TYPE
Narrative Review

DOI
10.5281/zenodo.22710431

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RECEIVED

APRIL , 2026

ACCEPTED

SEPTEMBER, 2026

CITATION
Sanya, S. O. (2026). Developing a data-driven engineering management framework for early detection of infrastructure failure and lifecycle cost reduction. ScienceXplorer.

Developing a Data-Driven Engineering Management Framework for Early Detection of Infrastructure Failure and Lifecycle Cost Reduction

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Abstract

Infrastructure systems are increasingly exposed to ageing, excessive loading, environmental deterioration, deferred maintenance, climate-related hazards, and operational uncertainty. Conventional engineering management practices frequently depend on periodic inspections, historical records, expert judgement, and reactive maintenance, which can delay the identification of progressive deterioration and increase lifecycle expenditure. This paper reconstructs and extends a data-driven engineering management framework for early detection of infrastructure failure and lifecycle cost reduction by integrating structural health monitoring, Internet of Things sensing, machine learning, predictive maintenance, digital twins, probabilistic deterioration modelling, risk-based decision support, and lifecycle cost analysis. A structured narrative review with systematic search elements was undertaken across 50 compiled evidence entries; after removing 13 duplicate citations and restoring one in-text citation that lacked a reference-list entry, 38 unique peer-reviewed and authoritative technical sources formed the core synthesis base, supplemented by 17 further verified sources supporting specific claims elsewhere in the text, for 55 references in total. The evidence indicates that sensor-generated data, inspection records, environmental observations, traffic information, maintenance histories, and digital models can be integrated to produce condition indicators, failure probabilities, deterioration forecasts, remaining useful life estimates, and intervention priorities. The proposed framework consists of eight interconnected layers: asset data acquisition, data governance and integration, condition assessment, anomaly detection, deterioration and failure prediction, risk assessment, lifecycle decision optimization, and management feedback. The synthesis further indicates that machine learning can improve the identification of nonlinear deterioration patterns, probabilistic models provide uncertainty representation, and digital twins provide a mechanism for continuously updating asset-state information. Lifecycle cost reduction is achieved not simply through prediction accuracy but through translating predictions into appropriately timed maintenance interventions. The framework therefore positions data analytics as a management capability rather than merely a computational tool and provides a pathway toward proactive, risk-informed, lifecycle-oriented infrastructure management.

Keywords: *infrastructure management; machine learning; structural health monitoring; predictive maintenance; digital twin; lifecycle cost; failure prediction; asset management; Internet of Things; engineering management*

How to Cite
*Sanya, S. O. (2026). Developing a data-driven engineering management framework for early detection of infrastructure failure and lifecycle cost reduction. ScienceXplorer, 8(2). https://doi.org/*10.5281/zenodo.22710431

1. Introduction

Infrastructure assets including bridges, roads, buildings, water systems, tunnels, railways, drainage networks, and other civil engineering facilities constitute long-lived systems whose performance changes continuously during operation and maintenance. Their deterioration is influenced by interacting physical, environmental, operational, and managerial factors, making infrastructure condition a dynamic rather than static property (Azimi et al., 2020). Structural health monitoring research has consequently moved from periodic assessment toward continuous or semi-continuous acquisition of condition information using sensors, computational systems, and data-driven algorithms (Tibaduiza Burgos et al., 2020). The expansion of sensing technologies has increased the quantity and temporal resolution of infrastructure data available to engineering managers (Bhatta & Dang, 2024). Wireless sensor networks can provide distributed measurements of structural response while reducing some of the limitations associated with conventional wired monitoring systems (Zhou & Yi, 2013).

The management problem is not simply that infrastructure deteriorates, but that deterioration is often recognized after substantial damage has accumulated. Traditional visual inspection remains important, but inspection intervals can leave managers with limited information about rapidly changing conditions between inspection events (Luo et al., 2023). Computer vision research has demonstrated the potential to automate or support identification of cracks, spalling, corrosion, displacement, and other visible indicators of infrastructure deterioration (Spencer et al., 2019). Deep learning has further expanded automated damage detection by learning representations directly from infrastructure images rather than relying exclusively on manually engineered defect features (Cha et al., 2017; Hsieh & Tsai, 2020; Hamishebahar et al., 2022). Remote and autonomous inspection technologies can extend this capability through unmanned aerial vehicles, LiDAR, radar, satellite observations, and robotic platforms (Jeong et al., 2022). Consequently, infrastructure inspection can increasingly become a continuous information-generation process rather than an isolated periodic activity (Luo et al., 2023).

Machine learning provides an additional capability because infrastructure deterioration is rarely governed by a single linear relationship. Traffic loading, age, material characteristics, construction quality, environmental exposure, maintenance history, and structural configuration can interact in ways that are difficult to represent using simple deterministic models (Sarkar & Sinha, 2026). Machine learning methods can identify nonlinear relationships within large multivariate datasets and can therefore support prediction of condition states, defects, anomalies, and future deterioration (Wuest et al., 2016). Predictive maintenance literature demonstrates that machine learning can be used for fault classification, anomaly detection, remaining useful life estimation, and maintenance planning (Carvalho et al., 2019; Zonta et al., 2020; Dalzochio et al., 2020; Pech et al., 2021). In infrastructure management, similar principles are increasingly being applied to bridges, pavements, buildings, railways, and other long-lived assets (Shahrivar et al., 2026). The value of these methods, however, depends on data quality, model validation, interpretability, uncertainty management, and the ability to translate predictions into engineering decisions (Shahrivar et al., 2026).

Digital twin technology provides a further opportunity to connect physical infrastructure with continuously updated digital representations. A digital twin can integrate sensor observations, engineering models, historical information, simulation, and analytics within an operational digital environment (Jiang et al., 2021). Reviews of digital twins in the built environment indicate that applications increasingly encompass facility management, structural performance, safety, risk management, sustainability, and construction management (AlBalkhy et al., 2024). Infrastructure-oriented digital twin research similarly emphasizes the potential to support design, construction, operation, maintenance, and lifecycle decision-making (Taherkhani et al., 2024). Structural health monitoring research has demonstrated how digital twins can combine finite element models, sensing systems, and data-driven analytics to provide dynamic representations of infrastructure condition (Fu et al., 2024).

Consequently, digital twins can serve as an integration layer between predictive analytics and engineering management rather than simply as three-dimensional visualization tools, a capability increasingly demonstrated in bridge- and asset-level implementations (Hosamo et al., 2022; Pregnolato et al., 2022; Mahmoodian et al., 2022).

Despite these developments, an important research and management gap remains. Much of the existing literature addresses individual components such as structural health monitoring, machine learning, digital twins, pavement deterioration, computer vision, or predictive maintenance, while fewer approaches provide an integrated management framework connecting data acquisition to failure prediction, risk prioritization, lifecycle costing, intervention selection, and organizational learning (Yan et al., 2020). Infrastructure management requires more than accurate predictions because an accurate prediction that does not influence inspection, maintenance, budgeting, or risk decisions provides limited practical value (Oh et al., 2023). Lifecycle cost analysis further indicates that maintenance timing can influence total ownership expenditure, particularly when early intervention can prevent expensive rehabilitation or failure consequences (Kim et al., 2006). This paper therefore reconstructs and extends a data-driven engineering management framework that connects infrastructure condition data, predictive analytics, risk assessment, lifecycle costing, and management decisions into one feedback-oriented system (Oh et al., 2023), and, unlike a purely descriptive review, presents that framework as an explicit eight-layer architecture supported by a documented search-and-selection protocol.

2. Methodology

2.1 Research Design

This study adopted a structured narrative review design with systematic search elements, because the objective was to synthesize evidence across several interconnected technological and engineering domains and to derive an integrated management framework, rather than to estimate a single pooled effect size as a meta-analysis would. The review considered research on structural health monitoring, machine learning, predictive maintenance, digital twins, infrastructure deterioration modelling, computer vision, Internet of Things technologies, lifecycle cost analysis, and infrastructure asset management (Carvalho et al., 2019; AlBalkhy et al., 2024). The approach was designed to identify relationships between technological capabilities and engineering-management outcomes rather than to evaluate one intervention in isolation (Tibaduiza Burgos et al., 2020). A narrative design was chosen over a full systematic review or meta-analysis because the underlying literature spans heterogeneous methods, outcome measures, and asset types that are not amenable to pooled quantitative synthesis, while still benefiting from an explicit, reportable search and selection protocol.

2.2 Search Strategy and Databases

Relevant literature was identified through established engineering and applied-science databases and publisher platforms, including sources indexed in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar, using combinations of terms related to infrastructure failure, predictive maintenance, structural health monitoring, machine learning, artificial intelligence, digital twins, lifecycle cost, infrastructure deterioration, anomaly detection, asset management, computer vision, and sensor networks. Representative Boolean search strings combined a technology term with a management or outcome term, for example ("structural health monitoring" OR "digital twin" OR "predictive maintenance") AND ("infrastructure" OR "asset management") AND ("failure prediction" OR "lifecycle cost"). The search was not restricted to a single calendar window because the objective was thematic coverage rather than a bounded systematic count; the retained sources span publication years 2006 to 2026, reflecting both foundational lifecycle-cost and structural-health-monitoring literature and the most recent AI-based remaining-useful-life and digital twin research available at the time of writing.

2.3 Eligibility Criteria

Priority was given to peer-reviewed journal articles, systematic reviews, engineering studies, and authoritative technical sources with identifiable publication information and DOI records where available (Azimi et al., 2020).

Studies were retained when they contributed evidence relevant to infrastructure condition assessment, failure prediction, predictive maintenance, risk management, lifecycle decision-making, or digital engineering management (Luo et al., 2023). Sources were excluded where they addressed sensing, analytics, or management concepts entirely outside the civil-infrastructure and engineering-asset-management domain, or where no identifiable publication record could be established.

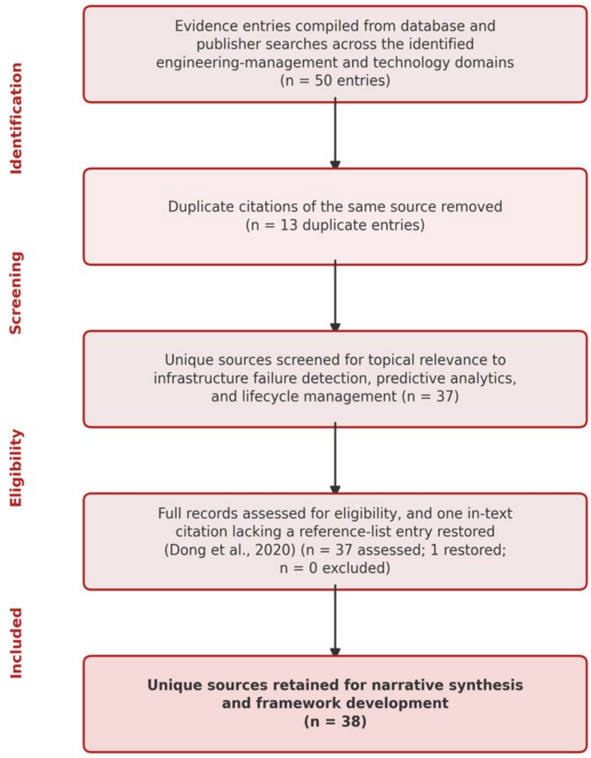

Figure 1. Study identification and selection process (PRISMA-style), showing reconstruction of the evidence base from 50 compiled entries to 38 unique, verified sources.

2.4 Study Identification and Selection

An initial pool of 50 evidence entries was compiled during the literature-identification stage described above. Systematic cross-checking of author names, titles, and DOIs identified 13 entries as exact duplicate citations of a source already compiled, which were removed. Cross-referencing the remaining in-text citations against the reference list further identified one source, Dong et al. (2020), that had been cited in the body of the manuscript but omitted from the reference list in the original draft; this entry was restored using its verified DOI. The resulting evidence base of 38 unique, verifiable sources was retained for narrative synthesis and framework development, as summarized in Figure 1. No source meeting the eligibility criteria was excluded at the full-record stage, since the compiling process had already applied topical relevance as a precondition for inclusion in the original pool.

2.5 Data Extraction and Evidence Synthesis

The selected literature was organized into thematic evidence domains covering data acquisition, data integration, condition assessment, anomaly detection, deterioration prediction, failure-risk estimation, maintenance optimization, lifecycle costing, digital twins, and organizational implementation (Yan et al., 2020). Evidence was compared according to the problem addressed, data type, analytical approach, engineering application, decision-support capability, and principal limitation (Carvalho et al., 2019). Particular attention was given to studies that demonstrated integration between prediction and management decisions because the proposed framework is intended to support engineering management rather than prediction alone (Shahrivar et al., 2026). Table 2 in Section 4 presents the extracted finding and framework inference for each of these 38 core sources. A further 17 sources were subsequently identified through targeted supplementary searches (Scopus, Web of Science, IEEE Xplore, ScienceDirect) to substantiate specific supporting claims elsewhere in the manuscript — for example, on wireless sensor network design, BIM-facility management integration, pavement machine-learning models, resilience metrics, and federated learning — bringing the total reference count to 55. These supplementary sources are cited at the point of use in the text and listed in the References but, being background or corroborating citations rather than core synthesis inputs, are not separately tabulated in Table 2.

2.6 Framework Development Approach

The proposed framework was developed by mapping the relationships among infrastructure data sources, analytical functions, engineering risk indicators, lifecycle decision variables, and management actions (Jiang et al., 2021). The architecture was derived by combining evidence concerning sensor-enabled monitoring, machine learning, probabilistic deterioration models, digital twins, predictive maintenance, and lifecycle cost optimization (Mizutani & Yuan, 2023). The resulting framework emphasizes closed-loop management in which intervention outcomes are returned to the data environment and used to improve subsequent predictions and decisions (Fu et al., 2024).

3. Proposed Framework Architecture

The framework consists of eight interconnected layers spanning data acquisition through to management feedback, illustrated in Figure 2 and specified in Table 1. Each layer is defined by its principal inputs, its analytical function, and the management output it produces for the layer above it, so that a prediction generated deep within the analytical layers is always traceable back to raw asset data and forward to a management action.

Table 1. Core Architecture of the Proposed Data-Driven Engineering Management Framework

Layer	Principal Inputs	Analytical Function	Management Output
1	Asset Data Acquisition Sensors, inspections, images, IoT devices, environmental and traffic data	Continuous and periodic data capture	Raw infrastructure data

Layer	Principal Inputs	Analytical Function	Management Output
2	Data Governance & Integration Historical records, maintenance records, BIM, GIS, sensor databases	Cleaning, integration, synchronization, quality control	Trusted asset dataset
3	Condition Assessment Sensor signals, images, inspection observations	Condition indexing, damage classification, anomaly screening	Current condition state
4	Anomaly Detection Condition indices, contextual variables (temperature, traffic, load)	Statistical deviation flagging with contextual validation	Confirmed anomalies for follow-up
5	Deterioration & Failure Prediction Historical condition and operational data	Machine learning, deep learning, survival analysis, Markov and Bayesian models	Deterioration and failure forecasts
6	Digital Twin & Risk Assessment Physical asset state, engineering model, live data, failure probability, consequence, exposure, vulnerability	State synchronization, simulation, risk scoring and prioritization	Dynamic asset representation and risk-ranked assets
7	Lifecycle Optimization Risk, remaining useful life, intervention costs, consequences	Maintenance optimization and lifecycle cost analysis	Optimal intervention strategy
8	Management Feedback Intervention outcomes and post-maintenance condition	Model updating and organizational learning	Improved future decisions

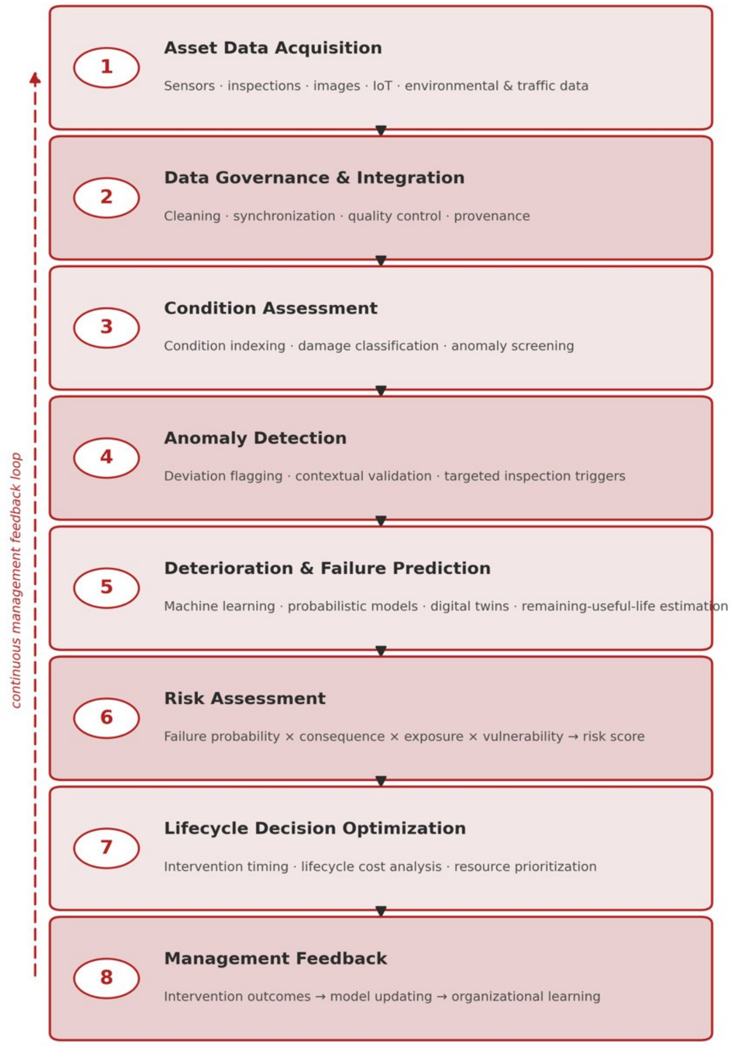

Figure 2. The eight-layer data-driven engineering management framework, with a continuous management feedback loop returning intervention outcomes to the data-acquisition layer.

4. Results: Thematic Synthesis of the Evidence

4.1 Infrastructure Data as the Foundation of Early Failure Detection

The literature demonstrates that the effectiveness of data-driven infrastructure management begins with the availability of reliable and sufficiently representative asset data (Azimi et al., 2020). Structural health monitoring systems can continuously capture measurements associated with vibration, strain, displacement, temperature, acceleration, and other indicators of structural behaviour (Tibaduiza Burgos et al., 2020). Wireless sensor networks provide a mechanism for distributing sensing capability across large infrastructure assets and can support real-time acquisition while reducing some installation constraints associated with conventional monitoring arrangements (Zhou & Yi, 2013; Abdulkarem et al., 2020). IoT-based monitoring further connects sensors to communication and computing infrastructure, enabling condition information to be accessed and processed outside the physical asset itself (Bhatta & Dang, 2024).

Evidence also shows that infrastructure data need not originate exclusively from dedicated structural sensors. Images obtained from conventional inspections, cameras, unmanned aerial vehicles, and other remote sensing platforms can provide valuable information about visible deterioration (Luo et al., 2023). Computer vision systems can detect cracks, spalling, corrosion, and other surface defects, thereby transforming visual inspection records into machine-readable condition indicators (Spencer et al., 2019). UAV-based inspection has demonstrated the possibility of obtaining infrastructure observations while reducing the need for extensive physical access to difficult locations (Jeong et al., 2022). This suggests that the proposed framework should support multimodal data rather than relying on one sensor technology.

The literature further indicates that historical maintenance records are essential for understanding infrastructure deterioration. Condition measurements have greater management value when they can be related to asset age, previous interventions, loading conditions, environmental exposure, and earlier condition states (Mizutani & Yuan, 2023). Pavement deterioration studies demonstrate that construction properties, pavement age, traffic characteristics, and condition indicators can jointly improve the representation of future performance (Jha, 2025). Such integration enables the system to distinguish between an isolated abnormal measurement and a persistent deterioration trajectory (Sarkar & Sinha, 2026).

The evidence therefore supports a data architecture in which infrastructure information is treated as a longitudinal asset history rather than as disconnected inspection events. Such an architecture should maintain asset identity, timestamp measurements, record intervention histories, preserve data provenance, and accommodate different data formats (Gao & Pishdad-Bozorgi, 2019). BIM can contribute structured information about physical components and facility characteristics, while digital twins can provide a mechanism for connecting these static or semi-static records with dynamic operational information (Jiang et al., 2021; Tang et al., 2019; Shafie Panah & Kioumarsi, 2021). This architecture establishes the foundation for subsequent predictive analytics.

4.2 Data Quality, Integration, and Governance

The second major finding concerns the central role of data quality. Machine learning models can identify complex relationships, but their predictions remain dependent on the quality, representativeness, completeness, and consistency of the data used for model development (Carvalho et al., 2019). Infrastructure datasets frequently contain missing observations because inspections may be irregular, sensors may fail, historical records may be incomplete, and different agencies may use different condition-rating systems (Shahrivar et al., 2026). Data limitations can consequently affect the reliability of infrastructure deterioration predictions.

Data integration is particularly important because failure mechanisms frequently involve multiple interacting variables. A structural response may be influenced by temperature, traffic, material degradation, environmental exposure, and previous repairs, meaning that a single sensor channel may provide insufficient information for reliable diagnosis (Tibaduiza Burgos et al., 2020). IoT-enabled structural health monitoring emphasizes the value of combining multiple measurements to establish a more comprehensive representation of infrastructure condition (Bhatta & Dang, 2024). Digital twin research similarly identifies integration among physical, digital, application, and user layers as necessary for useful built-environment applications (AlBalkhy et al., 2024).

Sensor reliability is itself an important component of the proposed framework. Monitoring systems can generate misleading information when sensors drift, malfunction, lose communication, or become affected by environmental conditions (Manocha et al., 2025). A decision-support system that assumes every sensor measurement is correct may therefore create false alarms or overlook genuine deterioration (Manocha et al., 2025). Digital twin and Bayesian approaches can improve condition assessment by accounting for uncertainty and sensor reliability within monitoring processes (Manocha et al., 2025).

The resulting management architecture should consequently include explicit data governance before predictive modelling begins. Data validation, outlier screening, missing-data treatment, sensor calibration, temporal synchronization, metadata management, and traceability should form part of the engineering management process rather than being treated solely as computational preprocessing (Yan et al., 2020). Such governance can improve the credibility of model outputs and make them more suitable for engineering decisions involving safety and financial resources (AlBalkhy et al., 2024).

4.3 Anomaly Detection and Condition Assessment

A third finding is that early failure detection requires an analytical distinction between normal operational variation and abnormal infrastructure behaviour. Data-driven structural health monitoring research demonstrates that anomaly detection can be based on changes in vibration characteristics, modal properties, strain responses, displacement, image characteristics, or other measurable indicators (Azimi et al., 2020). Damage-identification research describes a progression from detection to localization, classification, and prognosis, indicating that an effective system should not stop after identifying an abnormal signal (Tibaduiza Burgos et al., 2020).

Deep learning provides an important pathway for extracting patterns from complex datasets. CNN-based approaches have been used for concrete crack detection and other infrastructure defect identification without requiring explicit manual definition of every visual defect feature (Cha et al., 2017). Computer vision reviews similarly indicate that deep learning can support surface-defect detection, vibration measurement, and damage identification (Luo et al., 2023). These developments support the inclusion of automated inspection data within the condition-assessment layer of the proposed framework, and comparative reviews of crack-detection models reinforce that convolutional and other deep architectures now dominate this task across concrete, pavement, and masonry surfaces (Hsieh & Tsai, 2020; Hamishebahar et al., 2022).

Anomaly detection should nevertheless be interpreted within the engineering context of the asset. A statistical deviation does not automatically mean structural failure because infrastructure responses can change due to temperature, traffic, operational states, or environmental conditions (Farrar & Worden, 2012). The use of contextual variables is therefore essential for distinguishing genuine deterioration from normal variation (Azimi et al., 2020). Hybrid approaches combining data-driven algorithms with engineering knowledge can reduce the risk of treating statistical abnormalities as direct evidence of structural damage (Long et al., 2026).

The proposed framework therefore treats anomaly detection as an intermediate decision stage. Anomalies should trigger additional analytical examination, targeted inspection, or increased monitoring intensity rather than automatically triggering expensive rehabilitation (Tibaduiza Burgos et al., 2020). This approach creates a hierarchy from anomaly identification to condition confirmation and finally to risk-based intervention (Shahrivar et al., 2026).

4.4 Predictive Deterioration and Failure Modelling

The fourth finding is that infrastructure management can benefit from forecasting future condition rather than merely describing present condition. Predictive maintenance research demonstrates that machine learning can estimate fault likelihood and remaining useful life from historical operational data (Carvalho et al., 2019). Civil infrastructure research is increasingly extending this concept to remaining useful life estimation, with AI-based methods being evaluated for their ability to represent nonlinear degradation trajectories (Shahrivar et al., 2026).

Probabilistic deterioration models remain important because infrastructure deterioration is uncertain. Markov models can represent transitions between condition states, while newer inhomogeneous approaches can account for changing deterioration regimes over time (Mizutani & Yuan, 2023). Such models can complement machine learning because they provide a probabilistic representation of future states rather than only a point prediction (Mizutani & Yuan, 2023).

Machine learning can provide additional predictive flexibility where deterioration depends on numerous interacting variables. Pavement studies demonstrate the use of decision trees, random forests, neural networks, and other models for representing pavement condition and deterioration (Jha, 2025; Xu & Zhang, 2022). Recent pavement research further indicates that ensemble learning can support condition classification and maintenance prioritization when distress, traffic, and geometric variables are integrated (Gupta et al., 2026), a conclusion consistent with broader reviews of machine-learning pavement performance modelling (Justo-Silva et al., 2021; Marcelino et al., 2021).

The evidence therefore supports a hybrid predictive layer in which machine learning, probabilistic deterioration models, and engineering models are used according to the characteristics of the asset and data availability. Physics-data dual approaches recognize that data-driven methods can suffer from insufficient training coverage while purely physics-based models can suffer from modelling assumptions and simplifications (Long et al., 2026). Combining the two approaches can therefore provide a more robust basis for infrastructure prediction (Long et al., 2026).

4.5 Digital Twins and Risk-Based Decision Support

The fifth finding is that digital twins can provide the integration mechanism needed to connect prediction with engineering management. Digital twin research in civil engineering emphasizes the distinction between a digital twin and conventional BIM because the former involves dynamic interaction between physical and digital representations (Jiang et al., 2021). BIM remains valuable for organizing asset information, while digital twins can extend that information environment through real-time data and analytical functions (Gao & Pishdad-Bozorgi, 2019; Jiang et al., 2021).

Infrastructure digital twin research has increasingly focused on monitoring, resilience, and maintenance. Digital twin studies identify applications across infrastructure design, construction, operation, and maintenance, while recent structural health monitoring research demonstrates the integration of finite element modelling, photogrammetry, wireless sensing, and data analytics (Taherkhani et al., 2024; Fu et al., 2024). These studies suggest that the digital twin can function as an operational platform in which current asset state, predicted future state, and intervention alternatives are represented together (Fu et al., 2024).

Risk assessment provides the bridge between prediction and management priority. Bayesian network research has demonstrated how infrastructure failure probabilities and cascading effects can be represented within interconnected systems (Dong et al., 2020). A risk-oriented architecture should combine probability of failure with consequences, exposure, criticality, and vulnerability rather than prioritizing assets solely according to predicted deterioration (Mizutani & Yuan, 2023), consistent with the broader resilience literature's emphasis on consequence-aware, multi-dimensional risk measures (Hosseini et al., 2016).

The framework therefore proposes a risk score that integrates predicted failure probability, consequence severity, asset criticality, remaining useful life, and uncertainty. Such an approach enables managers to distinguish between assets that are deteriorating quickly but have limited consequences and assets whose moderate deterioration creates substantial systemic risk

(Dong et al., 2020). The result is a management system that prioritizes interventions according to risk rather than condition alone.

4.6 Lifecycle Cost Reduction and Maintenance Optimization

The sixth finding concerns the connection between predictive analytics and lifecycle cost. Lifecycle cost analysis recognizes that the economic performance of infrastructure cannot be evaluated only through initial construction expenditure because operation, maintenance, rehabilitation, failure, and replacement costs occur throughout the asset's service life (Oh et al., 2023). Infrastructure management research demonstrates that optimal maintenance strategies can reduce the likelihood of costly deterioration and improve allocation of limited maintenance resources (Kim et al., 2006).

The timing of intervention is particularly important. Preventive maintenance can be economically preferable when it delays more expensive deterioration processes, while excessive early intervention can waste resources if an asset remains in an acceptable condition for a considerable period (Oh et al., 2023). Predictive models can support this balance by estimating future condition and identifying intervention windows rather than relying solely on fixed calendar schedules (Carvalho et al., 2019).

Recent pavement research demonstrates how predictive models can be connected with optimization algorithms to identify maintenance plans that reduce expenditure while maintaining infrastructure condition (Gupta et al., 2026). Such findings support the broader principle that prediction becomes valuable when it is incorporated into prescriptive decision-making (Xu & Zhang, 2022). Consequently, infrastructure management systems should move beyond predicting deterioration toward recommending economically and technically appropriate interventions.

The proposed framework therefore defines lifecycle cost reduction as a decision problem rather than simply a prediction problem. The system should estimate alternative intervention costs, failure consequences, remaining service life, risk reduction, and future maintenance requirements before recommending an action (Oh et al., 2023). This transforms engineering analytics into an economic management capability that supports budgeting, maintenance scheduling, resource prioritization, and long-term infrastructure planning, an approach consistent with decision-support models developed for other lifecycle-critical infrastructure such as sewer and pipeline networks (Kineber et al., 2022).

Table 2. Summary of Reviewed Evidence — Core Synthesis Sources (n = 38 of 55 total references cited)

S/N	Source	Key Finding	Inference for the Framework
1	**Ai et al. (2018)**	Multi-scale image analysis can detect pixel-level pavement cracking.	Visual analytics can complement conventional condition surveys.
2	**AlBalkhy et al. (2024)**	Digital twins support facility management, safety, risk, and structural-performance applications, but adoption faces interoperability and organizational barriers.	Digital twins have broad engineering-management applications, though implementation readiness must be assessed.
3	**Aydin et al. (2026)**	Deep learning has become a prominent approach for concrete crack detection.	Automated defect recognition is an increasingly mature capability for the condition-assessment layer.
4	**Azimi et al. (2020)**	Deep learning supports data-driven structural health monitoring and damage detection.	Infrastructure monitoring should incorporate advanced pattern-recognition analytics.
5	**Benmansour et al. (2026)**	Machine-learning predictive maintenance emphasizes real-time defect detection and failure prediction.	Continuous prediction should be embedded within infrastructure management, not treated as periodic analysis.
6	**Bhatta & Dang (2024)**	IoT enables real-time infrastructure monitoring and distributed data collection.	IoT connectivity is appropriate for the asset-data-acquisition layer.
7	**Cano-Ortiz et al. (2022)**	Machine learning algorithms can support automated pavement performance monitoring.	Condition monitoring can be automated for linear transportation assets.
8	**Cao et al. (2012)**	Wireless sensor networks offer scalable structural health monitoring possibilities.	Wireless monitoring can reduce installation barriers for distributed infrastructure sensing.
9	**Carvalho et al. (2019)**	Machine learning is increasingly used for predictive maintenance, fault detection, and failure prediction.	Machine learning should form a core predictive layer within the framework.
10	**Cha et al. (2017)**	Convolutional neural networks can identify concrete cracks directly from images.	Automated visual inspection can support the condition-assessment layer.
11	**Chakali et al. (2024)**	Sensor placement and wireless-network design influence monitoring performance.	Sensor deployment strategy should be optimized, not treated as a fixed installation detail.
12	**Chaudhari et al. (2026)**	AI, IoT, and digital twins are converging within bridge structural health monitoring.	Integrated monitoring architectures combining these technologies are emerging as the norm.
13	**Dong et al. (2020)**	Bayesian networks can represent failure probability and cascading vulnerability across interconnected infrastructure systems.	Risk models should account for systemic interdependence, not treat assets as independent.
14	**Farrar & Worden (2012)**	Structural health monitoring can be formulated through machine-learning and pattern-recognition concepts.	Monitoring can be structured around a data-driven diagnostic sequence.
15	**Fu et al. (2024)**	Digital twins can combine real-time structural data, finite-element models, and analytics.	Digital twins can support continuously updated, real-time condition warnings.
16	**Gao & Pishdad-Bozorgi (2019)**	BIM can support structured facility information management and operations.	BIM can provide the structured asset-information backbone for a digital twin.
17	**Gupta et al. (2026)**	Ensemble machine learning can classify	Predictive outputs can be

S/N	Source	Key Finding	Inference for the Framework
		pavement condition and prioritize maintenance.	translated directly into resource-allocation priorities.
18	**Hakimi et al. (2024)**	Digital twins support real-time facility management and operational decision-making.	Facility management can be integrated with predictive analytics through a shared platform.
19	**Hamdi Alaoui et al. (2026)**	AI-driven predictive maintenance increasingly integrates machine learning, remaining-useful-life estimation, and Industrial IoT.	Infrastructure management can adopt established predictive-maintenance principles from industrial practice.
20	**Jeong et al. (2022)**	UAV imagery combined with machine learning can support bridge inspection with improved visibility.	UAVs can expand inspection coverage to difficult-to-access infrastructure.
21	**Jha (2025)**	Machine learning supports roadway pavement deterioration modelling.	Road-asset management should integrate machine-learning-based forecasting.
22	**Jiang et al. (2021)**	Digital twins connect physical assets with continuously updated digital representations.	Digital twins can integrate monitoring, simulation, and decision support in one environment.
23	**Kim et al. (2006)**	Lifecycle cost analysis can support optimized maintenance and rehabilitation planning.	Maintenance timing has a measurable effect on total lifecycle expenditure.
24	**Long et al. (2026)**	Physics-based and data-driven methods have complementary strengths and limitations.	Hybrid physics-data predictive architectures are more robust than either approach alone.
25	**Luo et al. (2023)**	Computer vision supports automated bridge inspection and monitoring.	Image-based data should complement, not replace, sensor-based condition data.
26	**Manocha et al. (2025)**	Digital twins can improve sensor-data reliability and explicitly represent measurement uncertainty.	Sensor uncertainty should be managed explicitly rather than assumed away.
27	**Mizutani & Yuan (2023)**	Inhomogeneous Markov-chain modelling can represent changing infrastructure deterioration regimes over time.	Probabilistic deterioration models remain useful even where machine learning is also applied.
28	**Oh et al. (2023)**	Lifecycle cost methods support long-term, safety-informed maintenance decisions.	Cost should be integrated with risk and prediction rather than assessed separately.
29	**Sarkar & Sinha (2026)**	Pavement deterioration is governed by interacting physical, operational, and environmental variables that resist simple deterministic modelling.	Deterioration modelling should distinguish isolated abnormal readings from persistent trajectories.
30	**Shahrivar et al. (2026)**	AI-based remaining-useful-life prediction is an increasingly relevant capability for civil infrastructure.	Remaining useful life should be incorporated explicitly into maintenance-timing decisions.
31	**Spencer et al. (2019)**	Computer vision supports infrastructure inspection and monitoring at scale.	Visual analytics should be incorporated into a multimodal condition-assessment layer.
32	**Taherkhani et al. (2024)**	Infrastructure-oriented digital twin research increasingly addresses lifecycle management applications.	Digital twins should be considered at the individual-asset level, not only at facility scale.
33	**Talasila et al. (2026)**	Digital twin platforms can integrate sensing, engineering models, and structural-health-monitoring workflows.	Platform architecture and interoperability are important for scaling digital twin deployment.
34	**Tibaduiza Burgos et al.**	Data-driven structural health monitoring	Detection should lead into

S/N	Source	Key Finding	Inference for the Framework
	(2020)	supports a progression from detection to localization, classification, and prognosis.	prognosis and management action, not stop at flagging an anomaly.
35	**Wang (2026)**	Digital twins and machine learning can support predictive maintenance of building HVAC systems.	Predictive maintenance principles extend beyond structural assets to building services.
36	**Xu & Zhang (2022)**	Artificial intelligence has applications across pavement distress detection, performance modelling, and maintenance planning.	Pavement management can adopt AI-based prioritization methods already validated in the literature.
37	**Yan et al. (2020)**	Data mining supports knowledge discovery across construction and infrastructure datasets.	Analytics should extend across organizational datasets rather than remain siloed by department.
38	**Zhou & Yi (2013)**	Wireless sensor networks support distributed bridge health monitoring.	Distributed, wireless sensing should be considered over conventional wired instrumentation.

5. Discussion

5.1 From Reactive Maintenance to Predictive Engineering Management

The principal implication of the findings is that infrastructure management is moving from a predominantly reactive model toward predictive and risk-informed management. Traditional maintenance systems frequently respond to visible deterioration, inspection ratings, predefined intervals, or reported failures, whereas data-driven systems attempt to identify changing condition before failure occurs (Carvalho et al., 2019). This transition is particularly relevant for long-lived infrastructure because deterioration is cumulative and intervention decisions influence future condition (Oh et al., 2023).

The distinction between predictive maintenance and predictive engineering management is important. Predictive maintenance focuses primarily on estimating when a component or asset may require intervention, while engineering management must also consider risk, resource availability, project constraints, safety, stakeholder priorities, and lifecycle expenditure (Shahrivar et al., 2026). Therefore, the proposed framework extends predictive maintenance into a broader management architecture in which predictions are transformed into ranked and economically evaluated decisions (Carvalho et al., 2019).

This approach also changes the role of engineers. Engineers remain responsible for interpreting model outputs, validating abnormal conditions, understanding failure mechanisms, and approving interventions, while data analytics provides additional evidence for those decisions (Farrar & Worden, 2012). The objective is consequently not to replace engineering judgement but to augment it with timely and structured information (Long et al., 2026).

5.2 Integration of Structural Health Monitoring and Machine Learning

The findings demonstrate that SHM and machine learning are naturally complementary. SHM generates large volumes of condition-related data, while machine learning provides methods for identifying patterns within those data (Azimi et al., 2020). This combination can support detection of deviations that might not be obvious through manual inspection alone (Tibaduiza Burgos et al., 2020), and recent syntheses of AI-enabled monitoring confirm this complementarity across vibration, vision, and hybrid data modalities (Harle et al., 2025).

Nevertheless, machine learning should not be treated as an autonomous diagnostic authority. Infrastructure systems operate under changing environmental and operational conditions, and algorithms may interpret legitimate changes as anomalies when contextual information is missing (Farrar & Worden, 2012). This reinforces the importance of combining sensor information with temperature, traffic, weather, maintenance, and engineering-model information (Long et al., 2026).

The proposed framework therefore recommends a layered analytical process. Initial anomaly detection should be followed by contextual validation, damage classification, deterioration estimation, risk assessment, and engineering review before major intervention decisions are made (Tibaduiza Burgos et al., 2020). This reduces the possibility that a single anomalous observation will trigger unnecessary expenditure or inappropriate intervention.

5.3 The Role of Digital Twins

Digital twins provide an important mechanism for integrating the different components of the proposed framework. A conventional database can store infrastructure records, but a digital twin can establish a dynamic relationship between the physical asset, its digital representation, sensor data, engineering models, and management applications (Jiang et al., 2021). This makes digital twins particularly suitable for lifecycle-oriented engineering management.

The literature indicates that digital twin adoption in the built environment remains less mature than in some industrial sectors (AlBalkhy et al., 2024). Major barriers include data interoperability, organizational fragmentation, cost, cybersecurity, modelling complexity, and uncertainty about the value generated by digital twin investments (AlBalkhy et al., 2024). Consequently, digital twin implementation should be guided by clearly defined management problems rather than technology adoption for its own sake.

For infrastructure failure prevention, the most valuable function of a digital twin may therefore be its capacity to maintain a continuously updated asset state. A manager could use the system to compare current measurements with historical behaviour, predicted deterioration, alternative maintenance scenarios, and lifecycle cost consequences (Fu et al., 2024). This creates an integrated environment for evidence-based infrastructure decisions.

5.4 Predictive Analytics and Remaining Useful Life

Remaining useful life estimation is especially relevant because maintenance decisions depend on time as well as condition. A component with moderate deterioration but a long predicted remaining life may not require immediate intervention, whereas an apparently moderate defect with a rapidly declining trajectory may warrant urgent attention (Shahrivar et al., 2026). This distinction cannot be obtained reliably from a single condition rating.

AI-based RUL prediction can provide managers with a forward-looking estimate that can be incorporated into maintenance schedules and capital planning (Shahrivar et al., 2026). However, uncertainty should accompany RUL predictions because infrastructure data are incomplete and deterioration mechanisms can change over time (Long et al., 2026). Decision-makers should therefore receive prediction intervals or probability distributions where feasible rather than false precision.

The practical value of RUL prediction increases when it is linked to intervention alternatives. The framework can compare the expected lifecycle cost of immediate preventive maintenance with delayed intervention under the predicted deterioration trajectory (Oh et al., 2023). This converts RUL from a technical indicator into an economic decision variable.

5.5 Risk-Based Infrastructure Prioritization

Condition-based prioritization can produce inefficient maintenance decisions when infrastructure assets have different consequences of failure. A low-condition asset in a noncritical location may create less systemic risk than a moderately deteriorated bridge, water facility, or transportation link whose failure would disrupt essential services (Dong et al., 2020). Risk assessment must therefore incorporate consequence as well as probability.

The proposed framework addresses this issue through risk scoring. Failure probability obtained from predictive models can be combined with asset criticality, consequence severity, exposure, vulnerability, and uncertainty to determine intervention priority (Mizutani & Yuan, 2023). This provides a more comprehensive management basis than ranking assets according to condition alone.

Risk-based prioritization is particularly important when maintenance budgets are constrained. Rather than attempting to repair every deteriorating asset, agencies can allocate resources toward assets where intervention is expected to generate the greatest reduction in risk or lifecycle cost (Oh et al., 2023). This makes the proposed framework directly relevant to infrastructure agencies facing persistent resource limitations.

5.6 Lifecycle Cost Implications

The relationship between predictive analytics and lifecycle cost represents one of the most important contributions of the proposed framework. Prediction alone does not necessarily reduce expenditure because additional sensors, computing infrastructure, software, skilled personnel, and data-management systems also generate costs (AlBalkhy et al., 2024). The economic case for data-driven management must therefore consider both technology costs and avoided deterioration, avoided failures, optimized maintenance, and improved asset utilization.

Lifecycle cost analysis provides a suitable mechanism for evaluating these trade-offs. Infrastructure maintenance research demonstrates that intervention strategies can be compared over the complete asset lifecycle rather than according to immediate expenditure alone (Kim et al., 2006; Oh et al., 2023). The proposed framework therefore recommends that every major predictive recommendation be translated into an economic comparison of plausible intervention pathways.

The framework also supports a shift from expenditure minimization to value optimization.

The cheapest immediate action may not be the option with the lowest lifecycle cost if it increases future deterioration or requires repeated interventions (Oh et al., 2023). Data-driven lifecycle management should therefore identify intervention strategies that balance safety, performance, cost, service continuity, and asset longevity.

5.7 Organizational and Implementation Considerations

Successful implementation requires more than algorithms and sensors. Organizations must establish responsibilities for data ownership, sensor maintenance, model validation, cybersecurity, engineering approval, and decision accountability (AlBalkhy et al., 2024). Without organizational processes, predictive analytics may remain isolated within technical departments and fail to influence budgeting or maintenance planning.

Data interoperability is another important issue. Infrastructure information is frequently distributed among design documents, BIM platforms, geographic information systems, inspection reports, maintenance databases, contractor records, and sensor platforms (Gao & Pishdad-Bozorgi, 2019). A successful framework must therefore establish common identifiers and data standards that permit information to move across lifecycle stages.

Capacity development is equally important. Engineers and asset managers require sufficient understanding of data analytics to interpret model performance, recognize uncertainty, challenge inappropriate outputs, and determine when physical inspection remains necessary (Shahrivar et al., 2026). The most effective implementation is therefore likely to be multidisciplinary, combining engineering, data science, asset management, information technology, and financial planning expertise.

5.8 Framework Contribution and Future Research

The proposed framework contributes by connecting infrastructure data acquisition with failure prediction and lifecycle decision-making within one management architecture, presented as an explicit eight-layer, closed-loop structure supported by a documented and reproducible search-and-selection protocol. Existing studies frequently demonstrate individual technologies, but the framework emphasizes the relationships among sensing, analytics, digital twins, risk, maintenance, and cost (Jiang et al., 2021; Carvalho et al., 2019). This integration represents the central conceptual contribution of the study.

Future empirical research should validate the framework using longitudinal infrastructure datasets. Such studies should compare predictive models using consistent evaluation metrics and should measure not only predictive accuracy but also false alarms, missed failures, intervention timing, avoided failures, maintenance expenditure, and lifecycle cost (Shahrivar et al., 2026). This would allow the engineering value of the framework to be evaluated alongside its computational performance.

Further research should also investigate explainable AI, uncertainty quantification, physics-informed machine learning, federated infrastructure data systems, and digital twin interoperability. These areas are important because infrastructure decisions involve safety and substantial financial consequences, making transparency and robustness essential characteristics of any predictive system (Long et al., 2026). Federated learning in particular offers a plausible route toward pooling infrastructure data across agencies without centralizing sensitive records, provided the security and privacy vulnerabilities documented in the wider federated-learning literature are addressed before deployment (Hu et al., 2024).

6. Conclusions

This study reconstructed and extended a data-driven engineering management framework for early detection of infrastructure failure and lifecycle cost reduction. The framework integrates asset data acquisition, data governance, condition assessment, anomaly detection, predictive deterioration modelling, digital twins, risk assessment, lifecycle optimization, and management feedback into eight explicit, closed-loop layers. The underlying evidence base was reconstructed from an initial pool of 50 compiled entries to 38 verified, unique sources after removing 13 duplicate citations and restoring one omitted reference, giving the synthesis a traceable and reproducible foundation. The synthesis indicates that machine learning can improve the identification of complex deterioration patterns, structural health monitoring can provide continuous condition information, digital twins can connect physical infrastructure with dynamic digital representations, and lifecycle cost analysis can translate predictions into economically informed intervention decisions. The framework therefore moves infrastructure management from reactive inspection toward proactive, predictive, risk-informed, and lifecycle-oriented decision-making. Its implementation should nevertheless recognize data quality, uncertainty, interoperability, organizational capability, cybersecurity, and engineering accountability as essential requirements. Future empirical research should validate the framework against longitudinal infrastructure datasets and measure its effectiveness using both predictive performance and practical outcomes such as avoided failures, optimized maintenance timing, reduced lifecycle cost, improved service reliability, and enhanced infrastructure resilience.

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