

## Review Article

# AI-Driven Predictive Maintenance for Aging Infrastructure: Challenges, Reliability Gaps, and Smart Monitoring Frameworks

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## Article Info

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## Abstract

Aging infrastructure systems, including bridges, pipelines, power grids, and water distribution networks, are deteriorating at a pace that increasingly exceeds available rehabilitation and replacement capacities, creating an urgent need for intelligent maintenance strategies. Although advances in artificial intelligence (AI), machine learning, and Internet of Things (IoT) sensing technologies have accelerated interest in predictive maintenance (PdM), real-world deployment across aging infrastructure environments remains fragmented, unreliable, and difficult to scale. Existing literature largely emphasizes algorithmic performance under idealized data conditions or isolated case-specific implementations, while insufficiently addressing the systemic barriers that constrain operational adoption. This review introduces the *Reliability-Readiness Gap (RRG)* as a diagnostic framework describing the mismatch between AI data requirements and the realities of aging infrastructure ecosystems. To address this challenge, the paper further proposes the *Stratified Infrastructure Intelligence Framework (SIIF)*, a staged pathway that aligns AI complexity with infrastructure data maturity and governance readiness. Drawing evidence from transportation, water, energy, and pipeline sectors across developed and developing contexts, the review demonstrates that the primary limitation to AI-PdM scalability is not model sophistication, but the immaturity of infrastructure data ecosystems. Effective deployment, therefore, requires co-development of sensing infrastructure, governance systems, and AI architectures rather than isolated algorithmic advancement.

## 1. Introduction

Aging infrastructure has emerged as one of the defining engineering and economic challenges of the twenty-first century. Across both developed and developing economies, critical infrastructure systems, including bridges, transportation corridors, pipelines, water distribution systems, and electrical transmission networks, are operating far beyond their originally intended design lifespans [1]. In the United States, the average bridge age now exceeds 45–50 years, with a substantial proportion approaching or surpassing their engineered service limits [2]. Similar patterns are observed across Europe, where post-war infrastructure expansion has resulted in aging transportation and utility

assets requiring extensive rehabilitation [3]. In Sub-Saharan Africa, infrastructure deterioration is compounded by underinvestment, deferred maintenance, rapid urbanization, and limited monitoring capacity, resulting in accelerated structural degradation and elevated operational vulnerability [4].

The economic implications of this infrastructure aging crisis are profound. The 2021 report by the American Society of Civil Engineers estimated trillions of dollars in deferred maintenance liabilities across transportation, water, and energy systems, highlighting the widening gap between infrastructure needs and available investment [5]. Similarly, the World Bank has repeatedly emphasized that low- and middle-income countries face severe infrastructure maintenance deficits that undermine economic productivity, public safety, and long-term development resilience [6]. Aging infrastructure, therefore, represents not only an engineering concern but also a systemic socioeconomic risk with implications for sustainability, energy security, and urban resilience.

Historically, infrastructure maintenance strategies evolved from reactive maintenance, characterized by post-failure intervention, toward preventive maintenance based on scheduled inspection cycles. More recently, advances in sensing technologies, industrial Internet of Things (IIoT) systems, and artificial intelligence (AI) have accelerated the transition toward predictive maintenance (PdM), where asset degradation is forecast before catastrophic failure occurs [7]. However, aging infrastructure environments complicate this transition substantially. Legacy systems often lack continuous sensing architectures, possess fragmented historical records, and exhibit heterogeneous degradation behaviors shaped by decades of repairs, retrofits, and environmental exposure. Consequently, the implementation of AI-driven predictive maintenance in aging infrastructure settings remains significantly more complex than in newly designed smart industrial systems [8].

### 1.1. The Promise and the Reality of AI-Driven Predictive Maintenance

AI-driven predictive maintenance has emerged as a transformative paradigm within modern infrastructure management. By leveraging machine learning, deep learning, computer vision, and data-driven analytics, AI-based PdM systems can facilitate anomaly detection, remaining useful life (RUL) estimation, failure mode classification, and condition-based maintenance scheduling [7, 9]. In principle, these capabilities enable infrastructure operators to optimize maintenance expenditure, reduce unplanned downtime, enhance operational safety, and improve asset longevity through data-informed decision-making [10].

Despite these promises, a substantial deployment gap persists between experimental AI performance and real-world infrastructure implementation outcomes. Numerous studies report exceptionally high predictive accuracies under laboratory or simulated conditions; however, field deployments frequently encounter degraded reliability, unstable model generalization, sensor inconsistencies, missing data streams, and poor interpretability under operational conditions. Consequently, many AI-PdM systems fail to transition from pilot demonstrations to scalable infrastructure-wide adoption [11].

Existing review literature provides important insights into algorithmic developments such as deep learning architectures, digital twins, federated learning frameworks, and edge intelligence systems. Nevertheless, most reviews remain disproportionately focused on computational performance metrics while underexamining the infrastructural and data-environmental conditions necessary for reliable deployment. Furthermore, published case studies often emphasize successful implementation narratives, while failed or partially successful deployments remain significantly underreported. Critically, there is limited scholarly attention devoted to the compounding constraints associated with legacy infrastructure ecosystems, including sparse sensing coverage, inconsistent inspection documentation, fragmented maintenance records, and non-standardized operational data environments.

### 1.2. Scope, Objectives, and Contributions

This review examines AI-driven predictive maintenance across four major categories of aging infrastructure systems: bridges and transportation structures, water and sewer networks, electrical transmission infrastructure, and oil and gas pipeline systems. Rather than focusing exclusively on algorithmic innovation, the paper adopts a systems-diagnostic perspective that interrogates the practical reliability constraints limiting real-world AI adoption in aging infrastructure environments.

The review is guided by three primary objectives. First, it seeks to diagnose the root causes underlying AI-PdM deployment failures within aging infrastructure contexts, particularly those associated with degraded data ecosystems, infrastructure heterogeneity, and operational uncertainty. Second, the paper introduces the concept of the *Reliability-Readiness Gap (RRG)* as a diagnostic construct describing the mismatch between AI model sophistication and infrastructure data preparedness. Third, the review proposes the *Stratified Infrastructure Intelligence Framework (SIIF)* as a practical and scalable pathway for phased AI adoption across heterogeneous infrastructure systems with varying levels of digital maturity.

Importantly, this paper is not intended as a meta-analysis of predictive model accuracy benchmarks or algorithmic superiority comparisons. Instead, it constitutes a conceptual and systems-oriented review aimed at reframing AI-driven predictive maintenance through the broader lens of infrastructure reliability, deployment readiness, and operational feasibility in aging infrastructure ecosystems.

## 2. Background: AI Methods in Predictive Maintenance

### 2.1. Taxonomy of AI Approaches in Predictive Maintenance

The evolution of predictive maintenance (PdM) has been closely linked to advances in artificial intelligence, data analytics, and sensing technologies. However, the suitability of different AI approaches varies substantially depending on infrastructure age, sensor availability, data quality, and operational complexity. In aging infrastructure environments, the effectiveness of predictive models is often constrained less by algorithmic sophistication than by the realities of fragmented and low-fidelity data ecosystems [9, 12].

Early predictive maintenance systems relied heavily on statistical signal-processing approaches such as autoregressive integrated moving average (ARIMA) models and Kalman filtering techniques. These methods remain valuable because of their relative robustness under sparse-data conditions and their ability to function with limited computational requirements. Such characteristics make them particularly relevant for legacy infrastructure systems where continuous sensing architectures are absent or minimally deployed. Nevertheless, statistical approaches struggle to capture highly nonlinear degradation trajectories commonly observed in aging structural systems exposed to

cumulative environmental and operational stressors [13, 14].

Machine learning models, including support vector machines (SVMs), random forests, and gradient boosting algorithms, introduced greater flexibility in identifying complex degradation patterns and classifying failure states. These approaches have demonstrated effectiveness in applications where labeled operational and failure datasets are available. However, aging infrastructure environments frequently lack reliable historical failure records, standardized maintenance logs, and consistent labeling practices. As a result, the predictive capability of supervised machine learning models is often undermined by severe label scarcity and data inconsistency [14, 15].

Recent years have witnessed the rapid expansion of deep learning architectures, particularly long short-term memory (LSTM) networks, convolutional neural network (CNN)-LSTM hybrids, and Transformer-based temporal models. These approaches excel in extracting hierarchical temporal features from large-scale sensor streams and have achieved impressive performance under controlled experimental settings. Yet their deployment within aging infrastructure contexts remains problematic because such systems fundamentally depend on dense, continuous, and high-quality temporal datasets that many legacy assets cannot provide. Consequently, the performance gains reported in laboratory environments frequently deteriorate under real-world infrastructure conditions characterized by irregular sampling intervals, missing sensor records, and heterogeneous operational histories [16].

To address some of these limitations, hybrid approaches such as Physics-Informed Neural Networks (PINNs) have emerged as promising alternatives. By embedding governing physical laws into machine learning architectures, PINNs reduce dependence on purely data-driven learning and improve generalization under sparse-data conditions. This characteristic makes them particularly attractive for aging infrastructure applications where sensor coverage is limited but engineering physics remains well understood [17].

Similarly, Digital Twin (DT) frameworks have gained significant attention for enabling virtual representations of physical assets capable of real-time monitoring and predictive analysis. Although conceptually powerful, high-fidelity digital twins require extensive sensor integration, geometric precision, and continuous data synchronization that most aging infrastructure systems currently lack. Federated learning has also emerged as a promising approach, particularly for infrastructure sectors involving distributed ownership and sensitive operational data, such as electrical grids and pipeline networks [18]. By enabling decentralized model training without direct data sharing, federated architectures offer potential solutions to privacy and governance constraints that hinder large-scale infrastructure intelligence systems.

## 2.2. What Existing Reviews Have Mapped

Existing review literature published between 2018 and 2024 demonstrates the rapid expansion of AI-driven predictive maintenance research across engineering disciplines. Most reviews have concentrated on algorithmic advancements, computational architectures, sensor integration strategies, and digital transformation pathways. Collectively, these studies map the technological trajectory of predictive maintenance toward increasingly autonomous and intelligent infrastructure management systems. However, the majority of these reviews implicitly assume idealized data environments characterized by continuous sensing, standardized records, and stable operational conditions.

Three major blind spots consistently emerge across the literature. First, data quality is commonly treated as an exogenous prerequisite rather than an endogenous infrastructure challenge shaped by maintenance history, institutional fragmentation, and technological underdevelopment. Second, the literature remains disproportionately centered on manufacturing and industrial automation environments, while aging civil infrastructure systems are comparatively underrepresented despite their distinct operational realities. Third, existing reviews rarely provide scalable frameworks linking AI model selection to varying levels of infrastructure data maturity. Consequently, there remains limited guidance regarding how infrastructure operators with heterogeneous digital capabilities can realistically transition toward AI-enabled predictive maintenance systems.

## 3. The Reliability-Readiness Gap (RRG): A Diagnostic Framework

### 3.1. Defining the Reliability-Readiness Gap

A central argument of this review is that the limited real-world performance of AI-driven predictive maintenance (AI-PdM) in aging infrastructure is not primarily due to algorithmic inadequacy but rather to a structural mismatch between model requirements and infrastructural data realities. This mismatch is conceptualized as the *Reliability-Readiness Gap (RRG)*, defined as the systemic divergence between the data ecosystem assumptions embedded in AI-PdM models and the actual condition of data generation within aging infrastructure systems [19].

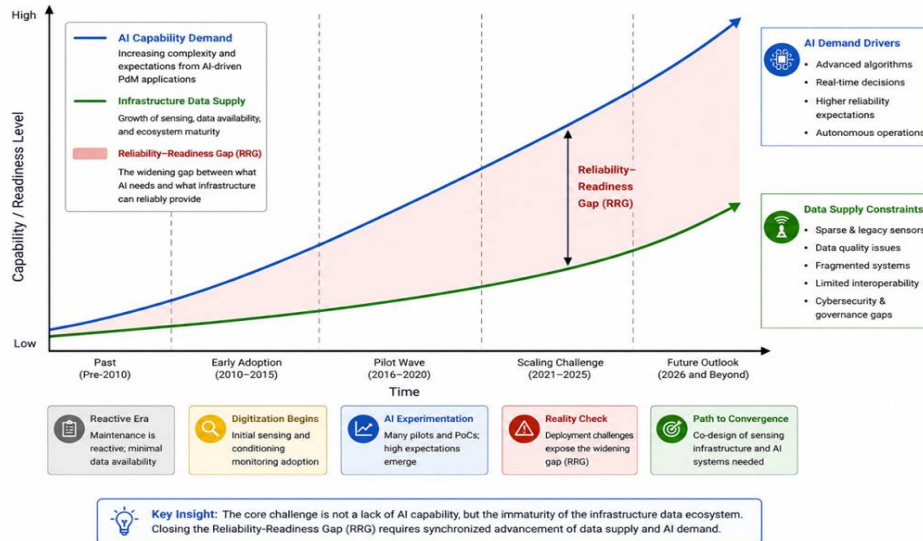
On the model side, contemporary AI-PdM systems implicitly assume the availability of high-volume, continuous, and high-fidelity datasets. These systems require temporally dense observations, consistent sensor calibration, rich labeled failure histories, and well-structured metadata to support robust training and generalization [20]. In contrast, the data environment of aging infrastructure is characterized by intermittent sensing, fragmented monitoring practices, heterogeneous instrumentation across decades of upgrades, incomplete or missing failure logs, and the absence of digitized as-built documentation in many cases [21]. The resulting mismatch creates a persistent structural constraint on model performance that cannot be resolved solely through algorithmic refinement.

Importantly, the RRG is not merely a technical limitation but an institutional and architectural one. Much of global infrastructure was originally designed for human-centered inspection regimes rather than machine-readable data acquisition. As a result, infrastructure systems evolved around visual inspection cycles, manual reporting, and localized engineering judgment, rather than continuous data ingestion pipelines required by modern AI systems [22].

Figure 1 conceptually illustrates the *Reliability-Readiness Gap (RRG)* by demonstrating the widening divergence between the rapidly increasing demands of AI-driven predictive maintenance systems and the comparatively slower maturation of infrastructure data ecosystems over time.

### 3.2. Five Dimensions of the RRG

The RRG can be operationalized through five interdependent dimensions that jointly determine AI-PdM feasibility in aging infrastructure systems.



**Figure 1:** The Reliability-Readiness Gap (RRG): Divergence Between AI Capability Demand and Infrastructure Data Supply Over Time. Conceptual illustration of the widening *Reliability-Readiness Gap (RRG)* between the increasing capability demands of AI-driven predictive maintenance systems and the slower evolution of infrastructure data ecosystems in aging infrastructure environments. The figure demonstrates how advances in AI sophistication increasingly outpace the maturity of sensing infrastructure, data continuity, interoperability, and governance systems, thereby constraining reliable large-scale deployment of AI-driven predictive maintenance.

Data continuity refers to the expectation of uninterrupted time-series data streams in AI models, whereas aging infrastructure typically relies on intermittent inspection schedules and episodic measurements, leading to unstable training dynamics and incomplete temporal representation [23].

Label availability reflects the dependence of supervised learning systems on well-documented failure events. In practice, infrastructure failure records are often sparse, inconsistently recorded, or absent, resulting in severe class imbalance and degraded remaining useful life estimation accuracy [24].

Sensor fidelity captures the requirement for calibrated, multi-modal sensing systems. Many legacy infrastructure assets rely on single-point or uncalibrated instruments, introducing measurement noise that propagates through feature extraction and model inference processes [25].

Semantic richness relates to the contextual information required for meaningful interpretation of signals, including operational loads, environmental exposure, and maintenance interventions. In aging infrastructure, such metadata is frequently stored in non-digital formats or not recorded systematically, limiting contextual learning [26].

Temporal depth describes the availability of long-term historical datasets spanning multiple operational cycles. Many infrastructure systems contain substantial pre-digitization gaps, restricting the applicability of long-horizon learning methods and constraining transfer learning potential [27].

Table 1 presents a structured diagnostic matrix of the *Reliability-Readiness Gap (RRG)*, mapping the core data and operational requirements of AI-driven predictive maintenance (AI-PdM) against the actual conditions observed in aging infrastructure systems. The table synthesizes the key dimensions through which mismatches emerge across infrastructure environments, highlighting how these gaps collectively constrain model performance and deployment feasibility.

**Table 1:** Reliability-Readiness Gap (RRG) Diagnostic Matrix Across Infrastructure Systems

RRG Dimension	AI-PdM Requirement	Aging Infrastructure Reality	Consequence for AI Deployment
Data Continuity	Continuous, High-frequency time-series data streams	Intermittent inspections, Irregular sensor sampling, and frequent data loss	Unstable model training and poor temporal learning performance [28]
Label Availability	Large, Well-annotated failure datasets for supervised learning	Sparse, Inconsistent, or non-existent failure labels due to undocumented events	Severe class imbalance and unreliable predictive accuracy [29]
Sensor Fidelity	High-precision, Calibrated, Multi-modal sensor networks	Legacy analog sensors, Degraded instrumentation, and Calibration drift	Measurement noise amplification and distorted feature representation [30]
Semantic Richness	Context-rich metadata (Load history, Environmental conditions, Maintenance actions)	Fragmented or paper-based records; Missing contextual annotations	Weak interpretability and Context-free anomaly detection [31]
Temporal Depth	Long-term historical datasets spanning multiple decades	Digitization gaps, Missing pre-digital records, and Incomplete lifecycle data	Limited model generalization and Constrained transfer learning capability [32]

### 3.3. The RRG Is Sector-Differentiated

A critical limitation in existing literature is the implicit treatment of infrastructure as a homogeneous category. In reality, the RRG exhibits strong sectoral variation. Bridge infrastructure typically demonstrates a high RRG due to reliance on visual inspections and limited embedded sensing. Electrical transmission systems exhibit a moderate RRG because of existing supervisory control and data acquisition (SCADA) infrastructures, although data fragmentation across utility boundaries remains significant. Water and sewer networks exhibit a very high RRG due to their subsurface nature, limited sensor accessibility, and reliance on indirect failure reporting, such as service complaints or secondary indicators. Oil and gas pipelines present a variable RRG profile, where newer segments may be well instrumented while older sections remain data-deficient [33, 34]. This heterogeneity underscores the inadequacy of generalized AI-PdM frameworks that do not account for infrastructure-specific data realities.

### 3.4. Why the RRG Is Widening, Not Closing

Rather than converging, the *Reliability-Readiness Gap* is structurally widening in many contexts. Advances in AI model complexity, including deep learning and foundation-model-based approaches, are accelerating at a significantly faster pace than the maturation of infrastructure data ecosystems. Although Internet of Things (IoT) retrofitting is expanding sensor deployment, it remains unevenly distributed, with new infrastructure benefiting disproportionately while legacy assets continue to operate under historically limited instrumentation regimes [35].

Simultaneously, digital twin adoption is advancing in conceptual and industrial domains without a commensurate development of foundational data infrastructure, further amplifying the mismatch between representation fidelity and data availability. Institutional dynamics further exacerbate this gap, as public infrastructure owners often lack direct incentives to invest in comprehensive data infrastructure systems whose primary value accrues to downstream AI solution providers rather than to immediate operational budgets [36].

## 4. Challenges in Deploying AI-PdM on Aging Infrastructure

### 4.1. Data-Layer Challenges

The deployment of AI-driven predictive maintenance (AI-PdM) in aging infrastructure is fundamentally constrained by deep-seated data-layer deficiencies that are intrinsic to legacy engineering environments rather than incidental technical limitations. One of the most critical issues is sensor degradation and calibration drift in long-deployed monitoring systems. Many legacy sensors were installed decades ago under design assumptions that did not anticipate continuous AI-based analytics. Over time, these sensors exhibit systematic drift, reduced sensitivity, and calibration instability, which introduce hidden bias into time-series data and significantly compromise downstream model reliability unless explicitly corrected [23, 37].

A further structural challenge is the non-random nature of missing data. In many infrastructure systems, the assumption that data are missing at random does not hold. Instead, sensor failure and data loss often occur precisely during high-stress operational conditions such as peak loads, extreme weather events, or pre-failure states. This results in a systematic absence of precisely the data required for predictive modeling of failure events, thereby undermining statistical validity and distorting model learning dynamics [38].

Historical maintenance records present an additional barrier. In many aging infrastructure systems, particularly in low- and middle-income regions, maintenance logs exist in fragmented paper archives or are entirely missing due to institutional discontinuities. The absence of structured failure labels severely limits the applicability of supervised learning approaches, forcing reliance on weak labels, proxy indicators, or synthetic annotation strategies that introduce additional uncertainty [39].

Multi-modal data fusion further complicates AI-PdM deployment. Structural health data, environmental measurements, load monitoring signals, and operational logs are typically generated across heterogeneous systems with incompatible formats, inconsistent sampling rates, and differing levels of reliability. The integration of such disparate data streams into a unified analytical framework remains a significant unresolved challenge in real-world infrastructure analytics [40].

### 4.2. Model-Layer Challenges

Beyond data limitations, AI models themselves encounter fundamental generalization barriers when applied to aging infrastructure systems. A key issue is domain shift between training and deployment environments. Models developed using data from modern, well-instrumented infrastructure frequently fail when applied to legacy systems, as degradation patterns, material properties, and operational histories differ significantly across infrastructure generations [41].

Another major challenge is the rarity of catastrophic failure. Critical infrastructure failures such as bridge collapses or pipeline ruptures occur infrequently, resulting in extreme class imbalance within datasets. Standard deep learning approaches struggle under these conditions, often requiring synthetic data augmentation or resampling techniques that may distort the true distribution of failure events [42].

The explainability deficit of many advanced AI models further limits adoption in safety-critical infrastructure domains. Black-box models, while often accurate under controlled conditions, provide limited interpretability, making it difficult for infrastructure managers, regulators, and engineers to validate or justify predictions in operational decision-making contexts where accountability is essential [43].

Additionally, physics-agnostic modeling approaches often produce unreliable outputs in infrastructure systems governed by well-established mechanical, hydraulic, and material degradation laws. Without integration of domain-specific physics, AI models may generate spurious anomaly detections that lack engineering plausibility, thereby reducing practitioner trust and limiting operational uptake [44].

### 4.3. Institutional and Governance Challenges

Institutional fragmentation represents a major non-technical barrier to AI-PdM deployment. Many infrastructure systems, including pipelines, electrical grids, and transportation networks, span multiple jurisdictions and ownership structures. As a result, no single entity maintains

complete control over the data ecosystem, creating coordination challenges for model training and deployment [11].

Data sharing is further constrained by regulatory, legal, and strategic considerations. Issues related to privacy, national security, and competitive advantage often restrict cross-organizational data integration, thereby limiting the scale and diversity of datasets required for robust AI model development [45].

A persistent workforce skill gap also exacerbates deployment challenges. Infrastructure asset managers typically lack advanced AI literacy, while AI practitioners often lack deep domain knowledge in structural engineering and infrastructure operations. This dual knowledge gap creates a translational barrier between model development and practical deployment [46].

In addition, procurement cycles in public infrastructure systems are misaligned with the rapid pace of AI innovation. While AI technologies evolve on 18–24 month cycles, infrastructure procurement and approval processes often span 5–10 years, resulting in significant technological lag and underutilization of emerging capabilities [47].

#### 4.4. Sustainability and Lifecycle Challenges

Even after deployment, AI-PdM systems face long-term sustainability issues. Model drift is a persistent problem, as infrastructure conditions evolve while deployed models remain static due to limited retraining capacity, budget constraints, or lack of operational expertise.

Energy and computational limitations further restrict real-time AI inference, particularly in remote, underground, or structurally embedded environments where power supply and connectivity are constrained. Edge deployment in such contexts often requires significant model simplification, which may reduce predictive accuracy [48].

Finally, climate change introduces a compounding source of uncertainty that is insufficiently captured in historical training datasets. Accelerating environmental stressors such as increased flooding frequency, temperature extremes, and corrosion acceleration alter degradation pathways in ways that historical data cannot fully represent, leading to systematic underestimation of future failure probabilities.

### 5. The Stratified Infrastructure Intelligence Framework (SIIF)

#### 5.1. Framework Rationale

A recurring limitation in current AI-driven predictive maintenance (AI-PdM) practice is the tendency to deploy high-complexity machine learning solutions into infrastructure environments that are structurally unprepared to support them. This mismatch between algorithmic sophistication and data ecosystem maturity represents one of the primary drivers of deployment failure in aging infrastructure systems. In most cases, advanced AI models are not failing because of inherent methodological weaknesses, but because they are introduced into environments that do not satisfy their foundational data assumptions [19].

The *Stratified Infrastructure Intelligence Framework (SIIF)* is proposed as a corrective response to this mismatch. Rather than treating AI adoption as a single-step technological upgrade, SIIF introduces a tiered alignment model in which the complexity of AI methods is explicitly matched to the maturity level of the infrastructure data ecosystem. Importantly, SIIF is not a static classification system. It is designed as a staged developmental pathway in which each tier progressively constructs the data, governance, and sensing infrastructure required to support more advanced predictive capabilities [49]. In this sense, progression through the framework is both technological and institutional, reflecting the co-evolution of infrastructure intelligence and data readiness.

#### 5.2. The Four SIIF Tiers

##### Tier 0: Data Foundation Layer

This tier applies to the lowest-maturity legacy infrastructure systems where digitalization is minimal or absent. The primary objective is not predictive analytics but the establishment of a reliable digital data foundation. Key interventions include retrofitting IoT sensors for basic monitoring, digitizing paper-based maintenance records using optical character recognition and natural language processing techniques, and implementing standardized data schemas for future interoperability. At this stage, only simple analytical methods such as statistical process control, rule-based threshold systems, and basic regression models are appropriate. Advancement to higher tiers requires the accumulation of at least 18 to 24 months of continuous, calibrated time-series data alongside a digitized multi-year maintenance history [50].

##### Tier 1: Interpretable Analytics Layer

The second tier introduces explainable and physics-guided machine learning approaches designed to operate effectively under conditions of limited labeled data. Methods such as Physics-Informed Neural Networks (PINNs), Gaussian process regression, and uncertainty-aware anomaly detection are emphasized due to their ability to incorporate domain knowledge directly into the modeling process. The primary advantage of this tier is interpretability, ensuring that predictions remain auditable and aligned with engineering reasoning. Progression to the next tier requires validated anomaly detection performance and the gradual accumulation of sufficient labeled failure events for supervised learning [51].

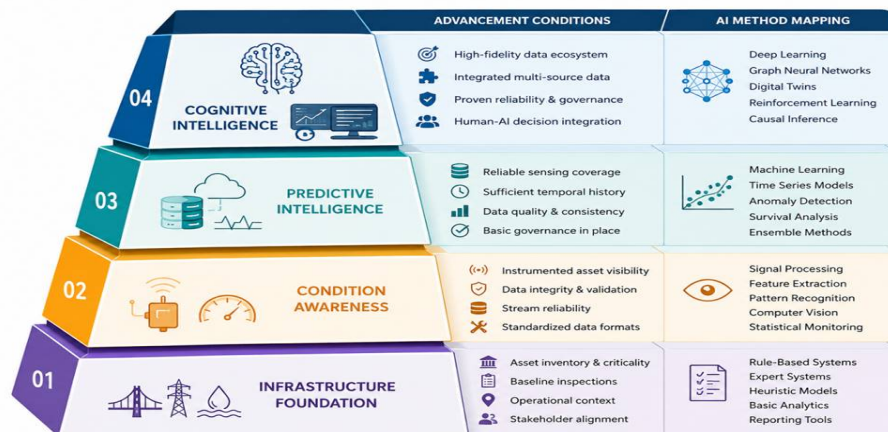
##### Tier 2: Adaptive Predictive Layer

At this stage, full predictive maintenance functionality becomes operational, including remaining useful life estimation and failure mode classification. Advanced temporal models such as LSTM and Transformer-based architectures, ensemble learning systems, and federated learning frameworks are introduced. However, these methods are only viable when the Tier 1 data ecosystem is stable, and a minimum threshold of labeled failure data has been achieved. A key feature of this tier is the integration of continuous monitoring systems, including automated retraining triggers activated by model drift detection and performance degradation [14].

### Tier 3: Integrated Digital Twin Layer

The highest tier represents a fully integrated digital twin ecosystem capable of real-time simulation, scenario analysis, and optimization of maintenance scheduling. This level incorporates high-fidelity structural and hydraulic digital twins, reinforcement learning for decision optimization, and multi-hazard risk modeling frameworks. Successful implementation requires dense sensor networks, full integration with building information modeling (BIM) or geographic information systems (GIS), and mature organizational AI governance structures [52].

Figure 2 presents the *Stratified Infrastructure Intelligence Framework (SIIF)*, illustrating the staged alignment between infrastructure data maturity, advancement requirements, and progressively sophisticated AI-driven predictive maintenance methodologies across aging infrastructure systems.



**Figure 2:** Stratified Infrastructure Intelligence Framework (SIIF): Tiered Progression Pathway for AI-Driven Predictive Maintenance in Aging Infrastructure. The Stratified Infrastructure Intelligence Framework (SIIF) illustrates a four-tier progression model for the staged adoption of AI-driven predictive maintenance (AI-PdM) in aging infrastructure systems. The framework aligns infrastructure data ecosystem maturity with appropriate levels of analytical and artificial intelligence complexity. Each tier defines the operational characteristics, advancement conditions, and corresponding AI methodologies suitable for progressively more intelligent infrastructure management. The framework emphasizes that successful AI deployment depends on the co-evolution of sensing infrastructure, governance capacity, data reliability, and predictive modeling sophistication rather than isolated algorithmic advancement.

### 5.3. SIIF Cross-Cutting Principles

Three foundational principles govern all SIIF tiers. First, explainability-by-default ensures that interpretability is maintained across all stages of deployment, and that black-box models are only permitted when augmented with sufficient explanatory mechanisms. Second, a federated-first data governance approach is adopted from the outset, ensuring that multi-owner infrastructure systems are architected for secure and scalable data sharing rather than retrofitted at advanced stages. Third, climate-adaptive baselines are incorporated into all modeling layers, ensuring that degradation predictions account for evolving climate stressors rather than relying solely on historical environmental conditions [53].

### 5.4. SIIF Positioning vs. Existing Frameworks

Existing standards and maturity models, including condition monitoring guidelines such as ISO 13374, transportation infrastructure monitoring frameworks such as those developed by the Federal Highway Administration, and various digital twin maturity models, provide important foundational guidance for infrastructure monitoring and digital transformation. However, SIIF differentiates itself by explicitly linking AI model selection to infrastructure data maturity levels while simultaneously defining a staged progression pathway with measurable advancement conditions. Rather than treating maturity as descriptive, SIIF operationalizes it as a dynamic transition process, thereby bridging the gap between theoretical AI capability and practical infrastructure deployment readiness [54].

## 6. Case Evidence and Framework Validation

### 6.1. Bridge Structural Health Monitoring

Empirical deployments of structural health monitoring (SHM) in aging bridge infrastructure provide a useful illustration of the *Reliability-Readiness Gap (RRG)* in practice. Large-scale and historically significant structures such as the Forth Bridge, the reconstructed monitoring systems associated with the I-35W Mississippi River bridge collapse, and the Millau Viaduct demonstrate the uneven maturity of sensing infrastructures across bridge assets [55].

Across these cases, a consistent RRG profile emerges: high structural complexity combined with relatively sparse embedded sensor coverage, particularly in older or retrofitted systems. As a result, bridge monitoring environments typically align with Tier 0 to Tier 1 conditions within the SIIF framework. Evidence from these deployments suggests that physics-guided anomaly detection approaches outperform purely data-driven methods when labeled failure data are scarce and degradation processes are governed by well-understood structural mechanics. In particular, incorporating engineering constraints into model design improves stability and reduces false positive rates in low-label environments, reinforcing the argument that domain-informed AI is essential in legacy structural contexts [55].

## 6.2. Water Network Leakage Detection

Water distribution systems present one of the most challenging domains for AI-PdM due to their subsurface nature and limited direct observability. Evidence from large-scale smart water initiatives, including programs coordinated by the UK Water Industry Research and the national digital water infrastructure systems operated by PUB Singapore, illustrates both the potential and limitations of AI deployment in this sector.

Water networks exhibit a very high RRG due to restricted physical access, intermittent sensing, and failure labeling that is often inferred indirectly through customer complaints or service disruption reports. This creates significant challenges for supervised learning approaches. However, emerging evidence indicates that combining acoustic sensor data with natural language processing of complaint records can partially reconstruct usable training datasets, enabling weakly supervised or hybrid learning strategies. These approaches demonstrate that meaningful predictive signals can still be extracted even in environments where direct labeling is structurally impossible [56].

## 6.3. Power Grid Transmission Asset Monitoring

Electrical transmission systems provide a comparatively more mature digital environment, although significant heterogeneity remains across jurisdictions. Monitoring programs implemented by organizations such as National Grid and pan-European coordination efforts under ENTSO-E demonstrate the partial success of AI-PdM applications in grid infrastructure.

In these systems, existing SCADA infrastructures provide moderate levels of structured operational data, positioning the sector within a moderate RRG classification. However, data siloing across utilities and national boundaries continues to limit model scalability. Evidence from federated learning implementations suggests that decentralized training across multiple utilities can achieve performance comparable to centralized models while preserving data sovereignty and addressing regulatory constraints. This makes federated architectures a key enabling technology for cross-jurisdictional infrastructure intelligence [57].

## 6.4. Synthesis: RRG Profiles Across Sectors

Comparative analysis across bridge, water, and power infrastructure systems highlights the sector-dependent nature of the RRG and reinforces the necessity of differentiated deployment strategies. Table 2 consolidates these observations by mapping sectoral RRG intensity, recommended SIIF entry tiers, dominant barriers, and priority interventions. Collectively, the evidence supports the central premise of this study: AI-PdM success in aging infrastructure is primarily determined not by model sophistication alone, but by alignment between algorithmic expectations and the underlying maturity of infrastructure data ecosystems.

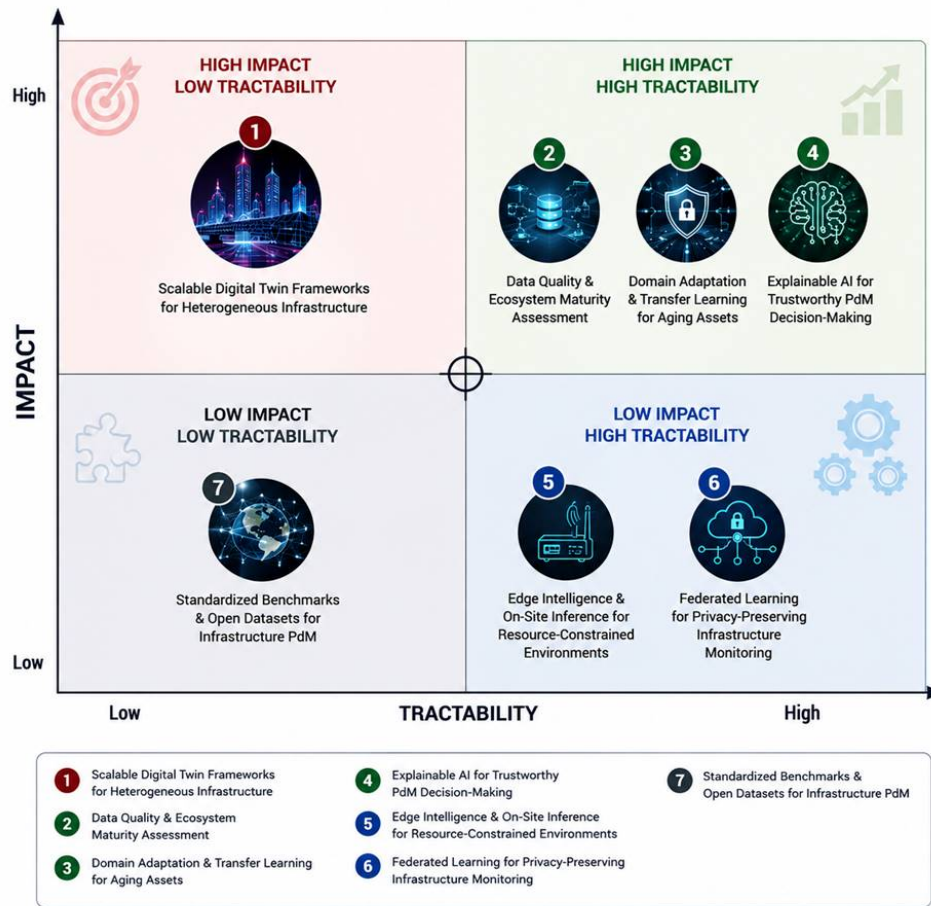
**Table 2:** Sectoral RRG Profiles and SIIF Alignment Pathways

Infrastructure Sector	RRG Intensity	Recommended SIIF Entry Tier	Primary Barrier	Priority Intervention
Bridges and transport structures	High	Tier 0–1	Sparse embedded sensing and reliance on visual inspection data	Sensor retrofitting and digitization of inspection archives
Water and sewer networks	Very High	Tier 0	Inaccessible assets and indirect failure labeling via complaints	Acoustic sensing expansion and NLP-based complaint data structuring
Power transmission grids	Moderate	Tier 1–2	Jurisdictional data silos and fragmented SCADA integration	Federated learning and cross-utility data harmonization
Oil and gas pipelines	Variable	Tier 1–2	Heterogeneous instrumentation across legacy and modern segments	Segment-wise digital upgrading and hybrid monitoring architectures

## 7. Research Gaps and Future Directions

Despite rapid advances in AI-driven predictive maintenance (AI-PdM), the application of these methods to aging infrastructure reveals several unresolved and structurally important research gaps. Rather than broad conceptual directions, the following gaps are formulated as specific, researchable questions that directly emerge from the *Reliability-Readiness Gap (RRG)* and SIIF framework.

Figure 3 maps the seven identified future research directions according to their projected scientific impact and practical tractability, thereby highlighting strategic priorities for advancing reliable and scalable AI-driven predictive maintenance in aging infrastructure systems.



**Figure 3:** Research Gap Map: Impact–Tractability Positioning of Priority Future Research Directions in AI-Driven Predictive Maintenance for Aging Infrastructure

Research gap matrix illustrating the relative scientific impact and implementation tractability of seven priority future research directions identified for AI-driven predictive maintenance (AI-PdM) in aging infrastructure systems. The framework categorizes research priorities according to their potential transformational value and practical feasibility, thereby highlighting areas requiring immediate translational focus versus long-term foundational investigation. The map emphasizes the strategic balance between high-impact theoretical innovation and operationally deployable infrastructure intelligence solutions [58].

First, to what extent can physics-constrained generative models, including diffusion-based architectures conditioned on structural mechanics, synthesize credible failure datasets capable of supporting supervised learning in scenarios where real failure observations are absent? This question addresses the persistent scarcity of labeled failure data in critical infrastructure systems.

Second, how effectively can predictive models trained on well-instrumented, modern infrastructure transfer to structurally similar but data-poor legacy assets, and what minimum threshold of operational similarity is required for reliable domain adaptation? This directly interrogates the limits of transfer learning under RRG conditions.

Third, how can AI-PdM systems incorporate non-stationary climate stressor projections into remaining useful life (RUL) estimation without overfitting to uncertain or speculative future climate trajectories? This reflects the increasing importance of climate-induced degradation variability in infrastructure systems.

Fourth, what technical architectures and legal governance frameworks are required to enable federated learning across multi-jurisdiction infrastructure networks characterized by heterogeneous data ownership, regulatory constraints, and security restrictions? This question is particularly relevant for cross-border power grids and pipeline systems.

Fifth, how do infrastructure practitioners integrate AI-generated predictions with tacit engineering knowledge during real-world maintenance decision-making, and which forms of model explainability most effectively support this human–AI interaction? This highlights the socio-technical dimension of AI-PdM adoption that remains underexplored in technical literature.

Sixth, does the deployment of AI-PdM systems risk exacerbating infrastructural inequality by disproportionately benefiting assets with mature digital ecosystems, thereby widening the reliability gap between well-resourced and underserved regions? This raises critical questions about equity in infrastructure intelligence deployment.

Seventh, what institutional mechanisms, including regulatory, contractual, and technical governance structures, are necessary to ensure continuous model retraining, validation, and auditing across the full lifecycle of infrastructure assets rather than only at initial deployment? This addresses the persistent issue of post-deployment model decay and governance neglect.

Collectively, these questions define a forward research agenda that extends beyond algorithmic innovation toward the structural, institutional, and environmental conditions required for sustainable and equitable AI-driven infrastructure management [59].

## 8. Conclusion

This paper has argued that the primary constraint limiting the real-world effectiveness of AI-driven predictive maintenance (AI-PdM) in aging infrastructure is not rooted in algorithmic insufficiency, but in a structural and systemic mismatch between AI data requirements and the realities of legacy infrastructure environments. This mismatch has been conceptualized as the *Reliability-Readiness Gap (RRG)*, which captures the divergence between the high-fidelity, continuous, and well-labeled data ecosystems assumed by modern AI models and the fragmented, sparse, and institutionally constrained data environments characteristic of aging physical infrastructure.

Two key contributions follow from this analysis. First, the RRG diagnostic framework provides a structured and sector-differentiated lens for explaining why AI-PdM systems fail to scale beyond pilot deployments in real infrastructure contexts. By explicitly mapping model-side data demands against infrastructure-side data availability, the framework enables more precise identification of deployment constraints across sectors such as bridges, water systems, and power grids. Second, the *Stratified Infrastructure Intelligence Framework (SIIF)* offers a staged and operational pathway for aligning AI complexity with infrastructure data maturity. Rather than assuming uniform readiness, SIIF provides a progression model that links foundational data development to increasingly advanced predictive and digital twin capabilities.

The broader implication of this work is that investment in sensor networks, data infrastructure, and governance systems must be recognized as a prerequisite for AI-PdM effectiveness, rather than an optional enhancement. Current deployment practices that prioritize advanced AI layers without addressing underlying data-layer deficiencies are structurally predisposed to failure or limited scalability.

Addressing this challenge requires sustained interdisciplinary collaboration between infrastructure engineers, artificial intelligence researchers, data governance specialists, and public policy stakeholders. Such collaboration is no longer peripheral; it is a necessary condition for translating AI-PdM from conceptual promise into operational reality.

Ultimately, aging infrastructure should not be viewed as an exceptional or temporary condition awaiting technological resolution. It represents the enduring baseline of the built environment. Consequently, effective AI-PdM systems must be designed for infrastructure as it exists today—data-sparse, institutionally fragmented, and physically heterogeneous—rather than for idealized conditions that rarely exist in practice.

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