate dynamic-response features and that regime-specific evaluation had been necessary for robust deployment. Most critically for operational relevance, modeled risk outputs had aligned with decision outputs such as speed restriction tiers and inspection priority ranks, indicating coherent translation from inference to action within the dataset and supporting the safety optimization framing in which uncertainty-aware risk estimates had served as the interface between monitoring evidence and constrained operational control. In sum, the study had supported an interpretation consistent with earlier rail and seismic SHM scholarship: AI-enabled monitoring had been most credible when it had combined regime-aware measurement design, reliability-validated feature construction, multicollinearity-controlled inference, and calibrated probabilistic outputs that had mapped transparently to inspection and operational decisions under real-world constraints.

RECOMMENDATIONS

Recommendations for AI-enabled structural health monitoring (SHM) and safety optimization models for high-speed rail infrastructure in seismic regions had emphasized rigorous measurement governance, decision readiness, and corridor-scale operational integration so that analytics outputs had remained defensible under nonstationary conditions and high-consequence decision contexts. SHM deployments had been recommended to implement a tiered sensing architecture that had preserved minimum viable coverage on all critical segments while providing dense multi-modality coverage at high-criticality assets, with accelerometers and temperature sensing treated as baseline requirements and strain or deformation sensing prioritized where damage mechanisms were expected to concentrate. Sensor network governance had been strengthened through standardized calibration schedules, drift logging, and synchronized time bases, and corridor operators had been advised to treat missingness as a structured risk factor by maintaining dropout registers and by explicitly modeling data integrity states in analytics pipelines. Data preparation had been recommended to include regime-conditioned segmentation that had grouped repeated-pass windows by speed and temperature bands to reduce confounding, and feature libraries had been structured into physically interpretable families so that redundancy could have been managed through pre-specified screening rules rather than ad hoc elimination. For model development, supervised learning had been recommended only where inspection-confirmed labels and traceable maintenance evidence had supported valid outcome construction, while unsupervised and semi-supervised inference had been prioritized for corridor-scale detection given label scarcity, with performance reporting focused on false-alarm burden per asset-month, missed detection probability under stress scenarios, and detection latency after seismic events rather than relying primarily on accuracy. Probabilistic condition estimation had been recommended as the default output format for operational use, and calibration monitoring had been treated as mandatory so that probability estimates had retained decision meaning across seasonal temperature shifts, speed-profile changes, and sensor replacement cycles. Threshold selection for alarms and action tiers had been aligned to explicit risk tolerance policies, and decision policies had been designed as tiered action sets that had mapped increasing risk and increasing uncertainty to progressively conservative actions, including inspection prioritization, speed restriction escalation, and closure triggers, while also incorporating feasibility constraints such as crew-hours, access windows, and timetable disruption caps. Safety optimization models had been recommended to incorporate stochastic representations of condition where uncertainty had been high, and sequential updating had been adopted so that post-event restrictions could have been revised as new passes and inspections had accumulated evidence, thereby improved stability and reducing unnecessary disruption. Evaluation protocols had been recommended to prioritize external validity through cross-asset and cross-corridor testing, with retraining triggers defined by measurable drift in false-alarm burden, calibration error, or regime-specific performance decline, ensuring that model maintenance had been proactive rather than reactive. Finally, reporting practices had been recommended to maintain auditability by documenting sensor health, label provenance, regime definitions, model versions, and decision-rule parameters in a traceable manner, thereby enabling safety cases that had connected SHM evidence to optimization actions transparently and consistently across corridor segments exposed to seismic hazard.

LIMITATION

Limitations of AI-enabled structural health monitoring (SHM) and safety optimization models for high-speed rail infrastructure in seismic regions had primarily reflected constraints in ground-truth availability, nonstationary operating environments, sensing heterogeneity, and the practical gap between analytical outputs and field-implementable decisions. Label scarcity and label uncertainty had remained the most influential limitation because inspection-confirmed damage states had been rare and had often been recorded with temporal imprecision, where discovery time had not necessarily matched damage onset time, and maintenance records had frequently represented operational actions rather than standardized severity evidence. This constraint had limited the statistical power for supervised severity modeling, had increased the likelihood that moderate and severe classes had been underrepresented, and had made misclassification analysis sensitive to small numbers of high-severity cases. The use of weak labels around earthquake windows and post-event inspection requirements had provided partial support for outcome linking, yet this approach had introduced ambiguity because not all post-event anomalies had reflected structural damage, and not all damage manifestations had produced immediately detectable signal shifts under routine traffic. Sensor heterogeneity had also constrained inference consistency because corridor-scale deployments had varied in modality availability, placement density, sampling rate, and uptime across assets, which had produced uneven evidence quality and had complicated cross-asset generalization claims. Communication interruptions and structured dropout during seismic events had further reduced observability precisely when monitoring evidence had been most critical, and sensor drift or calibration changes had risked creating spurious baseline shifts that could have been misinterpreted as condition change without rigorous sensor-health tracking. No stationarity had remained a fundamental limitation because train speed distributions, rolling-stock composition, track condition, and environmental regimes had changed over time, and these shifts had altered the data-generating process in ways that had challenged model stability, probability calibration, and threshold reliability, particularly under temperature extremes and seasonal transitions. Feature redundancy and multicollinearity had represented additional limitations for interpretability, since many engineered variables had captured overlapping constructs such as excitation magnitude or response energy, which had complicated causal interpretation of coefficients even after screening. The safety optimization layer had also faced limitations because optimization recommendations had depended on simplified representations of constraints and consequences, and real-world feasibility had been influenced by factors not fully observable in monitoring data, including emergency access constraints, workforce coordination delays, regulatory requirements, and broader network interactions that could have amplified disruption beyond the modeled segment. Additionally, the mapping from probabilistic condition scores to operational actions had depended on calibrated and stable probabilities, yet calibration had been vulnerable to regime shifts and to changing prevalence of abnormal windows, which had limited the certainty with which specific risk thresholds could have been treated as universally transferable across corridors. Finally, external validity had been constrained by the corridor context itself, because differences in construction typology, soil conditions, seismic hazard characteristics, and maintenance practices across regions had limited the extent to which a model validated in one setting could have been assumed to perform similarly elsewhere without explicit cross-corridor testing and adaptation evidence.

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