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AI-Driven Digital Twin for Predictive Lifecycle Management of Bridge Infrastructure: A Review, Conceptual Framework, and Proof-of-Concept Evaluation

Abhijit Jayvant Phanse[1*], Dr. Raju Narwade[2]

[1]PG Student, Department of Civil Engineering, Pillai Hoc College Of Engineering & Technology , Mumbai University, Rasayani, Tal. Khalapur 410207, Maharashtra

[2]Associate Professor, Department of Civil Engineering, Pillai Hoc College Of Engineering & Technology , Mumbai University, Rasayani, Tal. Khalapur 410207, Maharashtra

Abstract - Bridge infrastructure is increasingly impacted by age, growth in traffic volume and loading, environmental variability (i.e. climate change), extreme weather events occurrence, and limited maintenance funds. Standard practice for bridge-management systems primarily relies on periodic inspection and large-scale condition ratings, while ignoring the need for detailed models capable of predicting sudden structural state changes or the uncertainty in future deterioration. ProposalWORK presents: a systematic review, a six-level artificial intelligence operational digital twin modelling framework and is evaluated via proof concept for predictive bridge life cycle management. The framework connects the physical bridge with sensing, inspection imagery, traffic and environmental observations, bridge information modelling, geographic information systems, finite-element analysis, semantic data integration, artificial intelligence, lifecycle-risk assessment, and governed maintenance workflows. A hybrid physics-data approach is proposed for quality control, anomaly screening, damage diagnosis, virtual sensing, remaining-useful-life forecasting, maintenance optimization, uncertainty quantification, and explainable human decision support. The experimental demonstration used an ageing-bridge structural-health-monitoring time-series dataset containing 1,340 observations and 53 engineered numerical predictors. The 30-day degradation forecast achieved MAE = 8.9210, RMSE = 10.8718, and R^2 = 0.7851, whereas current-state degradation prediction produced R^2 = -0.0480 and structural-condition classification achieved accuracy = 0.3433 and weighted F1 = 0.2751, with no Severe-class detections.

Keywords: artificial intelligence; bridge digital twin; structural health monitoring; predictive maintenance; lifecycle risk; uncertainty quantification

1. INTRODUCTION

Bridges are long-lived infrastructure assets, and conditions impacting performance are affected through design assumptions, construction quality, load history, material degradation (environmental exposure), maintenance regimes and unique hazard events. These possibilities for a lack of uniform deterioration include local fatigue cracks, possible drainage failure in corrosion, altered foundations from scour without observable symptoms on the bridge deck, and very subtle changes to vibration response that are masked by thermal effects. This poses a fundamental observability problem for traditional bridge management. Although programme-based visual inspections provide uniquely expert evidence, the periods between inspections are relatively long when some defects can progress quickly and condition ratings themselves serve to collapse a diverse range of observations into broad categories. Digital twin provides an alternative management logic that connects a physical asset, its data history, its models of computation and models of decision making in a dynamic virtual environment. Digital-twin was conceived that very first time, on the basis of constant mapping between real product and its virtual representation [1]. Industrial research that followed reframed the twin not just as a static asset model, but as one for simulating and tracking information across the lifecycle [2]. Bidirectional data exchange, model updating, and decision feedback distinguish a mature digital twin from both a digital model and a digital shadow. Systematics characterization work has demonstrated that key properties are centered around identity, connectivity and synchronization, fidelity as well as lifecycle coverage [3]. As noted in [4], engineering-dynamics research highlights when the twin must model uncertainty, contribute to state estimation, and make predictions that remain accurate as both the asset and environment evolve. IoT sensing, cloud-edge

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computing, semantic data models, high-performance simulation, machine learning and visualization and secure communication are among the various enabling technologies today [5]. But in the construction and infrastructure domain, adoption is still inconsistent because different tools (building information models, inspection databases, structural analysis models and operational sensor platforms) often rely on incompatible data structures [6].

Widespread literature on digital twins highlights typical obstacles (shown in figure 1), such as a lack of interoperability, data quality, computational cost, cybersecurity, governance and organizational readiness [7]. These barriers are particularly relevant in the context of existing civil infrastructure, with incomplete drawings, sparse sensors, inconsistent asset identifiers and physical structure that has undergone hidden alterations. The proposed workflow by Civil Engineering 4.0 research combines surveying, sensing, modelling and analytics to form a continuum to progressively build an evidence base of existing assets [8]. Explorations of civil-engineering twins similarly contend that the twin should not simply reproduce geometry, but must support distributed sensing updates and structural inference9. Similarly to the other aspect, an intelligent maintenance lifecycle perspective connects Digital Twins with enabling data collected during operation affecting inspection and repair selection as well as future model fidelity [10].

A major reason to create Digital Twins is predictive maintenance. According to a systematic review of predictive-maintenance twins, successful systems combine condition monitoring, degradation models, forecasting and decision rules instead of using one algorithm [11]. In civil infrastructure, long service lives and few failures exacerbate the problem. A number of recent reviews on digital-twin technologies for civil assets emphasize the use of hybrid models that incorporate codes of physics, monitoring data and domain knowledge [12]. Bridge-specific scholarship has proliferated rapidly; a 2024 review chronicles the transition from trandy dimension models toward integrated bridge digital twins coupled with sensing, simulation, data fusion and decision support [13]. A bridge twin framework that has been proposed for structural health monitoring similarly integrates bridge information modelling, intelligent transportation data, geographic information systems and monitoring technologies to enhance operation and maintenance quality [14].

Efficient operation or optimization of large scale bridges need information at multiple spatial scales. Bridge information models can find components and defects; geographic information systems can relate the bridge to traffic corridors, floodplains, detours, and surrounding assets (the heavy machinery that works on these roads); finite-element models can predict structural response; maintenance databases serve as records of inspection results and intervention history. An example bridge twin from [15] merges GIS and BIM together to tie spatial information and asset information for operation and maintenance workflows. Bridge-twin modelling data-driven data-and knowledge further illustrates that sensor data can be fused with expert knowledge to bridge the at present extensive fragmentation between monitoring, diagnosis and action [16]. A review of digital twins for civil-infrastructure structural health monitoring suggests the integration of an acquired data with effective processing, modelling, and platform as coherent systems [17].

The domain is also transitioning from descriptive monitoring to predictive intelligence. Report on Digital-twin approaches in structural health monitoring: growing use of virtual sensing, model updating and data-driven diagnosis; Maintenance-oriented decision support [18] (2025). Systematic literature review of bridge management and in-structure monitoring suggests that for bridge digital twin to be valuable, it should not only have a visually sophisticated 3D visualization but also follow good practices in relating bridge information model (BIM), monitoring integration, and operational data flow [19]. Simultaneously, artificial intelligence is playing an important role in respect of concrete-bridge monitoring technologies, especially for automatic crack detection [19], multimodal evaluation [20] and pattern identification from large-scale monitoring data sets. Even the recent systematic synthesis of digital twins for bridges and tunnels contextualizes continuous monitoring and preventive maintenance as main life-cycle applications [21].

Several significant bottlenecks hindering traditional structural health monitoring are addressable through artificial intelligence. The characteristics that make machine-learning models useful here include their value for normalizing environmental and operational variability, anomaly detection, damage classification, gap-filling of measured values (where measurement lost the signal or a sensor was faulty), and generation of fast surrogates of phenomena/model simulations that are traditionally computationally expensive to analyze over large parameter spaces. Recent structural health diagnosis research is reported to have witnessed continuous integration of machine learning, digital twins and multisensor systems [22]. Current approaches on bridge SHM are also reviewed in [23] and results which include sensing, signal processing, damage identification and intelligence evaluation were organized to address the most relevant issues of real field application. Especially operational modal analysis, which obtains the structural dynamic characteristics from real service without interruption by ambient vibration, is still very relevant; together with bridges, it allows to calibrate dynamic digital twins based on exteroceptive data in actual operational conditions [24]. Yet data-driven decision-making in bridge operation and maintenance should be relatable

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with engineering mechanisms, inspection evidence, and consequence analysis to avoid recommendations that are statistically plausible but operationally unsafe [25].

During the last years, many papers on this topic have been published but some gaps still stay. Firstly, many bridge twins are built as prototypes that are specific to a single project and thus lack transferability to other bridge types, sensor acoustics or organizational contexts. Second, many work in AI studies improve diagnostic accuracy but do not shows how changes in predictions change inspection intervals, maintenance prioritization, lifecycle cost or network risk. Third, uncertainty representation is variable; deterministic condition scores mask sensor fault, sparse data, model-form error and future loading uncertainty. Fourth, governance is underdeveloped. Asset owners demand traceable data lineage, versioned models, role-based approval and cybersecurity controls and proof that an audit trail supports any maintenance recommendation. Already, these gaps determine that bridge digital twinning is better understood as a lifecycle decision system instead of a visualization project.

To this end, in this paper, a generic AI-based digital-twin framework is proposed for predictive lifecycle management of bridge infrastructure. The objectives are to (i) outline the system architecture and information flows needed to connect physical bridges, sensing, inspection, engineering models, AI and maintenance systems; (ii) propose a hybrid state-estimation and prognostics framework that integrates physics; data and expert knowledge;}(iii) translate predicted condition into risk-informed maintenance decisions;(iv) specify validation metrics including technical accuracy, uncertainty operational value and governance;(v) identify implementation phases & future research priorities. We offer a purely conceptual and methodological contribution. It does not assert new field-test performance but synthesizes recent evidence into a reproducible prototype for future experimental or agency-specific applications.

1.1 Motivation:

Bridge structures are subjected to the effects of ageing, rising traffic demands, environmental degradation, harsh events and scarcity of maintenance funds. Traditional bridge management strategies are based primarily on periodic visual inspections and coarse condition ratings which can miss close range breach development, concealed degradation, sensor uncertainty or shifts in the behaviour of structures between inspection intervals. Earlier studies on digital twin and artificial intelligence (AI) mostly focus on one bridge which are mainly dedicated to monitoring or damage detection, where the coordination of sensing and structural models, uncertainty estimation of their response, lifecycle risk assessment models human approval is generally minimal. The need for an integrated AI-driven digital-twin framework that keeps track of physical bridge conditions, multisource data, engineering models, predictive analytics and risk-informed maintenance decisions across the life cycle of a bridge throughout the design, construction and operation phases addresses these limitations.

1.2 Contribution:

This paper presents a digital-twin framework with six layers of AI-driven predictive lifecycle management of bridge infrastructure. It integrates physical sensing, inspection imagery, environmental and traffic data, bridge information modelling, geographic information systems (GIS), finite-element analysis (FEA), semantic data management (SDM), artificial intelligence (AI), lifecycle-risk assessment and governed maintenance workflows in real time. The paper proposes a hybrid physics–data paradigm for various tasks: data-quality control, anomaly detection, damage diagnosis, virtual sensing, degradation forecasting, remaining-useful-life prediction/estimation (RUL), uncertainty quantification (UQ), explainable decision support and maintenance planning/optimization. The proposed methodology provides validation metrics, cybersecurity requirements, audit trails, role-based approval and a staged implementation roadmap to transition bridge digital twins from static visualization and isolated monitoring tools into traceable, uncertainty-aware, and human-supervised lifecycle decision-support systems.

The rest of this paper is sectioned as follow. Section 2 provides an overview of the methodology for the structured review; section 3 synthesizes previous investigations and identifies the major technical and operational deficiencies. An AI-Guided Bridge Digital-Twin Architecture is proposed in Section 4. Sections 5-9 specify data and semantic integration, hybrid modelling, artificial-intelligence services, lifecycle decision support as well as governance requirements. Section 10 describes the dataset, preprocessing, modelling, validation and evaluation. Results from the proof-of-concept are laid out in Section 11, before concluding in Section 12 with implications and connections to prior work. An implementation and pilot-validation roadmap can be found in Section 13. Section 14 relates the study limitations, Section 15 explains future research directions and finally Section 16 closes the paper.

2. STRUCTURED REVIEW METHODOLOGY

2.1 Review Design and Scope

The process of a structured thematic review is adopted in this paper rather than claiming a PRISMA-complete systematic review. The review will focus on identifying the features, constraints and validation processes supporting AI-based digital

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twins for bridges. The term "synthesis" here encapsulates the way in which the specific framework/method detailed in a publication facilitates topics like structural health monitoring, digital-twin synchronization, hybrid modelling, lifecycle prognosis, maintenance decision support, interoperability concerns (cf.

2.2 Search Strategy

Studies related terms bridge digital twin, structural health monitoring, bridge information modelling, finite-element model updating, artificial intelligence, predictive maintenance and remaining useful life were queried to extract the relevant studies along with lifecycle risk and bridge asset management.

2.3 Eligibility and Synthesis

We retained studies addressing at least one lifecycle capabilities (i.e., physical-virtual synchronization, bridge monitoring, multimodal data integration, physics-based or data-driven state estimation and damage diagnosis [26], deterioration forecasting, risk assessment, maintenance optimization [27] and operational governance) in the final selection. These studies were only used as background, where we limited to static visualization without updating or decision support. Because the included studies used heterogeneous assets, sensors, datasets, performance metrics and validation designs that did not permit statistical meta-analysis, evidence was synthesized thematically.

2.4 Review Limitations

We are aware that terminology discrepancies, publication bias towards successful prototypes, selective outcome reporting and the rapid influx of new AI and digital-twin approaches could impact the review. The review is consequently deployed to design and rationalize the reference architecture than derive an aggregated effect size.

3. LITERATURE REVIEW AND CONSOLIDATED RESEARCH GAP

Five interacting dimensions can help you to understand a bridge digital twin: the physical asset, virtual asset, data connection, analytical services and decision environment. Enumeration of the physical asset: structure, foundation, bearings, joints, drainage system and protective systems and local environment exposure. The geometric, semantic, mechanical, deterioration and reliability model are models of each virtual asset. The system was made up of sensors, inspection tools, communication networks and data pipelines. Analytical services predict present condition and future movement. This is where the decision environment turns predictions into actions: inspections, restrictions, maintenance, rehabilitation or replacement. Digital twinning via Cloud-based approaches has shown that deep learning and remote computation can enable online structural health monitoring, but also exposes its reliance on communications durability, preprocessing consistency, and model governance [26].

Network-scale twins take it further than a single bridge. For example, a bridge-group digital twin (aka a composite-digital twin) combines machine-vision traffic-load monitoring with structural models to infer operating conditions at many bridges in a regional network [27]. Such approaches are essential because the act of maintaining a given bridge gets complicated—intervening on one asset alters detour demand, changes emergency access, disrupts freight movement, and reallocates budgetary resources away from other structures. In addition to the above, AIoT-informed communication research indicates that communication delay, bandwidth, resilience and edge processing are not secondary implementation issues; instead they directly impact a bridge twin's ability to update and respond timely [28]. Technical forwards shows that hybrid modelling is the main direction since neither pure physical or pure data-driven models are sufficient. [29]A physics-data framework for bridge twins provides a defined context in which the correspondence between and a finite-element representation and monitoring data can be formalized, targeting model parameters that are updated while retaining their structural meaning. Bridge digital twins have been adopted in transfer-learning research to synthesize or modify damage information when labeled field data are limited [30]. The also use learned surrogates to estimate response and assist with monitoring bridge structures at lower computational cost than repeated high-fidelity simulation [31], such as neural-network digital twins for reinforced-concrete bridges. To bridge the lifecycle, the twin must move from design and construction to operation. Using the context of cable-stayed bridges, digital-twin lifecycle modelling prepares for fidelity assessment and state evolution throughout a singleton twin [32] comprising design twin assumptions that need to be continuously inherited by its operational counterpart before being consistently revised based on evidence. A seismic performance assessment of a digital-twin-based long-span bridge service life and its implications of updated models for scenario analysis [33]. Bayesian bridge twinning based out of output-only model updating and seismic recordings is capable with using probabilistic tools to provide a means by which uncertain structural parameters may be updated [34]. Model updating based on UAV inspections has also been used prior to seismic assessment [35] in order to revise the representation of deteriorating aspects and fragility.

These specialized applications illustrate how the twin can enable component-level management. Orthotropic steel decks have seen the application of hybrid monitoring and fatigue evaluation, which relates measured response to physical models for

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evaluating accumulated fatigue demand [36]. Digital twin in load tests of railway-bridges illustrating comparisons between measurements and simulations to help calibrate models and aid in making acceptance or diagnostics decisions [37]. The effect of a twin model is shown by characterizing fatigue-state railway steel bridge stress histories and structural details which cannot be entirely instrumented [38]. For existing bridges characterized by weak information content from the past, an alternative pathway for creating numerical twins lies in direct load-testing – since controlled loading can provide insight into stiffness, energy dissipation and sensor response [39]. The connection of localized inspection evidence to the structural model through digital-twin based nondestructive testing allows for interpretation of defects in relation to component function and system response [40].

Most notably new work has started to bridge the gap between monitoring and actionable lifecycle management. This picture presents the real-time data-driven systems of structural health monitoring, including Bayesian modal Identification and warning logic applied jointly based on digital twins [41]. Integrated hybrid monitoring (IHM) combining model and data has enabled the estimation of unmeasured responses from sparse measurements with strict adherence to physical constraints [42]. This bridges the gap from existing information to digital assets that can be used for analysis through BIMification and BIM-based finite-element development [43]. A general digital-twin framework for bridges has also been proposed to combine sensing, computer vision and machine learning with structural integrity and maintenance applications [44]. The case of Stava Bridge shows that the operational value of IoT monitoring, physics-based methods and machine learning for damage detection or virtual inspection [45] is proven, but the organizational response procedures are equally important as algorithms. The recent literature is progressing bridge twins toward lifecycle risk, affordability, sparse sensing and advanced AI. A system digital twin implements Bayesian networks to combine data of different types to quantitatively assess lifecycle risk in bridge networks [46] Definition of monitoring objective and an IoT-enhanced framework at low-cost sensors can lead to near-real-time digital twinning with lower-cost sensors, open software [47]. Work on damage-state identification with the Z24 benchmark has looked into generative-AI-based digital twinning, further indicating where synthetic data and generative models could be used in situations when examples of damages are few [48]. Considerations for sparse sensing and scalable monitoring are well defined in a 2026 framework of already built bridge systems with large spans [49]. The latest systematic review on AI-enabled methods for bridge SHM [50] identified multimodal sensing, physics-informed learning, explainability, data efficiency and integration with digital twins as requirements of field-ready systems.

4. PROPOSED AI-DRIVEN BRIDGE DIGITAL-TWIN FRAMEWORK

Figure 1 illustrates the six layers of the proposed architecture Because the layering is sensibly agnostic to the vendor, different agencies can implement the functions via commercial platforms, open-source components or a combination of both. The 1st layer called physical and sensing collects the information from the bridge, its loads, its environment and the outcome of any interventions. This is where we apply the edge, communication and cybersecurity layer to assure that all measurements are timestamped analyzed, compressed, transmitted and protected. Structured and unstructured data with a governed repository and semantic linkage makes up the data, integration layer. A tempered digital-twin layer keeps up-to-date geometric, structural, degradation, and network models. The AI and prognostics layer generates diagnostic and prophetic services. Evidence → Approved Action + Rationale: The lifecycle decision & governance layer

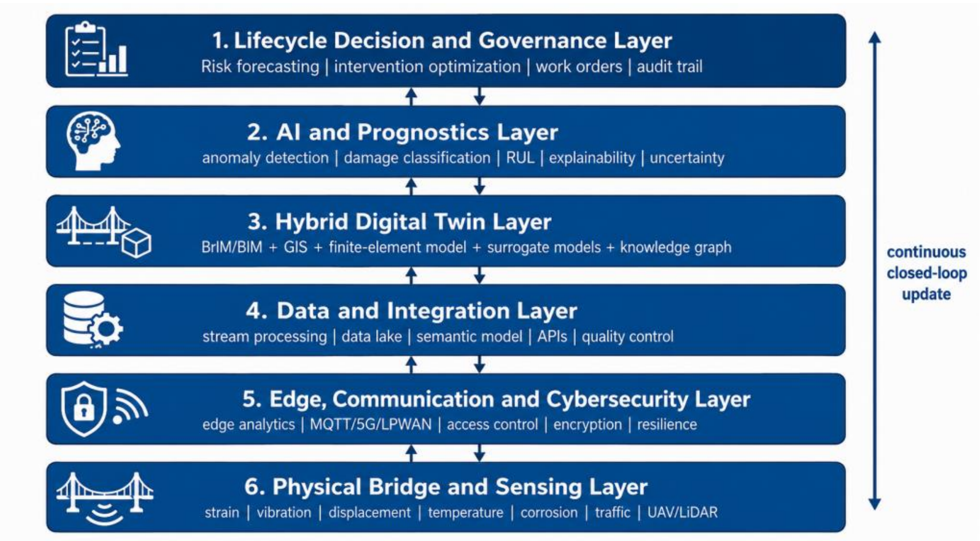

Figure 1. Layered architecture of the proposed AI-driven digital twin for bridge lifecycle management.

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The architecture centers on closed-loop updating. The authoritative condition state does not change as a result of a measurement. Rather, it filters through data-quality assessment, contextual normalization, anomaly screening and consistency versus other sources. The twin subsequently updates the chosen parameters or latent states with the method that fits its timescale. Fast variables (e.g., traffic response) may update every seconds or minutes, temperature-normalized modal baselines (> Daily), time since some corrosion or fatigue states were last revised (> Monthly), and geometry may change after inspection or intervention. This multirate approach circumvents unnecessary computation and mitigates the implicit assumption of treating ephemeral noise as structural change. A minimum state definition should exist for every bridge twin. The state consists of the observable response variables, the inferred structural parameters, observables of deterioration, environmental and loading context, data-quality indicators, model-fidelity indicators and decision status. It should also keep uncertainty for each key state. Hence, the twin is capable of retaining not only a best estimate but also confidence bounds and evidence provenance. This allows a maintenance engineer to distinguish between a high-risk prediction with strength from multiple independent sources vs a numerical risk score resulting from sparse or spurious data.

Digital Twin depicted across the complete lifecycle figure 2 Geometry, materials, prestress, reinforcement, foundations and component identifiers are fed by information generated during design and construction. Commissioning tests give the first calibrated baseline. When you operate, the condition and exposure are updated by sensing and inspections. Diagnosis and prognosis characterize damage mechanisms and future behavior. Maintenance, renewal: The physical asset changes state, the virtual changes state with it. Finally, there is the stage of organizational learning: residuals, false positives, inspection results and intervention effectiveness feed back into models, thresholds and asset policies.

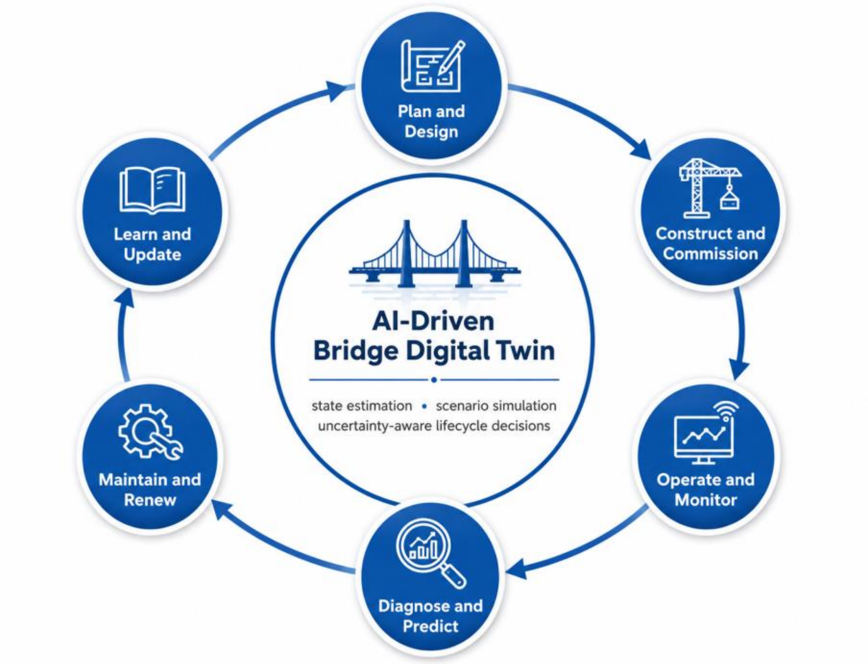

Figure 2. Closed-loop integration of the bridge digital twin across lifecycle stages.

Table 2. Core data sources and their role in the bridge digital twin

Data source	Examples	Primary lifecycle role	Typical update
Design/as-built records	Drawings, materials, reinforcement, prestress, foundations	Initial geometry and priors	At commissioning and after modification
Permanent sensors	Acceleration, strain, displacement, temperature, corrosion	Dynamic state and long-term trends	Milliseconds to hours
Traffic and environment	WIM/video, wind, rainfall, water level, humidity	Loads, exposure and EOV normalization	Seconds to days
Manual inspection	Ratings, defect dimensions, notes, photographs	Verified condition evidence	Periodic and event-based

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Remote inspection	UAV imagery, LiDAR, photogrammetry, thermography	Geometry and surface defects	Periodic or targeted
Maintenance records	Work orders, quantities, costs, as-built repair data	Action history and intervention effect	At each work event
Network context	Route, detour, traffic, emergency role, equity indicators	Consequence and prioritization	Annual or after network change

5. DATA ACQUISITION AND SEMANTIC INTEGRATION

Data should be fused with variations in format, frequency, spatial resolution and accuracy and typically organization (or person) ownership a bridge lifecycle twin must combine this data. Continuous sensors can produce high frequency acceleration or strain; weather stations yield slower contextual variables; weigh-in-motion or video analytics provide traffic estimates; inspectors create text, photos, defect measurements and ratings; UAV and terrestrial laser scanning generate dense point clouds; maintenance systems record work orders and costs, and design records document materials and details. Thus, a single database solves neither the integration problem. An architecture that can actually be deployed utilizes a time-series store for monitoring, an object store for files and imagery, has a spatial database for GIS and a graph or semantic layer for relationships, as well as some kind of transactional asset-management system to hold approved records.

For each observation there should be a canonical identifier that ties the bridge, span, component, location, sensor, inspection event and time together. Model swapping should not break the component hierarchy. For example, semantic relationships can express that a crack appears on a girder web, the girder is part of a span, the span is part of a route and the route has an assigned consequence classification. The semantic layer makes the same evidence accessible to visualization, structural analysis and maintenance planning, and reporting. Widespread adoption of open formats like IFC, CityGML, GeoJSON, Sensor Things API, OPC UA, MQTT or standard web APIs can be helpful in reducing vendor lock-in but extendibility for bridge-specific extensions and careful mapping are required12[14].

Table 3. Recommended state variables maintained by the bridge digital twin

State group	Representative variables	Evidence source	Update cycle
Geometry	Component dimensions, alignment, section loss	Survey/BIM/LiDAR	After survey or intervention
Structural parameters	Stiffness, damping, mass, boundary conditions	Model updating	Daily to event-based
Deterioration	Crack, corrosion, fatigue, scour, bearing/joint state	Inspection + AI + physics	Monthly to event-based
Loading/exposure	Traffic, temperature, moisture, wind, flood	Sensors and external feeds	Real time to daily
Data quality	Completeness, sensor health, synchronization	Automated QC	Continuous
Uncertainty	Parameter, model, measurement, scenario uncertainty	Probabilistic inference	Every update
Decision status	Alert, review, approved action, work completion	Workflow system	On workflow change

Consider data quality as a first-class citizen state. The completeness, timeliness, plausibility, calibration status, synchronization error and sensor-health indicators should populate each stream. Even a physically possible measurement could be misleading if the sensor has drifted or timestamp is offset. Automated Quality Control (QC) should integrate the following algorithm types: range checks, rate-of-change rules, cross-sensor correlation, spectral consistency, and model residuals. Quarantine suspect data, do not silently delete it — in other words, delete if you need to, but leave evidence for investigation later. Regarding sparse sensing, instead of measuring every response, you are inferring decision-relevant states. Hence sensor placement should be driven by observability, damage sensitivity, redundancy, install ability, power, communications and life-cycle cost. Virtual sensing allows estimating unmeasured responses from a model calibrated on a few selected measurements, but uncertainty

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needs to expand in regions or operating conditions which are poorly observed. To supplement permanent sensors and limit the sustainability of permanent hardware, periodic mobile sensing, drive-by monitoring, UAV surveys, and load tests can be beneficial.

6. HYBRID DIGITAL-TWIN MODELLING AND MATHEMATICAL FORMULATION

Let the latent bridge state at time t be represented by x_t, including stiffness parameters, boundary-condition variables, damage indices, deterioration states, and load or environmental context. A general nonlinear state-space formulation is: $x_t = f(x_{t-1}, u_t, m_t) + w_t$, where u_t denotes measured inputs such as traffic and temperature, m_t denotes maintenance or event actions, and w_t represents process uncertainty. Sensor and inspection observations are expressed as $y_t = h(x_t, u_t) + v_t$, where h is the observation model and v_t captures measurement uncertainty. This formulation permits Kalman filters, particle filters, Bayesian updating, optimization-based calibration, or learned estimators depending on model complexity.

$x_t = f(x_{t-1}, u_t, m_t) + w_t$ (1)

$y_t = h(x_t, u_t) + v_t$ (2)

In Equations (1) and (2), x_t is the latent structural and deterioration state; u_t contains measured loads and environmental inputs; m_t represents maintenance, operational, or hazard events; y_t is the observation vector; f is the state-transition model; h is the observation model; and w_t and v_t are process and measurement uncertainties.

The finite-element model supplies structural constraints, load paths, and physically interpretable parameters. It should not be calibrated indiscriminately: parameters must be identifiable from available data, bounded by plausible values, and linked to deterioration mechanisms. Surrogate models may approximate computationally expensive simulations for real-time use. Suitable surrogates include Gaussian processes, neural networks, graph neural networks, reduced-order models, polynomial chaos, and neural operators. Surrogate validity must be checked within the operating domain; extrapolation beyond trained load, temperature, or damage ranges should trigger a warning or fall back to a physics-based analysis.

A hybrid calibration objective can combine data fit, physical consistency, regularization, and prior knowledge:

$L_{total} = lambda_y L_{data} + lambda_p L_{physics} + lambda_r L_{regularization} + lambda_k L_{knowledge}$. L_{data} measures the difference between predicted and observed response; $L_{physics}$ penalizes violation of equilibrium, compatibility, material laws, or governing differential equations; $L_{regularization}$ discourages unrealistic parameter changes; and $L_{knowledge}$ encodes expert constraints such as known bearing replacement or observed crack location. The weights should reflect uncertainty rather than convenience, and their sensitivity should be documented.

$L_{total} = \lambda_y L_{data} + \lambda_p L_{physics} + \lambda_r L_{regularization} + \lambda_k L_{knowledge}$ (3)

Twin fidelity should be assessed at multiple levels. Geometric fidelity addresses dimensions and component locations. Behavioral fidelity measures agreement in static response, modal properties, strain, displacement, and other relevant variables. Diagnostic fidelity measures whether the twin correctly identifies damage or abnormal behavior. Decision fidelity assesses whether the twin recommends actions consistent with observed outcomes and engineering judgement. A high-resolution geometric model with poor behavioral calibration is not a high-fidelity lifecycle twin.

Model updating must be event-aware. An abrupt residual change may represent damage, but it may also result from resurfacing, bearing replacement, sensor relocation, traffic-control changes, or an unrecorded calibration reset. The system should therefore ingest work orders and operational events before declaring structural anomalies. Change-point analysis can identify the time of a shift, while causal reasoning and model comparison can test competing explanations. Human review is required when the proposed explanation affects safety-critical decisions.

7. ARTIFICIAL INTELLIGENCE FOR DIAGNOSIS, PROGNOSIS, AND EXPLAINABILITY

The AI services are categorized into five different functions. They are used, as first group of models to detect faulty sensors, classify anomalies, reconstruct missing data and create reduced volume from the data. Perception models take in images, video, LiDAR, acoustic data, and thermography to identify cracks, corrosion, delamination, deformation from a given component. Third, diagnostic models deduce location, type and extent of damage based on vibration, strain, displacement and multimodal evidence. Fourth, prognostic models predict heath degradation (even), fault recognition of reliability and end-of-life. Fifth, decision models optimize inspections and interventions within budget, capacity, risk and traffic constraints.

The data and decision task should point the way for model choice. Convolutional networks are well suited for local visual patterns, vision transformers capture longer-range context but can require much data and compute management to train efficiently, recurrent networks and temporal convolutional networks (TCNs) model sequences, while transformers are nice (and often necessary) because they support long range temporal dependence and also easy multimodal fusion; autoencoders and one-class classifiers can be used to target anomaly detection with comparatively few damage labels in practice; graph

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neural networks represent the connectivity of components/computational elements; probabilistic models quantify uncertainty associated with predictions as a matter of course; physics-informed networks apply governing constituent level relationships. Ensemble may be better when failure modes are diverse and the representation in one is not dominantly outperformed by others.

Table 4. AI methods and evaluation focus within the proposed twin

Function	Representative models	Bridge task	Primary metrics
Data quality	Autoencoder, one-class SVM, change-point model	Sensor fault, missing data, drift	False-alarm rate; reconstruction error
Visual inspection	CNN, vision transformer, segmentation network	Crack/corrosion/delamination detection	Precision; recall; IoU; localization error
Dynamic diagnosis	Temporal CNN, transformer, probabilistic classifier	Damage detection and localization	F1; detection delay; calibration
Virtual sensing	Gaussian process, neural operator, reduced-order network	Unmeasured response estimation	RMSE; spectral error; interval coverage
Prognosis	Bayesian model, survival model, recurrent network	RUL and threshold crossing	MAE; Brier score; interval coverage
Decision support	Bayesian network, optimization, reinforcement learning	Inspection and maintenance planning	Risk reduction; lifecycle cost; constraint compliance

One of the main sources of false alarms is environmental and operational variability. Also, climate-related factors such as temperature and humidity, changes in traffic patterns or wind, and certain boundary-condition alterations may influence modal frequencies and response statistics. Hence, the AI layer must characterize contextual variation from deterioration with methods which could include normalization, domain adaptation, covariate modelling, seasonal baselines, or conditional anomaly detection. The time ordering of the data and adjacent windows cannot leak into each other when generating a train-test split. Performance should be reported across seasons, loadings, sensors and bridge types instead of just on random samples.

For most bridges, remaining useful life is not an observed label. Probabilistically with respect to deterioration mechanism, current state, future exposure, inspection evidence and intervention policy. Define T_f as the time when a limit state is crossed $P(T\_f \mid D\_(1{:}t), M)\ with\ D\_(1{:}t)$ all the evidence up to time t and M the set of models be the output of a prognostic. Examples of useful outputs are median remaining life, prediction interval, the probability of crossing a threshold within given horizons, and the drivers of uncertainty e.g. This is more informative than a single deterministic date.

$P(T\_f \mid D\_(1{:}t), M)$ (4)

Explainability should be balanced against engineering purpose. Explanation for image models possibly emphasizes defect pixels and the component context. For the time-series models, they can find the sensor, frequency band, event or environment variable that may be contributing to an alert. The expectation is identifying joint behavior of probability of failure, consequence or model uncertainty for risk models and complementary inspection evidence. Feature attribution is insufficient If you have any correlated variables or model extrapolation. Estimate of the potential impact: explanation should be coupled with the results in counterfactual or alternative scenario, like confirming a bearing defect or reducing heavy-vehicle loads. Residual distributions, calibration error, feature-distribution change and degradation relative to outcomes of confirmed inspections Retraining must be performed on controlled data versions with clear documentation of labels, and requires freeze benchmark verification. A production model should never be discarded just because the new model has better aggregate accuracy, but it needs to satisfy robustness, uncertainty calibration, latency, interpretability and safety criteria.

8. LIFECYCLE RISK AND MAINTENANCE DECISION SUPPORT

Two bridges with similar condition may require different priorities because their detour lengths, traffic, redundancy, and social importance differ.

$HI_t = \Sigma_i w_i s_{i,t}$ (5)

$R\_t = \Sigma\_j\, P(F\_j \mid D\_t)\, C\_j$ (6)

In Equation (5), s_(i,t) is a normalized component or deterioration score and w_i is its importance weight. In Equation (6), F_j is a defined failure or serviceability event, $P(F\_j \mid D\_t)$ is its probability given current evidence, and C_j is the associated consequence.

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Actions may include no action, targeted inspection, monitoring enhancement, load restriction, preventive maintenance, repair, strengthening, rehabilitation, or replacement. The twin evaluates how each action changes future deterioration, reliability, disruption, and cost.

$$\min E\left[\Sigma_t \gamma^t \left(C_{inspection} + C_{maintenance} + C_{user} + C_{failure} + C_{carbon}\right)\right] \quad (7)$$

Table 5. Consolidated notation used in the mathematical formulation

Symbol	**Category**	**Definition**	**Equation(s)**
x_t	State vector	Latent structural, deterioration, loading, and contextual state at time t.	(1)-(2)
u_t	Input vector	Measured traffic, environmental, and operational inputs.	(1)-(2)
m_t	Action/event vector	Maintenance, operational, or hazard event applied at time t.	(1)
w_t, v_t	Uncertainty	Process uncertainty and measurement uncertainty, respectively.	(1)-(2)
y_t	Observation vector	Sensor, inspection, or derived observation available at time t.	(2)
f, h	Model functions	State-transition and observation functions.	(1)-(2)
L_{data}	Loss term	Mismatch between predicted and observed response.	(3)
$L_{physics}$	Loss term	Violation of equilibrium, compatibility, material, or governing constraints.	(3)
$L_{regularization}$	Loss term	Penalty discouraging implausible parameter changes or overfitting.	(3)
$L_{knowledge}$	Loss term	Expert, inspection, or maintenance constraints encoded in calibration.	(3)
$lambda_y, lambda_p, lambda_r, lamb$	Weights	Relative importance of data, physics, regularization, and knowledge terms.	(3)
T_f	Random time	Time at which a defined failure or serviceability limit state is crossed.	(4)
$D_{1:t}$	Evidence set	All observations and records available up to time t.	(4), (6)
M	Model set	Candidate prognostic models or model assumptions.	(4)
HI_t	Health index	Weighted bridge or component health score at time t.	(5)
$s_{i,t}, w_i$	Score and weight	Normalized component/mechanism score and its importance weight.	(5)
R_t	Risk	Expected lifecycle risk at time t.	(6)
F_j, C_j	Event and consequence	Failure/serviceability event and associated consequence.	(6)
Gamma	Discount factor	Weight applied to future lifecycle cost.	(7)
$C_{inspection}, C_{maintenance}, C_{user}, C_{failu}$	Cost terms	Inspection, intervention, user disruption, failure, and carbon costs.	(7)

Allows for three decision timescales Operational issues deal with immediate incurrences, outliers and constraints. 1) Tactical decisions timetable inspections and repairs over months to years. Strategic decisions on rehabilitation and replacement, climate adaptation, and network investment have time horizons of multiple decades leading to long-term impacts. All three use the same twin, but differ in treatment of model resolution and uncertainty. Fast conservative thresholds drive immediate decisions; scenario analysis for traffic growth, climate, discount rates, deterioration and technology change drive strategic planning.

Value of Information must be embedded in decision rules. If uncertainty is causing the risk, an inspection or temporary sensor may be more advantageous than immediate repair. The expected value of sample information compares the decrease in

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decision loss due to additional evidence with its cost and delay. This avoids the twin from suggesting costly interventions simply because uncertainty is high. On the other hand, if both consequence and failure probability are high then the system should not wait for more data that is unlikely to change the decision.

A package of evidence should underpin maintenance recommendations, not black-box scores. Description: Each recommendation is described by the affected component, anticipated mechanism of action, data source(s), version of the model deployed (if applicable), uncertainty level, outcome category (insured lives averted and treated individuals), alternative interventions available, forecasted risk reduction in metric to be evaluated following implementation, cost range including high and low value estimates if appropriate; expected secure volume trend (increasing/decreasing) on aggregates traffic as well as detailed list whether inspection will take place for individual roads/ bridges/ maintaining costs, construction stage information e.g. approval rates etc The twin is updated after work completion with the physical change and as-built information. After the intervention, monitoring confirms if the expected benefit happened and allows the system to learn how effective the intervention was.

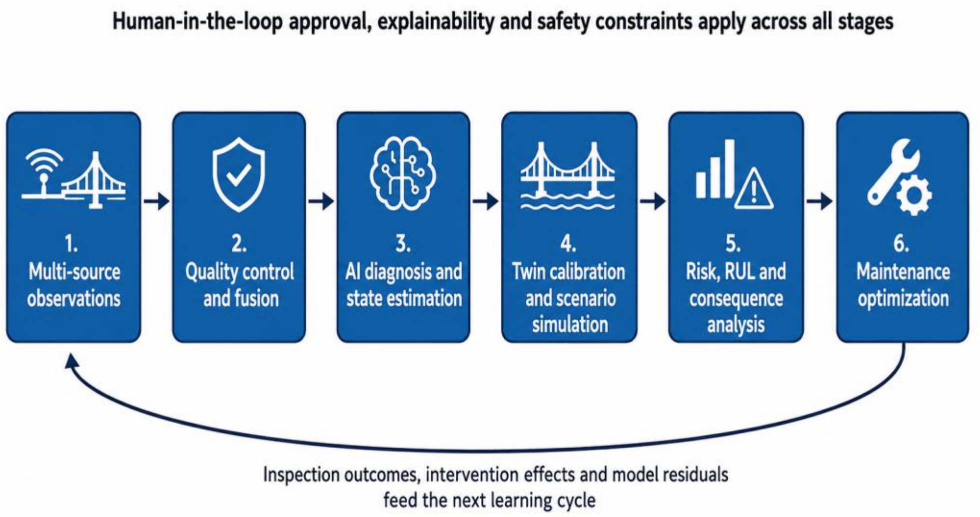

Figure 3. Evidence-to-action workflow with continuous learning and human oversight.

Table 6. Example risk-informed decision classes

Class	Interpretation	Typical action	Approval
Normal	Condition within calibrated baseline; low short-term risk	Continue monitoring and routine inspection	Automated logging
Watch	Small persistent deviation or rising uncertainty	Review data quality; increase observation	Monitoring specialist
Investigate	Probable defect or significant model residual	Targeted inspection or load test	Bridge engineer
Intervene	Confirmed deterioration with material risk increase	Maintenance, restriction or strengthening plan	Qualified engineer and asset manager
Emergency	High probability or consequence of unsafe performance	Immediate restriction, closure or emergency response	Authority emergency procedure

9. CYBERSECURITY, GOVERNANCE, AND HUMAN OVERSIGHT

The attacker can utilize the existing bridge digital twin which bounds the cyber-physical attack surface. Sensor data manipulation and forged credentials can also lead to bad decisions or malignant model updates, and even ransomware, denial of service or fraud in work records. Thus, security should be based on defense-in-depth: Device identity; secure boot; encryption during transit and at rest; network segmentation; least-privilege access; signed model artifacts; tamper-evident logs; backup and recovery; vulnerability management, incident response. Safety-critical functions need to degrade cleanly in case of lost connectivity, keeping local alarms and conservative operating rules. Governance determines the source of truth and where the models exist. That raw observations, cleaned data, derived features, state estimates and condition records that have been

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accepted should all be in separate areas. A model should have an owner, usage, description of training data, validation status, known limitation, review date and change history. System should keep log of who accepted, rejected or changed recommendation. The audit trail holds the engineering accountable and prevents it from seeming to readers as though the AI independently decides when maintenance is performed.

Human oversight should be risk-based. Low-risk and smaller scale data-quality fixes may be automated as a part of the routine. Alerts that may cause harm but are relatively mild should be reviewed by a monitoring expert. Closure, load restrictions, rehabilitation beyond major work or otherwise of a public safety addressing nature shall be subject to qualified bridge engineer approval and appropriate authority. Data presented at appropriate levels through its various interfaces: operators need alert status and procedures, engineers need model residuals and uncertainty, managers risk and resource implications and auditors, traceability. Network prioritization can also give rise to issues of data ethics and fairness. An optimization that is only based on traffic volume, or on economic value (like the new Bill) may systematically deprioritize rural or socially important bridges. These agencies should provide transparent definitions, both for what consequences and equity criteria mean, weight them against each other to see how resource allocation can change with weighting, and be transparent about the choices that they make in deciding on policies. The twin has to embrace public accountability without revealing details of the infrastructure or data that pertain to security.

10. RESEARCH METHODOLOGY AND EXPERIMENTAL SETUP

10.1 Validation Strategy and Acceptance Criteria

The validation should be top down validate the components leading to decisions. Calibration, synchronization, drift, packet loss and environmental performance are all part of sensor validation. Data–pipeline validation, which confirms that units, timestamps, identifiers and transformations are correct. Model validation compares static and dynamic response between the simulation and measurements, while diagnostic validation uses known defects, controlled tests, and confirmation by inspection or benchmark datasets. Back-testing of prognostic validation uses historical periods and predicts intervals, not just point error. Decision validation is a method used to compare what was recommended versus the actions taken, measure risk reduction, and quantify avoided disruption and economic cost. Use a validation dataset to distinguish between development, tuning and independent evaluation periods. When monitoring over time, it is better to block or use rolling origin than to randomly split. Cross-bridge validation assesses transferability. Model challenges cover a wide range such as sensor failure, inclement weather, seasonal extremes, and uncharacteristic levels of traffic allowing for maintenance interventions and those which are not represented in the training set. In the absence of many real damage examples, this domain gap can be quantified using simulation and laboratory data to augment field data, while cautioning that field confirmation is still required.

The important diagnostic metrics include precision, recall, F1-score, false-alarm rate and detection delay, localization error and severity error (these two are falling into the domain of detect & localize) as well as calibration. For probabilistic outputs: the Brier score, log score, reliability diagram and coverage of prediction intervals. In addition, MAE, RMSE error normalized, the correlation are used for virtual sensing and response prediction (also called localization), while spectral error and mode-shape similarity may be applied for modal analysis. For life-cycle decisions, a metric would scale from inspection reduction to avoided emergency closures, risk avoided per cost unit, budget compliance (in particular for maintaining and upgrading bridge family), user-delay savings, carbon impact and percentage of recommendations accepted by engineers.

Table 7. Validation metrics for an operational bridge digital twin

Dimension	Representative metrics	Purpose
Data	Availability, packet loss, timestamp error, calibration drift	Trustworthiness of input evidence
Model fit	RMSE, modal frequency error, MAC, residual distribution	Behavioral fidelity
Diagnosis	Precision, recall, F1, detection delay, localization error	Ability to detect actionable abnormality
Uncertainty	Brier score, reliability, interval coverage, sharpness	Calibration of probabilistic output
Prognosis	RUL error, threshold-crossing accuracy, back-test performance	Future condition prediction
Decision	Risk reduction, cost savings, value of information, acceptance rate	Operational value

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System	Latency, uptime, recovery time, cybersecurity findings	Deployability and resilience

It should be compared to simpler baselines on the data (such as its twin). A sophisticated model must provide additional benefit beyond periodic inspection, threshold rules, statistical process control, traditional finite-element updating and standard bridge-management deterioration models. Quantifying the contribution of physics constraints, additional data sources, semantic integration, explainability and uncertainty modelling should be conducted via ablation studies. This disallows complexity from being confused for effectiveness. Latency, availability, scalability, performance and maintainability (often in a more abstract way also usability), cybersecurity, disaster recovery. Offline models that perform well but cannot be served at agency response times, or require staff with specialized expertise which may not be possible to maintain, are not deployable. Hence pilots acceptance criteria should be defined before deployment and related to specific use cases like bearing anomaly detection, fatigue monitoring, post-event evaluation or inspection prioritization.

11. RESULTS OF THE PROOF-OF-CONCEPT EVALUATION

The Experimental Results from aging bridge SHM time-series dataset is explained in this section. The dataset comprises 1,340 observations and 15 varibles of the populat list This resulted in the use of 53 numerical sensor and environmental predictors for current degradation prediction, future degradation forecasting, structural-condition classification and unsupervised anomaly detection following cleaning and temporal feature engineering. In the supervised tasks, a chronological 80:20 split was performed providing records for training (n=1,072) and test (n=268) data.

11.1 Dataset and Experimental Configuration

Only 1,340 observations were left for analysis as there are no duplicate records identified. The original variables were made up of a range of 2 triaxial accelerations, temperature, humidity, wind speed for all FFT peak frequency and magnitude as well used degradation score and structural-condition class damage class feature with a 30-day forecast score. Furthermore, other lag, change and rolling-window variables have been created to depict short-term temporal behavior. The experimental setup is summarized in table 8.

Table 8. Dataset and experimental configuration

Item	Value
Dataset size	1,340 rows × 15 original columns
Duplicate rows removed	0
Engineered numerical predictors	53
Training records	1,072
Testing records	268
Regression model	Extra Trees Regressor
Classification model	Extra Trees Classifier
Anomaly model	Isolation Forest
Temporal validation	Chronological 80:20 split and TimeSeriesSplit

11.2 Overall Predictive Performance

An easily identifiable difference between the current-state and future-state would be: when look at Table 9. The R^2 value for the future degradation model was 0.7851, meaning that about this fraction of variation in the target for the 30-day forecast is explained in each held out period. MAE 8.9210 and RMSE 10.8718 which were remarkably lower than that of the existing degradation model was attained by using this method. Despite cross-validation being applied, time naive cross-validation also maintained a positive score at 0.7360, suggesting that forecasting behavior across sequential folds is comparatively constant. In comparison, the degradation model implemented as per the code produced an R^2 = -0.0480 and cross-validation score of -0.0271. A negative R^2 means that the model is slightly worse than predicting mean degradation value for all test records. So the current-state regression should not be seen as a direct estimator of degradation observed at arrival time. This shortcoming is also visible in the MAE and RMSE of 19.5237 and 23.4128 from M274 CV, respectively, which seem to be quite high.

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Table 9. Summary of predictive performance

Task	Model	N	MAE	RMSE	R^2	Accuracy	F1	CV score
Current degradation prediction	Extra Trees Regressor	1340	19.5237	23.4128	-0.0480	-	-	-0.0271
Future degradation forecast	Extra Trees Regressor	1340	8.9210	10.8718	0.7851	-	-	0.7360
Structural condition classification	Extra Trees Classifier	1340	-	-	-	0.3433	0.2751	0.2471

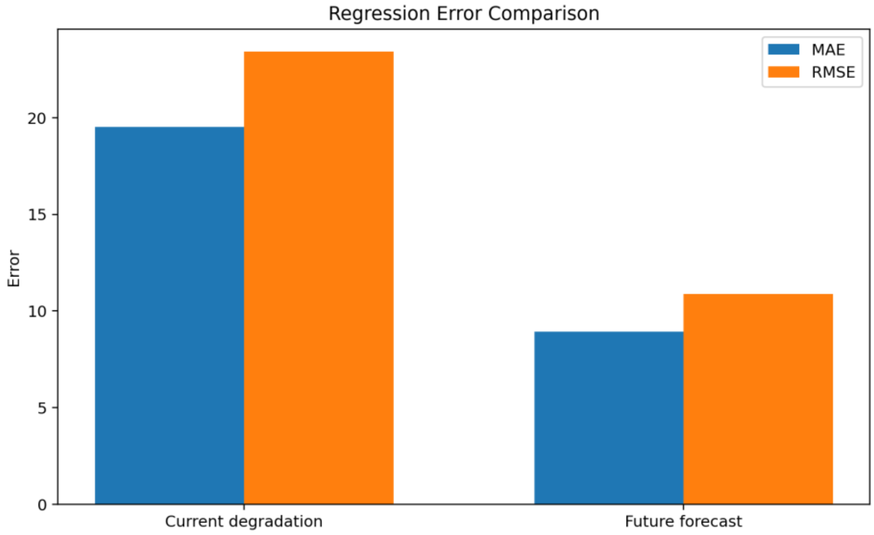

Figure 4. Comparison of MAE and RMSE for current degradation prediction and future degradation forecasting.

Figure 4 confirms that the future forecasting task was considerably easier for the fitted model than reconstruction of the current degradation score. One likely reason is that the forecasting model included the current degradation score and degradation-history variables as predictors, whereas the current-state model relied only on sensor and environmental features. This makes the forecast target strongly conditioned on an already informative degradation measure. The result is useful for short-horizon prediction, but it should be validated carefully to ensure that the 30-day forecast label is not a deterministic transformation of the current score.

11.3 Structural-Condition Classification

The structural-condition classifier achieved an accuracy of 0.3433, balanced accuracy of 0.2471 and weighted F1-score of 0.2751. These values indicate limited discrimination among the four condition classes. The model was most effective for Class 1 (Minor), with a recall of 0.76 and F1-score of 0.50, but it failed to identify any Class 3 (Severe) observations. Because only 16 severe records were present in the test set, the classifier was strongly affected by class imbalance and insufficient representation of high-damage cases. Detailed class-wise results are reported in Table 10.

Table 10. Class-wise structural-condition performance

Class	Precision	Recall	F1-score	Support
0 - No Damage	0.27	0.11	0.15	74
1 - Minor	0.37	0.76	0.50	98
2 - Moderate	0.25	0.12	0.17	80
3 - Severe	0.00	0.00	0.00	16

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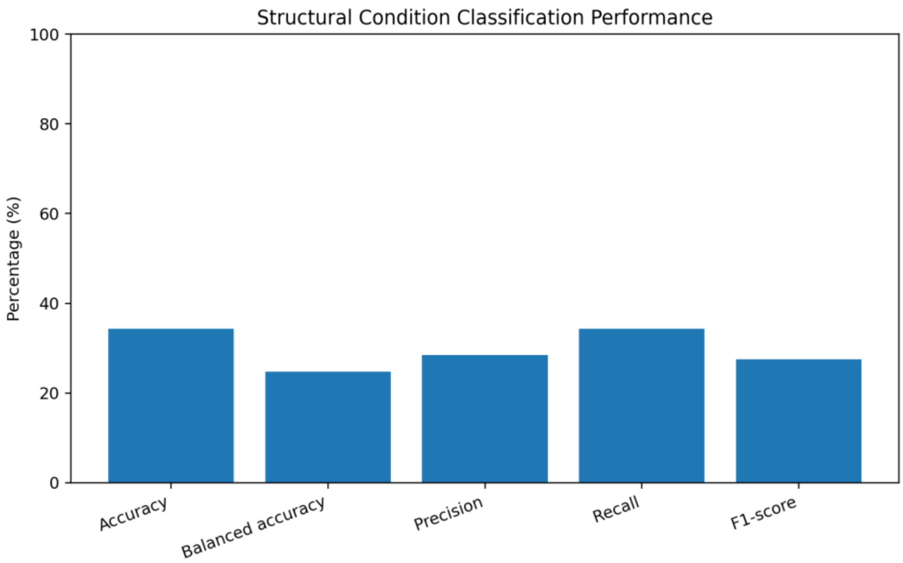

Figure 5. Aggregate classification metrics for the structural-condition model.

The confusion matrix in Figure 6 shows that 198 of the 268 test cases were predicted as Class 1. This strong prediction bias explains why recall for the Minor class was relatively high while performance for the other classes remained poor. Among 74 No-Damage records, only 8 were classified correctly; among 80 Moderate records, only 10 were correctly recognized; and none of the 16 Severe records were detected. These results mean that the classifier is not suitable for safety-critical bridge condition screening in its present form.

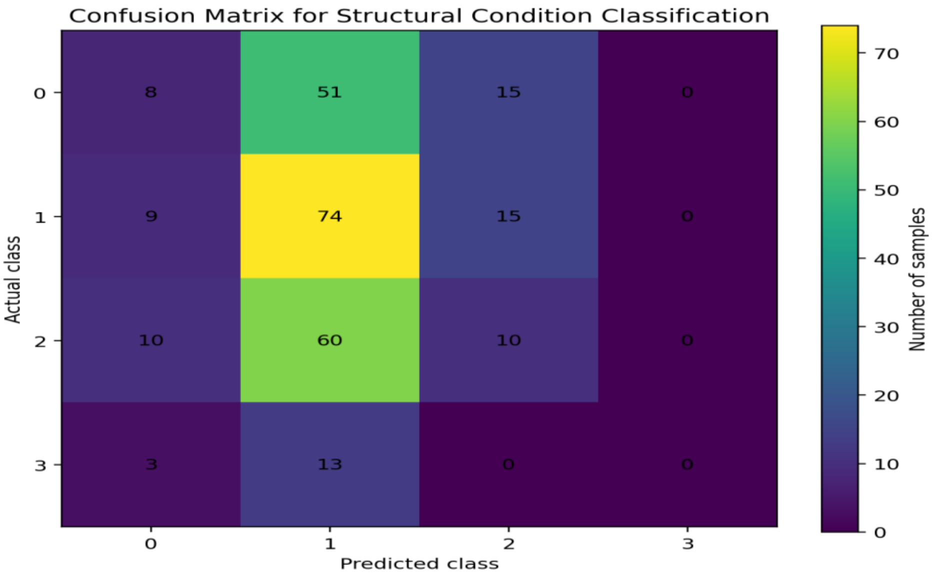

Figure 6. Confusion matrix for the four structural-condition classes.

Improvement requires bridge-wise and sensor-wise sequence modelling, stronger class balancing, cost-sensitive learning and explicit evaluation of the Severe class. Class weights were already enabled, but the very small severe-class sample remained insufficient. Oversampling confined to the training set, focal loss, balanced random forests, gradient boosting, temporal convolutional networks or multi-task learning with the degradation score may improve minority-class sensitivity. However, all resampling and feature engineering must be performed within each training fold to prevent optimistic bias.

11.4 Anomaly Detection and Current Digital-Twin State

The Isolation Forest identified 39 anomalous observations, corresponding to an anomaly rate of 2.91%. This is a relatively small proportion and is appropriate for a screening layer intended to flag unusual combinations of vibration, frequency-domain and environmental variables. Nevertheless, unsupervised anomalies are not equivalent to verified structural damage. They may also represent sensor faults, unusual weather, operational changes or records belonging to different bridges and sensor locations. The resulting current-state indicators are summarized in Table 11.

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Table 11. Current AI-driven bridge digital-twin state

Digital-Twin Indicator	**Current State**
Current predicted degradation	40.5643
Future degradation forecast	35.8481
Bridge Health Index	54.12
Anomaly Score	50.64
Structural Condition	2 - Moderate
Lifecycle Risk Score	47.31
Lifecycle Risk Class	Moderate
RUL Proxy	726.9 observation intervals
Recommended Action	Increase monitoring frequency and review sensor trends

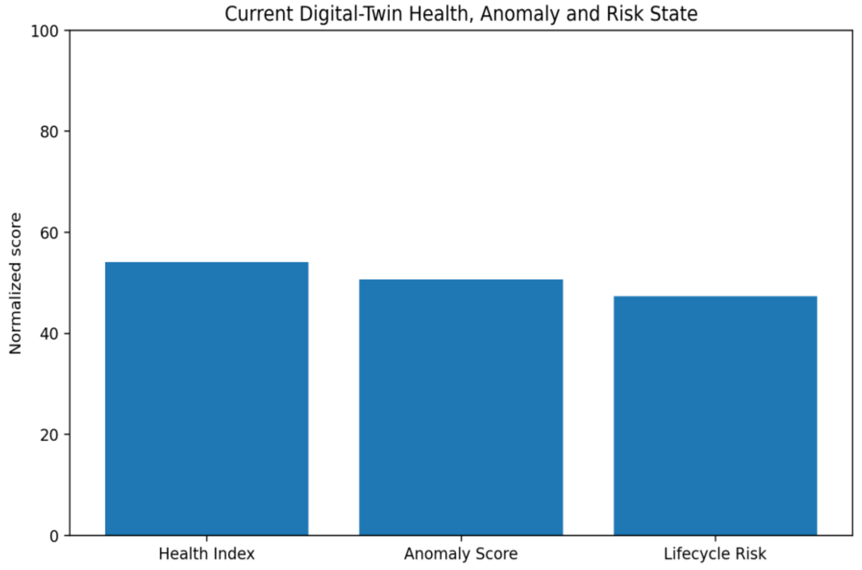

Figure 7. Current bridge health, anomaly and lifecycle-risk indicators.

The last record predicted a degradation value of 40.5643 and the future prediction was 35.8481 Bridge Health Index of 54.12, anomaly score at 50.64 and lifecycle risk score at 47.31 classifies the state in Moderate risk band. Structural condition Class 2 is classified as Moderate damage according to the dataset coding. Thus, the recommended course of action which is high-frequency monitoring and review of sensor trends drives consistency with the resulting risk class rather than over-reacting to a model predicting one output.

The RUL proxy of 726.9 intervals is nothing more than a crude extrapolation on the basis of trends It is not to be seen as calendar life, since records from different bridges and sensors were globally ordered. RUL estimation should be treated independently for separate bridge–sensor pair with the associated thresholds and uncertainty bands setting.

11.5 Feature Importance and Physical Interpretation

The feature-importance analysis indicates that frequency-domain variables, wind exposure, thermal effects, humidity and rolling vibration variability contributed most strongly to the current degradation model. FFT magnitude was ranked first, followed by wind speed, lagged FFT peak frequency and lagged FFT magnitude. Environmental variables such as thermal deviation and humidity also appeared among the leading predictors, supporting the need to normalize bridge response for environmental and operational variability. The ranked values are listed in Table 12.

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Table 12. Fifteen most influential features

Rank	Feature	Importance
1	$fft_{magnitude}$	0.023167
2	$wind\_speed\_mps$	0.021891
3	$fft_{peak_{freq_{lag2}}}$	0.021275
4	$fft_{magnitude_{lag2}}$	0.020868
5	$thermal_{deviation}$	0.020543
6	$fft_{magnitude_{lag1}}$	0.020273
7	$humidity_{percent}$	0.020100
8	$accel_{magnitude_{rolling_{std_5}}}$	0.020020
9	$humidity_{percent_{lag2}}$	0.019935
10	$fft_{peak_{freq}}$	0.019930
11	$temperature_{c_{lag1}}$	0.019759
12	$fft_{magnitude_{change}}$	0.019644
13	$fft\_peak\_freq\_rolling\_mean\_5$	0.019619
14	$temperature_{c_{lag2}}$	0.019591
15	$acceleration_{y_{rolling_{mean_5}}}$	0.019560

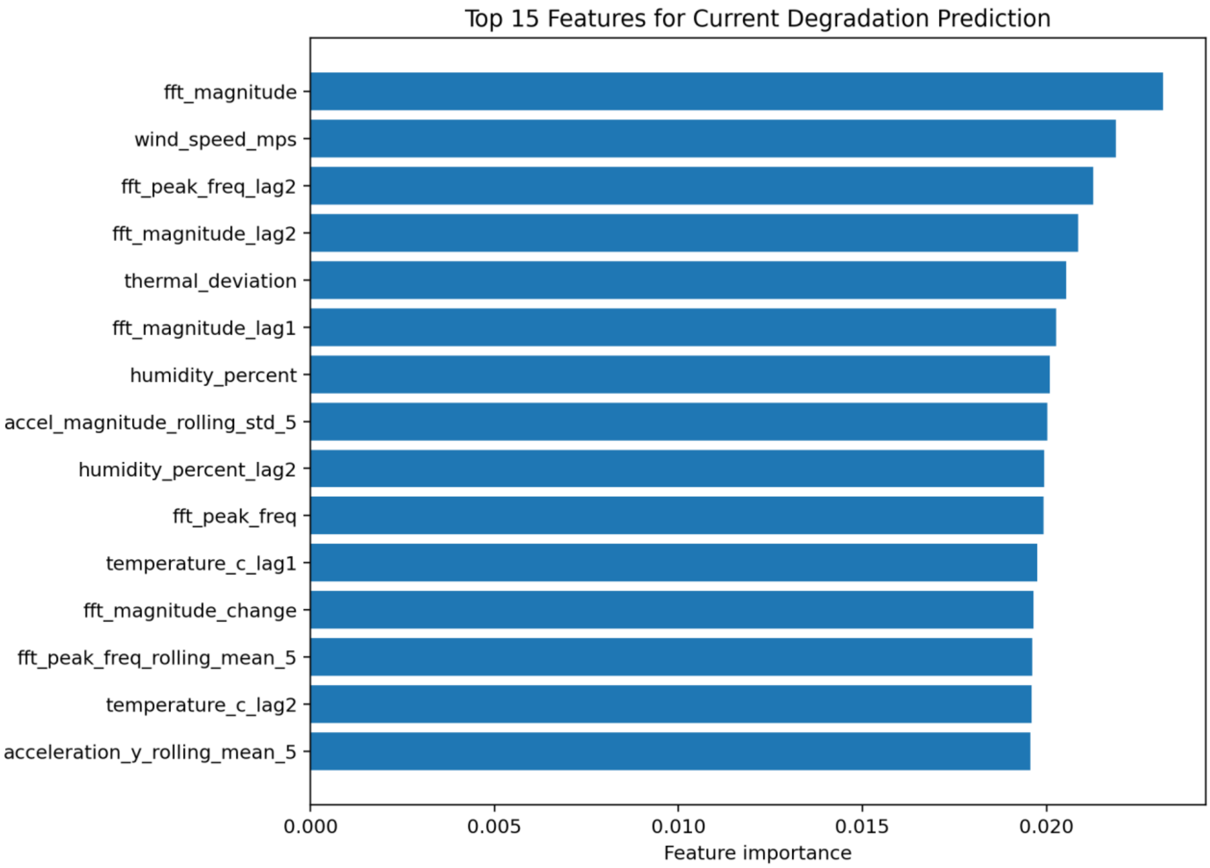

Figure 8. Top 15 feature-importance values for current degradation prediction.

No feature had an importance greater than 0.0232, and the leading values were tightly clustered. This diffuse pattern indicates that the Extra Trees model did not identify a single dominant degradation indicator. It also helps explain the weak current-degradation R^2: the model appears to distribute prediction weight across many weakly informative variables. In a physical bridge twin, this issue can be addressed by grouping features by bridge, sensor and structural component, extracting modal

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parameters more explicitly, and incorporating engineering priors such as stiffness change, strain exceedance, corrosion progression or component-level damage labels.

12. DISCUSSION

The strongest result is the future degradation forecast, which achieved $R^2 = 0.7851$ and maintained a positive time-series cross-validation score. This demonstrates the potential of an AI-assisted digital twin to support short-horizon lifecycle forecasting when the model has access to the current degradation state and its recent evolution. Such a forecasting layer can be used to rank inspections, test maintenance timing and estimate whether a condition threshold may be crossed within a planning horizon. However, the poor current-state regression and classification results show that reliable bridge diagnosis cannot be obtained from the present global feature matrix alone. The model did not adequately map raw sensor and environmental variables to the degradation and condition labels. This can be due to poor target-feature relationship, observations amalgamated from heterogeneous bridges and sensors, insufficient sequence length, label generation in synthetic datasets or absence of geometry, traffic loading and maintenance history per bridge. As such, the current framework should be perceived as a prototype analytics pipeline instead of being seen as an operational validated digital twin. The most prominent methodological shortcoming is that lag and rolling features were generated post- global timestamp sorting of the dataset. Due to the fact that records are identified by a combination of bridge and sensor identifiers, a lagged value might be from an entirely different bridge or different sensor. This can distort temporal relations and reduce interpretability. Consequently, all future modelling should be grouped first on bridge_id and sensor_id, with lags and rolling stats calculated within the groups. Likewise, the train–test split should also be group-aware as to quantify generalization capacity against unseen bridges, separate from forecasting against seen bridges. The findings provide additional support for a strategy to build a hybrid digital-twin. The regression without reacting is weak; the one in which we condition on degradation history is much stronger. Better would be a real-world system that incorporates finished element or condition space models, sensor-quality checks (eg, normalizing to environmental noise), and AI-based residue investigation and engineer-review evidence of good state. The principle of Governance and human-oversight we propose in the main paper is to not have automatic intervention, but periodical monitoring for risk also applies at this moderate state of current risks. The proof-of-concept findings are consistent with the broader literature in showing that digital-twin value depends on the integration of sensing, contextual normalization, physics-based interpretation, and governed decisions rather than on predictive accuracy alone. The strong future-forecast result is not sufficient evidence of lifecycle validity because the target may be strongly conditioned on the current degradation variable. Conversely, the weak current-state and class-level results demonstrate the difficulty of inferring structural condition from mixed observational records without bridge geometry, component context, verified damage labels, and bridge-specific temporal sequences. The revised interpretation therefore treats the experiment as a diagnostic demonstration of the proposed analytical pipeline and not as field validation of an operational bridge twin.

12.1 Research Priorities and Practical Implications

The synthesis indicates that practical bridge twinning is an integration problem before it is an algorithmic problem. Sensing, inspection, bridge information models, finite-element analysis, artificial intelligence and maintenance systems create value only when observations retain common identifiers, time references, quality states and evidence provenance. The proposed six-layer architecture therefore separates acquisition, integration, hybrid modelling, prognostics and decision governance while maintaining controlled feedback between the physical and virtual assets.

The most significant technical challenge is reliable inference under sparse and nonstationary evidence. Environmental and operational variability can resemble structural deterioration; field damage labels are rare; and model-form uncertainty grows when a bridge departs from its assumed boundary conditions. Hybrid physics-data models, calibrated probability, multiple-model comparison and explicit validity domains are consequently more defensible than unrestricted black-box prediction. Their success should be measured through confirmed inspections and maintenance outcomes rather than laboratory accuracy alone.

For asset owners, the immediate research and implementation priority is a minimum viable twin attached to a material decision problem. A bounded pilot should document the existing process, quantify uncertainty and consequences, operate first in shadow mode, and demonstrate measurable improvement over inspection schedules, threshold rules or conventional deterioration models. Portfolio scaling should proceed only after technical validity, cybersecurity, human usability, lifecycle value and organizational ownership have been independently reviewed.

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12.2 Cross-Cutting Research Priorities

Table 13. Priority research gaps and recommended directions

Research gap	Recommended direction
Sparse and heterogeneous data	Multimodal fusion, active sensing and calibrated virtual sensing
Limited damage labels	Transfer learning, physics-informed learning and synthetic-data validation
Environmental variability	Context-conditioned baselines and domain adaptation
Uncertain prognosis	Probabilistic RUL, Bayesian model averaging and scenario ensembles
Model trust	Explainability, calibration, independent validation and assurance cases
Portfolio scaling	Reusable ontologies, templates and network-level risk models
Operational adoption	Human-centered workflows, cybersecurity and measured business value

13. IMPLEMENTATION AND PILOT ROADMAP

13.1 Data Governance and Semantic Dictionary

A bridge digital twin remains maintainable only when every observation can be traced to a stable asset, component, location, time, unit, source and quality state. The minimum semantic dictionary below can be implemented in a relational database, an asset information model or a knowledge graph. Common identifiers must be preserved across BIM, GIS, sensing, finite-element, inspection, work-order and document systems.

Table 14. Minimum semantic fields for lifecycle data integration

Field group	Minimum fields	Control requirement
Asset identity	bridge ID, route, owner, coordinates, commissioning date	Permanent identifier; no reuse after retirement
Component identity	system, element, sub-element, span, support, station	Hierarchy aligned with inspection and maintenance coding
Observation	variable, value, unit, timestamp, duration, sampling rate	Machine-readable units and synchronized time
Evidence source	sensor/inspection/model/document ID, device type, operator	Traceable source and version
Spatial context	global coordinates, local axis, surface/volume region	Transform between GIS, BIM and analytical coordinates
Quality state	completeness, calibration, drift, uncertainty, validation flag	Quality travels with every value
Damage state	mechanism, location, extent, severity, confidence	Separate observation from engineering interpretation
Model state	model ID, parameters, calibration date, validity domain	Version-controlled and reproducible
Decision state	alert, reviewer, recommendation, approval, due date	Auditable human accountability
Intervention	work order, method, quantity, cost, completion, verification	Closed-loop update after physical change

The semantic fields in Table 14 form the minimum governance layer for linking BIM, GIS, monitoring, inspection, finite-element and work-order information. Agencies should extend the dictionary with local component codes while preserving persistent identifiers, machine-readable units, version control and traceable quality metadata.

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13.2 Monitoring and Inspection Deployment Strategy

Monitoring design should begin with a decision question rather than a sensor catalogue. The strategy below links common bridge concerns to observable evidence, update frequency and independent verification. Permanent sensing is justified for dynamic or high-consequence phenomena; mobile or targeted inspection is often more economical for slowly evolving deterioration. Redundancy should be risk-based, and every automated alert should identify a feasible confirmation method.

Table 15. Decision-led sensing and inspection plan

Lifecycle concern	Primary evidence	Typical frequency	Independent verification
Global stiffness or modal change	accelerometers, temperature, operational modal analysis	continuous or scheduled campaigns	load test or calibrated finite-element review
Fatigue-sensitive detail	strain, traffic spectrum, weld inspection	event/continuous plus periodic	ultrasonic or magnetic-particle testing
Scour and foundation response	sonar, water level, tilt, vibration, bathymetry	storm-triggered and seasonal	diver/ROV survey and hydraulic assessment
Bearing or joint malfunction	displacement, rotation, temperature, imagery	daily to seasonal	close visual inspection and movement measurement
Corrosion and section loss	potential/resistivity, humidity, UT thickness, imagery	monthly to annual	material sampling or targeted NDT
Crack growth	high-resolution imagery, acoustic emission, gauges	event-based to monthly	manual gauge or NDT confirmation
Deck delamination	GPR, infrared thermography, impact echo	targeted campaign	cores or chain drag where permitted
Overload and abnormal traffic	weigh-in-motion, strain, CCTV/ANPR metadata	continuous	traffic record and structural analysis
Extreme-event damage	strong motion, displacement, imagery, inspection	event-triggered	emergency engineering inspection

The deployment strategy in Table 15 should be reviewed after significant inspections, interventions and extreme events. Permanent monitoring is justified where change can be rapid or consequences are high, whereas targeted mobile sensing and nondestructive testing may be more economical for slowly evolving defects.

13.3 Predictive Model Selection and Assurance

Model complexity should match the decision, available data and consequence of error. A transparent baseline is required before deep learning is introduced. Hybrid and probabilistic models are preferred for high-consequence prognosis because they can preserve physical feasibility and represent epistemic and aleatory uncertainty. Deployment approval should consider calibration, robustness, maintainability, explainability and inference latency in addition to aggregate accuracy.

Table 16. Model families matched to bridge lifecycle tasks

Task	Practical model family	Strength	Main control
Sensor quality and drift	rules, robust statistics, autoencoder, change-point model	early isolation of unreliable evidence	avoid confusing damage with sensor failure
Image defect detection	CNN/vision transformer with segmentation	rapid localization and quantification	domain shift, scale calibration and human review
Dynamic anomaly detection	PCA, OMA features, temporal CNN/transformer	uses ambient response trends	temperature/traffic normalization
Virtual sensing	Gaussian process, state-space model, neural operator	estimates unmeasured response	interval coverage and extrapolation warning
Damage localization	model updating, graph learning, Bayesian inference	connects response to components	identifiability and multiple-model ambiguity
Deterioration forecasting	survival, Markov, recurrent	time-to-threshold and RUL	censoring, calibration and

	model, physics-informed model	prediction	scenario sensitivity
Risk forecasting	Bayesian network, Monte Carlo, reliability model	combines probability and consequence	transparent assumptions and tail risk
Maintenance planning	mixed-integer optimization, dynamic programming, RL with constraints	portfolio and timing optimization	safety gates and feasible action space
Explainability	feature attribution, counterfactuals, sensitivity, rule extraction	supports review and evidence gathering	engineering meaning, stability and causality limits

Model approval should follow the controls in Table 16 and include comparison with a transparent baseline, blocked temporal validation, uncertainty calibration, extrapolation warnings, documented failure modes and independent engineering review. Higher model complexity is justified only when it produces measurable decision value.

13.4 Lifecycle Risk and Decision Documentation

The twin should compose evidence departments, not black boxes. You should retain the basis evidence, uncertainty and consequence tracker assumptions, recommended action on approver challenge for closure of each decision record. The following register is ready for pilot and operational deployment. It can be integrated with an Enterprise Asset management solution; Thresholds need to be tuned together, around classes and redundancy of prominence weight traffic access and emergency. So register in Table 17 links evidence, risk interpretation, approved action, execution and post-work verification all as an auditable trace. And it must be linked into the agency work-order process, so that physical interventions automatically drive updates to model, geometry, condition and maintenance-history.

Table 17. Minimum risk and intervention register

Register item	Required content	Lifecycle purpose
Issue identifier	bridge/component, timestamp, mechanism and source	unambiguous tracking
Current condition	observed state, trend and comparison with baseline	shared situation awareness
Evidence quality	completeness, calibration, conflicts and confidence	prevents false precision
Forecast	future state/RUL distribution and assumptions	supports timing decisions
Consequence	safety, service, economic, environmental and network impact	risk-based prioritization
Recommended action	observe, inspect, restrict, repair, strengthen or replace	actionable output
Alternatives	feasible options, costs, disruption and expected risk reduction	transparent trade-off
Approval	reviewer, authority, decision, rationale and date	human accountability
Execution	work order, resources, traffic plan and completion evidence	connects digital and physical change
Verification	post-work inspection/sensing and updated model residual	confirms effectiveness
Learning record	false alarm, missed detection, model or process update	continuous improvement

13.5 Pilot Evaluation and Acceptance Criteria

A pilot should test an operational hypothesis on a bounded set of components and decisions. Shadow-mode operation is recommended before workflow integration: the twin generates outputs while engineers continue normal practice and compare recommendations prospectively and retrospectively. Acceptance requires technical performance, usable evidence, resilient operation, cybersecurity controls, human trust and demonstrated decision value. Table 18 supports a reproducible evaluation report.

Table 18. Pilot acceptance and reporting checklist

Evaluation area	Evidence to report	Example acceptance question
Use case and baseline	decision, users, current process, costs and pain points	Is the problem measurable and worth solving?
Asset and data scope	components, sensors, records, missingness and ownership	Can all inputs be traced and legally used?
Ground truth	inspection/NDT/load-test labels and adjudication process	Is validation independent of model output?
Technical validity	accuracy, error, calibration, robustness and ablations	Does the twin outperform a simpler baseline?
Temporal validity	blocked/rolling tests and event performance	Does performance persist through time?
Operational validity	latency, uptime, recovery, maintainability and integration	Can the service be sustained by available staff?
Decision value	inspection reduction, avoided delay, cost/risk change and VOI	Does it improve a real decision?
Human factors	review time, explanation usefulness, overrides and training	Can engineers understand and appropriately challenge it?
Security and governance	access, logs, model versions, incident tests and approvals	Is accountability preserved under failure?
Scale-up decision	accepted limitations, remediation, owner, budget and next gate	Is expansion justified and controlled?

Overall, a credible AI-driven bridge digital twin is a governed, continuously updated decision system rather than a static three-dimensional model. Its lifecycle value depends on reliable sensing, hybrid physics-AI inference, calibrated uncertainty, transparent human approval and verified maintenance outcomes. Pilot evidence should determine whether portfolio-scale deployment is justified.

14. LIMITATIONS AND THREATS TO VALIDITY

This study is not an actual physical bridge deployment, but a mixture of structured review, conceptual architecture, and analysis of proof-of-concept datasets. Consequently, the results cannot verify operational safety, cost efficiency, or maintenance effectiveness for actual bridge stock. The temporal features on things in regards to the time periods are obtained after explicitly global-ordered records. Lagged and rolling variables can confuse unrelated sequences since observations may belong to different bridge and sensor identifiers. This imperils whatever temporal validity exists and also necessitates future experiments to group bridge_id-sensor_id. The 30-day forecast is based on both actual degradation and degradation history variables, leading to a potential target-information advantage. To assess if the model only propagates a score already given by noise (or not) through sensors, these characteristics need to undergo ablation. Class imbalance, combined with the Small number of Severe observations affects the structural condition classifier. Its inability to detect the Severe class makes it not appropriate for safety-critical screening. Unsupervised Isolation Forest alerts are also not equivalent to validated damage and might flag sensor failures, environmental extremes or operational changes. The Bridge Health Index, anomaly score/lifecycle-risk score/action thresholds are exemplary ones. Their associated weights, normalization rules and decision boundaries are not calibrated to bridge-specific reliability analysis, inspection outcomes or agency risk policy. Your reported RUL proxy is in observation intervals, which must not be interpreted as calendar service life. Without boundaries on bridge geometry, component hierarchy, traffic loading, maintenance history, hazard records and documented effective interventions in the case of failure events or damage propagation from hazards to failures making inter-bridge comparisons also leaves open questions of external validity. Publication bias, variation in terminology and substandard reporting of failed bridge-twin implementations may also impair the review.

15. FUTURE RESEARCH

Benchmark bridge-twin datasets that include long-term sensors, inspection imagery, interventions, environmental context and verified defects should be constructed for future research. Commonly existing datasets either cadge a single modality or scale lifecycle outcomes. Federated learning, along with privacy- and security-preserving data sharing (by keeping sensitive details

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private), may allow agencies to work together without having to share the most deeply proprietary slices of their customer bases or risk damaging them. Benchmarks should include cases of data faults and negative results so that we can realistically assess the performance of algorithm systems with respect to false alarms, which are costly for applications. Physics-informed foundation models and neural operators have a future with transferable structural surrogates but they need validation in excitable boundary conditions and infrequent hazards. If implemented as monolithic models graph-based twins may better reflect component dependence and network-dependent consequences. Such comparisons may be confounded by environmental variation, and causal inference can help to separate deterioration from this fact, as well as ascertain the effectiveness of interventions. These active learning and value-of-information methods identify inspections that reduce uncertainty in decision-making most.

Multi-hazard lifecycle management is also an area that needs investigation. The first issue is climate change, which results in changes in the exposure for flooding, scour, heat, corrosion, wildfire and wind; the second one is traffic combined with vehicle technology that determines load spectra. Digital twins should encompass hazard projections, adaptation alternatives and deep uncertainty instead of relying on historical conditions extrapolations. Cascading effects, detour capacity, emergency access and equity should be part of network-level twins. Finally, governance standards must mature. Approaches for certification of safety-relevant AI, model updates, digital evidence and human machine decision responsibilities are necessary. However, future bridge twins will need to give machine-readable assurance cases that map requirements to tests and model limitations as well as coverage from monitoring tools on the physical system and who has approved all of this. The end-game is not autonomous bridge management, but a responsible enhancement of engineering judgement. Future experiments need to incorporate group-aware feature engineering and validation, report known-bridge and unseen-bridge performance separately, and compare with transparent engineering statistical baselines as well as hybrid models. Severe-class sensitivity, prediction interval coverage, and engineer-validated false alarms should be used as the primary acceptance metrics.

16. CONCLUSION

We proposed here a structured literature review, a six-layer governed architecture along with works to test our concept of an Ai based bridge digital twins. This framework is linking physical sensing and inspection and semantic information about the assets, hybrid physics-data modelling, artificial-intelligence services, uncertainty-aware lifecycle risk, maintenance optimization, cyber security and qualified human approval to solve the challenges faced with data transmission across batch processes. This proof-of-concept experiment offers a potential to classify degradation over 30days (MAE = 8.9210, RMSE = 10.8718 and $R^2 = 0.7851$), yet current structural-condition leveled prediction and further classification remain associated with poor performance because the model failed to detect cases at the Severe-class level. Autonomous Safety based on these findings is not supported. They instead indicate points within the analytical pipeline where useful insights can be gained and where continued methodological controls are needed. It should utilize the domain expert answer as evidentially based training data for classification labels in a model-driven sense, which means a defensible operational bridge twin requires that it be built as an evidence-based knowledge graph, using bridge-specific temporal sequences, transparent baselines tied to their respective hybrid physical constraints with calibrated uncertainty along both axes for arc length rated strains in Newton-metric non-incremental lengths and max strain severity quotient damage or intervention labels over senes. The main contribution is hence not a predictive maintenance ready for deployment but rather a reproducible blueprint for research and pilot implementation.

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