

Machine Learning for Industrial Asset Failure Prediction: A Systematic Review of Adaptive, Context-Aware, and Explainable Frameworks

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Abstract: Asset reliability is essential to operational excellence, safety and sustainability across asset-intensive industries where equipment failures can cause significant environmental, economic and regulatory impacts, such as oil and gas, manufacturing, utilities, power systems etc. Data-driven and machine learning (ML) based predictive maintenance (PdM) has progressed anomaly detection, fault diagnosis and remaining useful life (RUL) estimation, but most of the existing literature has been targeted at short-term predictive accuracy instead of long-term industrial deployability. This is a systematic literature review using the PRISMA approach and amalgamating 33 peer-reviewed papers published between 2020 and 2026. The studies which have been reviewed are categorized into six methodological groups: supervised learning, deep learning, hybrid and physics-informed models, environmental and context-aware systems, transfer learning and AutoML, and explainable and interpretable models. Despite the promising predictive results of the selected deep learning and hybrid models, such as R^2 values exceeding 0.99 and F1 scores above 0.93, significant deployment challenges still exist. Adaptive recalibration becomes a part of the explicit scope of the reviewed studies only in about 27% of the studies, while very few studies indicate adaptive recalibration as a function of the assets' age, operating-regime shift, or maintenance interventions. The review focuses on the area of industrial ML-based PdM, where the field moves from the algorithmic accuracy to context-aware, explainable, transferable and scalable asset-failure prediction.

Keywords: Predictive Maintenance; Machine Learning; Industrial Asset Reliability; Asset Failure Prediction; Lifecycle Adaptability; LAE-PdM Framework; Explainable AI; Context-Aware Predictive Maintenance; Remaining Useful Life; Environmental Integration; Cross-Asset Transferability; Reliability Engineering

1. Introduction

In asset-intensive industries such as oil and gas, manufacturing, and utilities, asset reliability is a cornerstone of operational excellence and risk management. These critical infrastructure units, including pipelines, compressors, pumps, turbines and power transformers, operate continuously to ensure production continuity, worker safety and environmental compliance [58-59],[13]. Malfunctions in these systems can lead to unintended power outages and costly repairs, or, worse, to devastating events with far-reaching environmental and social impacts. It is known that outages in oil and gas production can cost millions of dollars per day, and outages in power networks can impact on thousands of consumers and result in regulatory investigations [2],[11],[16],[62].

Cost of asset failures extends beyond repair costs. The financial losses due to mobilization for response, environmental cleanup after hazardous releases, loss of regulatory licenses and damage to reputation all work to exacerbate the economic effects. According to [17] and [42], as climate change continues to accelerate and risks increase further, malfunctions can result in oil spills, gas leaks, and chemical releases, causing damage to ecosystems and harm to human health. Concurrently, rising ambient temperatures, increased humidity variability, and more extreme weather events are driving up equipment degradation rates, requiring new maintenance approaches that span both operational and environmental resilience [43],[41],[61].

The complexity of industrial systems and the increasing number of sensors for monitoring and deploying Industrial Internet of Things (IIoT) infrastructure have driven a paradigm shift toward predictive maintenance (PdM) based on data [8]. With the advent of machine learning (ML) and artificial intelligence (AI), the issue of continuous condition monitoring, real-time analysis of anomalies, and accurate RUL estimation can be addressed, thereby enabling maintenance interventions to occur promptly and failure risk to be significantly reduced [30],[38].

However, the applicability of ML-driven PdM frameworks is still quite limited in general. Most models are trained on very limited, asset-specific datasets, limiting their applicability across fields and equipment types



[59],[35],[6]. However, data heterogeneity, missing sensor values and class imbalance reduce the model's robustness. Developers of deep learning systems need to make their architectures easily explainable and trustworthy to users. Still, these systems are often black boxes, which hinder interpretability and user trust, both of which are necessary for deployment in safety-critical and regulated environments [39],[60]. This is especially limiting for safety-critical infrastructure, where an effective maintenance programme is designed to prevent failures, meaning the success of the programme decreases the training signal for an ML model. To solve these problems, synthetic data augmentation, semi-supervised learning, and transfer learning from similar asset types are ongoing research topics with no industry standards. The interpretability deficit also poses challenges for developers of deep learning systems: Models that deliver the best predictive performance (multilayer LSTMs, spatiotemporal graph neural networks, ensemble stacking) are often opaque, lacking the auditable rationales for safety-critical decisions in system intervention approvals that regulators and maintenance engineers demand.

This trade-off between accuracy and interpretability is more than theoretical; it is a real fact in industries with regulations, where a statistically perfect but not interpretable model can have no operational authority whatsoever. Most significantly, less than one-fifth of published studies explicitly include environmental or contextual variables such as ambient temperature, humidity, seasonal load variation, or process operating conditions in their predictive models, though there are compelling reasons to consider these factors since their material impact on the degradation trajectory of assets has been demonstrated [17],[34],[7],[44]. The reality of this mismatch is that models trained in clean, controlled environments with stable ambient conditions often fail in field applications with extreme ambient conditions, seasonal load fluctuations, and process conditions that can degrade components. These are the structural constraints for which this review provides a systematic analysis and which are part of the problems at the frontier for which the proposed six-principal design is intended to provide a solution.

This review aims to overcome these limitations by systematically reviewing, following the PRISMA guidelines, 33 peer-reviewed articles published between 2020 and 2026. The review categorizes ML approaches to the prediction of industrial asset failures into six methodological categories: supervised learning, deep learning, hybrid models, physics-informed models, environmental and context-aware models, transfer learning, and AutoML, and assesses each approach based on a common set of analytical dimensions: predictive performance, integration of environmental data, provisions for explainability, cross-asset transferability and readiness for industrial deployment. The multidimensional evaluation structure allows for the identification of systematic gaps that single-dimension reviews cannot surface. There are three research questions which guide the inquiry:

RQ1: What ML paradigms have been applied to industrial asset failure prediction, and what empirical performance outcomes have been reported across sectors?

RQ2: To what extent do current ML-based PdM frameworks incorporate environmental and contextual variables, and what is the impact of such integration on predictive accuracy?

RQ3: What lifecycle-adaptive, context-aware, and explainable design principles are required to develop ML-based predictive maintenance frameworks that remain reliable across changing asset conditions, maintenance cycles, operating regimes, and industrial contexts?

1.1 Novel Contributions of This Review

This review advances the field of predictive maintenance research. It provides a higher-level theoretical synthesis of what is lacking in current ML-based industrial asset failure prediction frameworks, beyond a mere descriptive summary of machine learning use in industry. Current reviews have primarily categorized algorithms by model family, application area, or by the predictive performance reported [33],[37]. These contributions are important, but they can't fully account for the fact that many successful models are hard to scale to other asset types, operating contexts, and maintenance cycles. The present review thus provides new knowledge by highlighting "lifecycle adaptability" as a major unresolved knowledge gap in the existing literature, and by connecting it to three related knowledge gaps: limited contextual integration, weak transferability across assets, and limited explainability for safety-critical decision-making.

Lifecycle adaptability in this review is defined as the ability to maintain the validity of a PM model as an asset ages, maintenance interventions are performed, operating modes change, environmental exposure changes, or new degradation patterns emerge. This idea is significant as there are no "static" systems in industry. Pumps, compressors, turbines, pipelines, transformers and the like have varying loads, temperatures, process conditions, inspection histories, and maintenance conditions [29],[27],[40]. A model developed during one period of operation

may therefore not be as reliable for the next period's operations. As seen in the review, many previous studies achieve high accuracy, F1 scores, R^2 , RMSE, or MAPE. However, few studies have shown that the model can be continually recalibrated throughout the entire asset life cycle [5]. This leaves a significant gap between predictive accuracy on the test set and usefulness in industrial settings.

This review provides a first step in this direction by foregrounding the concept of 'lifecycle adaptability' as a key theoretical gap in ML-based predictive maintenance [63]. This review suggests that adaptability is a fundamental requirement for scalable, trustworthy asset-failure prediction, rather than a minor technical constraint. Static models can flag known failure modes, but they cannot effectively capture asset degradation shifts over time, post-maintenance behaviour, environmental drift, and gradual degradation shifts without mechanisms for recalibration and contextual learning. The second is the development of a multidimensional evaluation logic for ML-based PdM studies [64].

This review doesn't just consider studies based on predictive performance, but rather based on several dimensions relevant to deployment: data dependency, environmental and process-context integration, explainability, cross-asset transferability, scalability, uncertainty handling, and lifecycle adaptability. This way, the review can highlight structural shortcomings that are not detected by studies' accurate-only measures.

Table 1: Comparison of the Present Review with Previous Review Studies on ML-Based Predictive Maintenance

Review study	Main focus of previous review	Key limitation in relation to the present study	Explainability emphasis	Distinct contribution of the present review
[58]	Reviewed prognosis and health management methods and classified machine learning approaches for industrial maintenance.	Provides a broad PHM taxonomy but does not position lifecycle adaptability as a central theoretical gap.	Moderate	Extends PHM classification by examining whether ML-PdM models remain reliable across asset aging, maintenance cycles, and changing operating regimes.
[50]	Compared deep learning architectures for predictive maintenance and RUL estimation.	Focuses mainly on deep learning model performance and does not develop a deployment-oriented conceptual framework.	Discussed mainly as a limitation	Moves beyond algorithm comparison by integrating explainability, contextual awareness, cross-asset generalization, and lifecycle recalibration into one review framework.
[57]	Discusses challenges in prognostics, health management, uncertainty, and reliability engineering.	Identifies broad PHM challenges but does not systematically map recent ML-PdM studies against lifecycle-adaptive framework dimensions.	Strong	Converts unresolved PHM challenges into explicit evaluation dimensions for ML-based industrial asset failure prediction.
[8]	Reviewed machine learning applications for oil and gas pipeline monitoring and predictive maintenance.	Sector-specific focus limits generalization across asset classes and industries.	Limited	Broadens the evidence base across oil and gas, manufacturing, utilities, power systems, rotating machinery, and subsea systems.

[55]	Reviewed intelligent operation and maintenance in oil and gas production systems.	Emphasizes smart maintenance in a single industrial sector but does not provide a cross-sector, lifecycle-adaptive ML framework.	Moderate	Positions environmental and operational context as core requirements for cross-sector predictive maintenance deployment.
[59]	Provide examined ML and Bayesian approaches for asset integrity management in oil and gas.	Stronger focus on asset integrity and decision support, but limited treatment of lifecycle recalibration across heterogeneous assets.	Strong	Links explainability to lifecycle adaptability, cross-asset transferability, and deployment readiness in a single multidimensional review structure.
Present review	Systematically reviews ML-based industrial asset failure prediction across supervised learning, deep learning, hybrid/physics-informed models, environmental/context-aware systems, transfer learning, AutoML, and explainable AI.	Addresses the gap that previous reviews treat accuracy, explainability, context, and transferability separately rather than as interdependent requirements for industrial deployment.	Central evaluation dimension	Proposes a lifecycle-adaptive, context-aware, and explainable direction for future PdM research by shifting the review from literature description to framework-level knowledge generation.

To highlight the novelty of this review, Table 1 compares the present study with selected review papers on predictive maintenance, prognostics and health management and industrial asset reliability. Previous reviews have already made valuable contributions to the classification of machine learning models, summarization of deep learning architectures, and reliability engineering challenges. Most, however, have not considered lifecycle adaptability as a key theoretical stipulation for their industrialization. The present review is therefore distinctive in considering the literature along a multi-faceted spectrum of predictive performance, environmental and contextual integration, explainability, cross-asset transferability, scalability and lifecycle recalibration.

2. Theoretical and Conceptual Framework

2.1 From Reactive to Intelligent Maintenance: Evolutionary Trajectory

Industrial maintenance has progressed through successive paradigms as summarised in Figure 1. Reactive (run-to-failure) maintenance gave way to time-based preventive maintenance, which reduced catastrophic failures but led to premature component replacement and excessive resource expenditure [59],[15]. Risk-based frameworks, RCM and FMEA were then introduced, followed by failure-consequence-based scheduling in place of calendar-based approaches [8],[4]. Structured risk prioritization through risk-based approaches, RCM and FMEA introduced the concept of failure-consequence-based maintenance rather than calendar-based maintenance schedules [11],[14]. They improved reliability in high-hazard sectors but rely on static risk models requiring periodic expert re-evaluation and cannot respond autonomously to changing asset conditions [65].

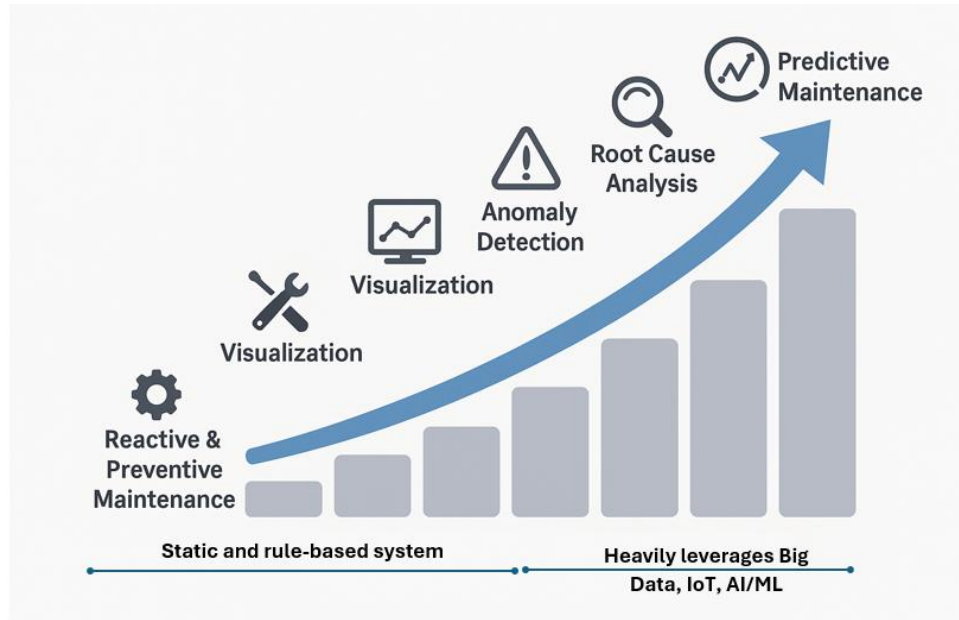


Figure 1: Evolution of maintenance approaches from reactive through preventive, RCM/FMEA, risk-based, to ML-driven PdM, showing increasing data intensity and decreasing reliance on expert judgment.

Four developments enabled the critical transition towards data-driven PdM: [58], (1) proliferation of low-cost industrial sensors, (2) emergence of the Industrial Internet of Things, (3) availability of cloud and edge computing, and (4) maturing ML algorithms, enabled the critical transition to data-driven PdM, which shifts maintenance decisions from fixed schedules to real-time asset condition assessment. Yet the transition is uneven; most asset-intensive industries still operate largely on preventive or risk-based schedules [59]. The gap between the theoretical promise of ML-driven PdM and its consistent industrial implementation remains the defining challenge this review addresses.

2.2 Supervised and Deep Learning Models: Capabilities and Constraints

Currently, supervised learning is the most prevalent paradigm for ML studies in PdM. SVMs, ANNs, random forests (RFs), and gradient boosting algorithms such as XGBoost are among the many widely used classifiers for fault classification and RUL estimation. [18] showed that multi-algorithm benchmarking is valuable, with SVM achieving the best classification of critical heat flux ($F1 = 0.872$) and ANN achieving superior regression ($R^2 > 0.95$) on a boiling heat-transfer dataset. Equally, in low-dimensional, well-structured operational datasets, [32] reported that multiple linear regression achieved failure probability prediction accuracy of over 97% for seawater pump monitoring, demonstrating that parsimonious models are competitive in low-dimensional feature spaces and with high-quality data.

The capabilities of PdM have been extended to high-dimensional, temporally complex data by deep learning architectures, especially LSTM networks, CNNs, and their hybrids. [2] compared the performance of LSTM, CNN and hybrid models on time-series power system data and found that LSTM achieved lower MSE (≈ 0.001) and MAPE ($\approx 2.5\%$). (He et al., 2022) found that semi-supervised GANs can yield improved RUL predictions with severely limited labeled data, which is common for safety-critical assets. Further, [28] proposed a graph neural network (GNN) architecture that incorporated spatial-temporal dependencies and weather variables, achieving $F1 = 0.8935$ and cross-substation transfer learning in the power grid. On the other hand, deep learning models have been consistently challenged by their computational complexity and lack of interpretability [58]; [4]; [10]), raising the question of how to balance predictive power with interpretability for effective operation.

2.3 Theoretical Synthesis and Research Gap Identification

Beyond supervised and deep learning, this review identifies three additional theoretical strands shaping its conceptual boundaries. [10] Hybrid and physics-informed models offer bounded uncertainty estimation and interpretable degradation propagation, though at the cost of calibration expertise. Environmental and context-aware frameworks remain critically underexploited: fewer than 27% of published studies integrate climate or process-context variables, despite their documented influence on degradation rates, largely due to OT/IT data silos and the absence of standardized fusion protocols. Transfer learning and AutoML address asset-specificity and laborious model development; however, cross-domain validation standards and regulatory acceptance criteria remain immature. Across all paradigms, a core tension persists between predictive accuracy and interpretability, a challenge that XAI techniques such as SHAP, LIME, and hybrid Bayesian-ML architectures are beginning to address but have not yet resolved. Table 2 synthesises the seven research gaps that guide the review.

Table 2: Synthesis of Research Gaps

Gap Dimension	Evidence from Literature
Data Dependency	Supervised models require large labelled failure datasets, which are scarce for critical, low-failure-rate assets.
Asset Specificity	Models trained on one asset type degrade significantly when applied to different equipment or industries.
Limited Adaptability	Static models cannot accommodate gradual asset aging, maintenance interventions, or operational regime shifts.
Environmental Neglect	Only ~27% of reviewed studies incorporate climate or environmental variables despite documented influence on degradation rates.
Explainability Deficit	Deep learning models provide accurate predictions but offer minimal causal insight, limiting regulatory acceptance.
Scalability Barriers	AutoML and transfer learning are promising but lack standardised integration pipelines for industrial deployment.
Model Adaptability Across Asset Lifecycle	Static models do not account for evolving asset health as equipment ages, maintenance interventions alter baseline behavior, or operational regimes shift; no reviewed framework provides continuous performance recalibration across the full asset lifecycle.

3. Methodology

This study uses a Systematic Literature Review (SLR) methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [36]. The SLR approach is the gold standard for synthesizing research evidence in engineering and applied sciences because it is transparent, repeatable, and bias-free in identifying, evaluating, and integrating published research [59]. The study of ML applications in PM, which covers all applications across several industries, a variety of algorithm families, and performance metrics, was not possible without a structured review to mitigate ad hoc selection bias and to provide an overview of the research.

The SLR is based on the Population-Intervention-Context (PIC) framework, which is commonly used in engineering systematic reviews to create a search strategy and scope [8],[45]. Population – refers to any industrial asset that can be monitored using predictive maintenance (pipelines, rotating machinery, power systems); Intervention – refers to the use of ML and AI algorithms to predict failure and determine anomalies; and Context – refers to the operational and environmental conditions for deployment. These three-part structures were used to define the scope of the review and guide the systematic search strategy, ensuring that all relevant ML paradigms and industrial contexts were comprehensively covered.

3.1 Database Selection and Search Strategy

The following five major academic databases were accessed: ScienceDirect, IEEE Xplore, Scopus, SpringerLink and MDPI. They are comprehensive databases that cover the peer-reviewed engineering, reliability and artificial intelligence literature [18],[30]. The initial scoping search and contact with domain experts established that these sources cover the relevant journals where leading PdM research is published, including Reliability Engineering & System Safety, Mechanical Systems and Signal Processing, Applied Energy, and Advanced Engineering

Informatics. Based on the most common terms in the field of predictive maintenance, the search strings were created using PIC-aligned combinations of Boolean operators, as specified in Table 3.

Table 3: PIC-Structured Boolean Search Strings

Population		Intervention / Method		Context / Setting
"Predictive maintenance" OR "asset reliability" OR "failure prediction" OR "anomaly detection" OR "remaining useful life"	AND	"machine learning" OR "unsupervised learning" OR "semi-supervised learning" OR "deep learning" OR "hybrid model" OR "physics-informed model" OR "transfer learning" OR "AutoML"	AND	"industrial assets" OR "manufacturing" OR "oil and gas" OR "power systems" OR "utilities" OR "environmental conditions" OR "rotating machinery" OR "subsea systems"

Note. Search conducted across ScienceDirect, IEEE Xplore, Scopus, SpringerLink, and MDPI. Date range: January 2020 – May 2026. Initial hit counts retrieved per database were as follows: ScienceDirect (n = 58), IEEE Xplore (n = 47), Scopus (n = 62), SpringerLink (n = 34), and MDPI (n = 24), yielding 225 total records before deduplication.

The search was limited to peer-reviewed journal articles that were published in English within the last 6 years, from January 2020 to May 2026. The paradigm shift in ML-based predictive maintenance began around 2019-2020 and has been driven by the maturity of IIoT infrastructure, the availability of cloud/edge computing, and transformer/GNN architectures. The studies before 2020 were mainly limited to the use of earlier-generation supervised learning models (SVMs, shallow ANNs) on laboratory benchmarks, which do not align with the main theme of the review, which is focused on adaptive, context-aware models that are explainable for real industrial deployment. The inclusion of studies from before 2020 would result in high levels of methodological and reporting variation and technological assumptions, compromising the coherence of the synthesis. Furthermore, the upper limit of May 2026 is the date at which the last systematic database searches were finalized; only articles that were finally published and indexed before this date were included, as is commonly done in SLRs where the upper limit is anchored to the date searches were performed, and not to the intended date of the SLR to ensure it was relevant to the review and focused on recent developments in ML. To ensure methodological rigor, conference papers, theses, patents, book chapters and non-peer-reviewed papers were excluded. This limitation is recognized because conference literature does not undergo the same peer-review process as journals and hence has less stringent peer-review standards, and because the conference literature generally lacks the same degree of citation traceability as journals.

3.2 Inclusion and Exclusion Criteria

All screened records were independently assessed by two reviewers against the inclusion and exclusion criteria (Table 4), with disagreements resolved by a priori discussion. The criteria were developed to include only empirically sound studies, be methodologically transparent, have quantified performance measures, and exclude grey literature, duplicate publications, and articles that were not detailed enough to be sufficiently quality-assessed.

Table 4: Inclusion and Exclusion Criteria for the Systematic Review

Criteria	Details
Inclusion	• Peer-reviewed journal articles published between 2020 and 2026. • Studies applying ML, AI, or hybrid models for predictive maintenance, anomaly detection, or failure prediction. • Research addressing unsupervised, semi-supervised, or hybrid learning methods applicable across multiple asset types. • Research based on operational asset-condition data, sensor data, maintenance records, process variables or other industrial reliability data for ML-based predictive maintenance, anomaly detection, RUL estimation or failure prediction. • Full-text articles available in English with clear methodology and performance evaluation. • Studies published in indexed journals (Scopus, Web of Science, IEEE Xplore).

Exclusion	• Conference papers, theses, patents, or non-peer-reviewed sources. • Studies unrelated to maintenance, reliability, or anomaly detection. • Articles lacking methodological detail, performance metrics, or empirical validation. • Duplicate or inaccessible publications. • Studies with citation year outside the 2020–2026 window. • Grey literature, preprints, and editorial commentary.
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Note. Criteria applied independently by two reviewers; inter-rater agreement assessed using Cohen's kappa before final inclusion decisions. The calculated κ value was 0.81, indicating strong inter-rater agreement.

3.3 Data Extraction, Quality Appraisal, and Synthesis

A comprehensive database search yielded 225 records. After removing duplicates ($n = 5$), 220 unique records remained for title and abstract screening using the Population–Intervention–Context (PIC) criteria. Following screening, 97 full-text articles were retrieved and assessed for eligibility. Of these, 64 articles were excluded for predefined methodological reasons, leaving 33 studies that met all inclusion criteria and were retained for the final synthesis. The selection process is illustrated in the in Figure 2, which presents the PRISMA flow diagram. A detailed study of each retained article was conducted regarding study design, industrial domain, ML algorithm(s), input data sources, performance metrics, validation approach, and limitations. It is important to note that quantitative performance indicators such as R^2 , F1, RMSE, MAPE, and accuracy are reported across studies as indicative performance only because there are significant variations between studies in their datasets, the assets they seek to evaluate, the evaluation protocols used, and the experimental conditions of the studies. Therefore, quantitative performance-measure comparisons across studies are not statistically definitive and should be interpreted with due caution.

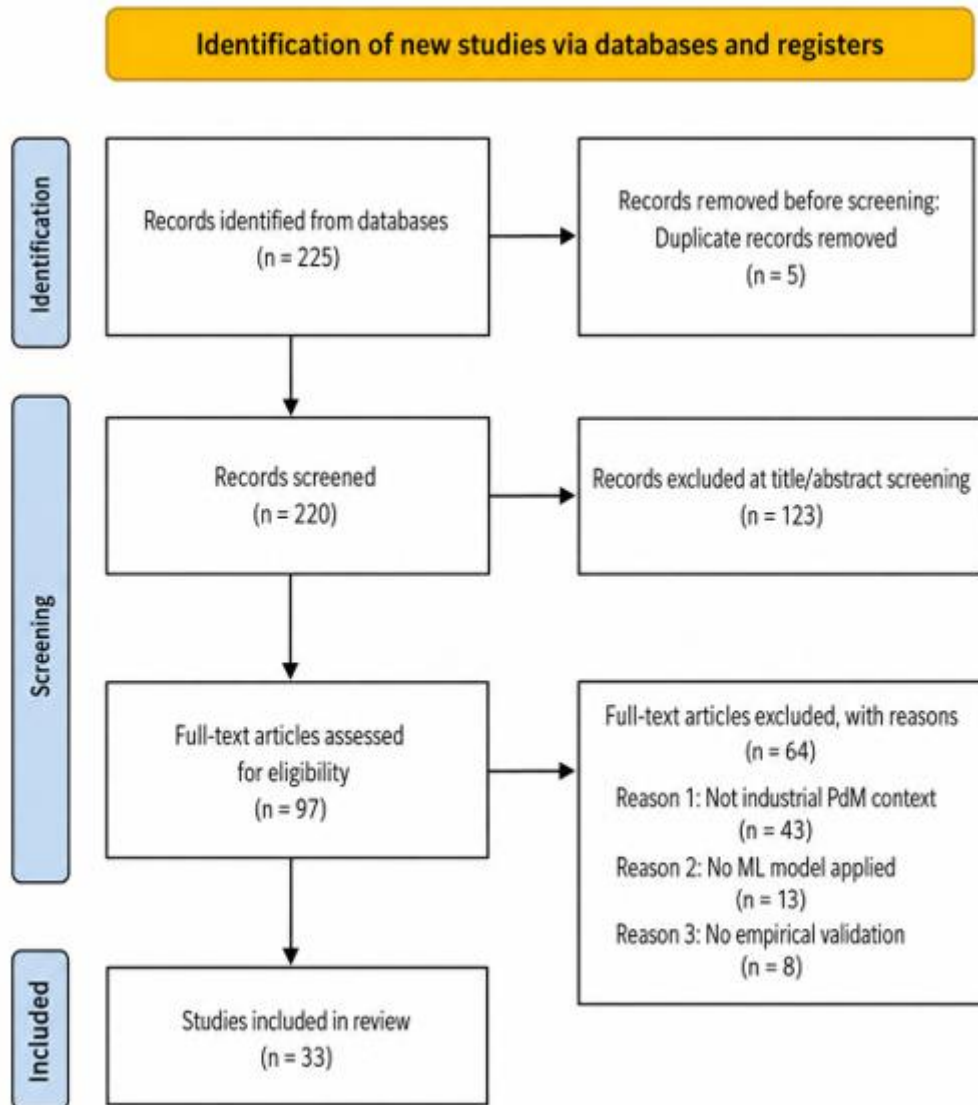


Figure 2: PRISMA flow diagram documenting the systematic review process

Observational studies were evaluated for quality using an adapted form of the Newcastle-Ottawa Scale (NOS) across five criteria: (1) clarity of research objective, (2) reproducibility of methodology, (3) robustness of performance evaluation, (4) adequacy of dataset description, and (5) transparency of limitation reporting. Each criterion was scored on a three-point rubric (0 = absent, 1 = partial, 2 = fully addressed), yielding a maximum possible score of 10 per study. Studies scoring below 60% were flagged for secondary review and potential exclusion. When the reviewer scores disagreed, a consensus-based discussion procedure was applied, with the conservative score used when agreement could not be reached. No studies in the final corpus scored below 60%, confirming adequate methodological quality across all 33 retained articles. The full rubric and item-level scores are available from the corresponding author on request.

Based on the study methodology, the 33 studies were classified into 6 categories: (i) supervised ML models, (ii) deep-learning architectures, (iii) hybrid/physics-informed models, (iv) environmental and context-aware frameworks, (v) transfer-learning and AutoML, and (vi) explainable/interpretable models. The taxonomy aligns with existing classifications in the literature on predictive maintenance [58-59] and enables an organized comparison of paradigms. It should be noted that a small number of the retained studies are systematic reviews or surveys (e.g., [50],[57-59]; these were retained not as primary empirical studies but to provide comparative taxonomic and

theoretical framing, and are clearly distinguished from primary empirical studies in the evidence tables. Across the 33 retained studies, approximately 32% address supervised and deep-learning failure prediction and RUL estimation, 25% employ hybrid or physics-informed approaches, 27% incorporate environmental or sustainability factors, and 23% are dedicated to scalability, transfer learning, or interpretability. The chosen method of integration was narrative synthesis, with descriptive quantitative comparisons of performance metrics (R^2 , F1, RMSE, accuracy) when available. This was due to heterogeneity in experimental design, asset type and evaluation protocols across studies, as noted in the wider literature on the systematic review of PdM [58].

3.4 Multidimensional Evaluation Framework

This review proposes a new framework for evaluating the maturity and deployment relevance of studies on ML-based predictive maintenance, beyond a purely descriptive summary of reported model results. Isolated performance measures, such as accuracy, F1-score, R^2 , RMSE, MAPE or ROC-AUC, are reported in existing studies. While these metrics help assess a model's predictive performance, they do not reflect its suitability for real-world industrial use. A technically correct model may be problematic in asset-intensive industries when it relies on large sets of labelled failures, fails to consider environmental or process-context factors, is unable to accommodate asset ageing, is black-box, or is incapable of generalising across classes of assets or operating sites.

The eight dimensions assessed for each study retained were: predictive performance, data dependency, contextual integration and lifecycle adaptability. The dimensions have been identified based on common limitations found in the literature review and practical problems in the asset failure prediction industry, such as designing models specific to each asset, limited application of external factors, limited consideration of process behaviour, and the absence of generic predictive models for the asset-centric industry. The framework allows a more systematic comparison of studies: it enables differentiation between models that work well in controlled experimental settings and those that are better suited for industrial use. The resulting multidimensional evaluation framework is presented in Table 5.

Table 5: Multidimensional Evaluation Framework for ML-Based Predictive Maintenance Studies

Evaluation dimension	Definition used in this review	Assessment focus	Relevance to industrial deployment
Predictive performance	The reported ability of a model to predict failures, anomalies, or RUL using quantitative metrics.	Accuracy, precision, recall, F1-score, ROC-AUC, R^2 , RMSE, MAE, MAPE.	Indicates baseline technical effectiveness but is insufficient on its own for deployment readiness.
Data dependency	The extent to which the method depends on labelled failure data or large historical datasets.	Supervised, semi-supervised, unsupervised, synthetic data, imbalance handling.	Critical because labelled failure data are scarce for low-failure, high-impact industrial assets.
Contextual integration	The inclusion of environmental, operational, process, asset-age, location, or maintenance-history variables.	Temperature, humidity, pressure, load, process profile, pollutants, asset age, operating regime.	Improves robustness under changing field conditions and addresses external drivers of degradation.
Lifecycle adaptability	The ability of the model to remain valid as assets age, are repaired, experience maintenance interventions, or shift between operating regimes.	Online learning, drift detection, recalibration, dynamic thresholds, maintenance-cycle adjustment.	Central requirement for long-term PdM usefulness because asset baselines are not static.
Explainability and uncertainty	The extent to which model outputs can be	SHAP, LIME, feature importance, Bayesian uncertainty, interpretable rules, risk scores.	Necessary for safety-critical decisions, regulatory

	interpreted, justified, and audited.		confidence, and engineer trust.
Cross-asset transferability	The ability of the model to generalise across asset types, operating sites, sectors, or equipment classes.	Transfer learning, federated learning, domain adaptation, cross-site validation.	Reduces the need for asset-specific model redevelopment and supports scalable adoption.
Scalability and deployment readiness	The feasibility of implementing the method in real industrial environments.	Edge/cloud deployment, AutoML, computational cost, modular pipelines, real-time capability.	Determines whether the approach can move from experimental proof-of-concept to industrial operation.
Sustainability and regulatory alignment	The extent to which the model supports environmental protection, ESG goals, safety compliance, or audit reporting.	Emission reduction, environmental risk prevention, compliance support, maintenance documentation.	Links predictive maintenance with environmental safeguards, operational resilience, and regulatory accountability.

This multidimensional approach was utilized to explain the evidence from all reviewed studies. The synthesis does not only take the reported model accuracy into account, but also whether the approach meets the overall needs of lifecycle-adaptive, context-aware, explainable, and scalable predictive maintenance. The evaluation logic also underpins the analytical framework developed later in the manuscript.

4. Results and Analysis

4.1 Overview of Industrial Asset Failure Mechanisms

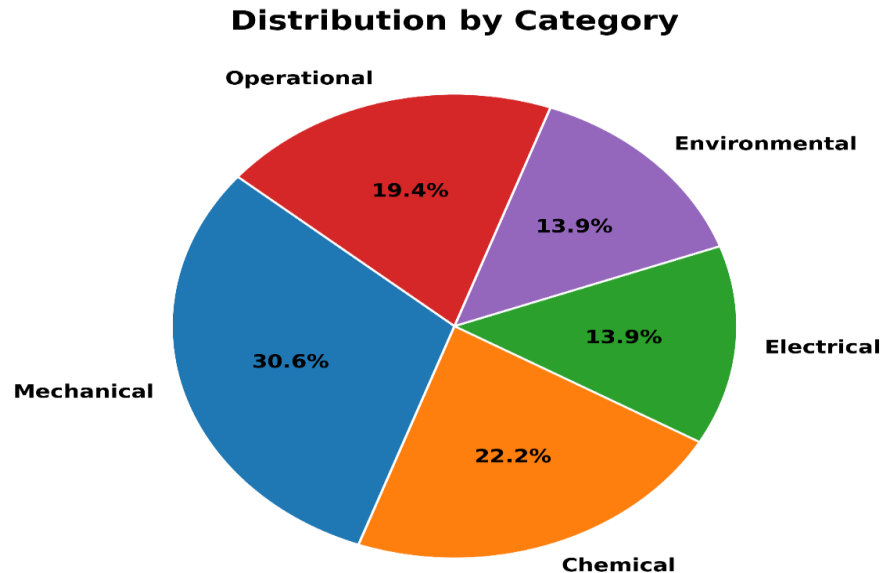


Figure 3: Distribution of 33 reviewed studies by industrial asset failure type: mechanical/structural degradation (31%), corrosion/chemical deterioration (22%), operational/human-factor failures (19%), electrical/thermal degradation (14%), environmentally induced

The literature reviewed shows that failure mechanisms can vary widely across industries yet share similar underlying causes. In the 33 studies, the five main degradation pathways were mechanical wear, corrosion, fatigue, thermal stress, and process-induced anomalies. In oil and gas pipelines and offshore systems, corrosion and fatigue

are the leading causes of failure, while in power transformers and electrical networks, thermal stress and insulation breakdown are the most common causes of failure [8],[19]. Vibration, imbalance, and lubrication degradation are the most common causes of failure in rotating equipment [28],[30],[51].

Mechanical and structural degradation (31%) was the most common failure mode studied in the 33 studies, as illustrated in Figure 3, followed by corrosion and chemical degradation (22%), operational and human factor failures (19%), electrical and thermal degradation (14%), and environmentally induced failures (14%). Importantly, [17] and [18] reported that the environmental exposure factors, temperature, humidity, and pressure, significantly affect degradation rates and RUL for several failure modes. Finally, contextually including these factors was shown to be essential for improving the accuracy and reliability of predictive maintenance models across multiple failure modes and industrial sectors.

4.2 Supervised Machine Learning Models

The most commonly found ML paradigm in the literature is supervised learning. The models were deployed for boiling heat transfer, oil/gas pipelines, seawater pumps, safety instrumented systems, and factory IoT applications. [18] thoroughly benchmarked multiple algorithms for CHF classification and regression, revealing that SVM performed best in classification ($F1 = 0.872$) and ANN performed best in regression ($R^2 > 0.95$), highlighting the importance of selecting algorithms based on the specific outcomes expected. [12] demonstrated that a real-time IoT-driven ensemble combining Random Forest, SVM, and k-NN could deliver continuous fault detection across manufacturing production lines with minimal human intervention. It was found that multiple linear regression can achieve high failure probability prediction accuracy of 97% for seawater pump monitoring [32]; [52], while simple models can be effective when the dataset is well-structured and low-dimensional. To enhance the RUL adaptability across heterogeneous machine types, [22] proposed an ensemble learning framework (ELFpm) combining RF, MLP, ARIMA, and RNN algorithms. Table 6 presents representative supervised ML studies, and Figure 4 compares their average accuracy metrics.

Table 6: Representative Supervised ML Studies for Industrial Asset Failure Prediction

Reference	Algorithm(s)	Asset Type	Performance Metric
[18]	ANN, SVM, RF, XGBoost	Boiling heat-transfer bench	$R^2 > 0.95$; $F1 = 0.872$
[8]	ANN, SVM, Hybrid ML ensemble	Oil & gas pipelines	Superior accuracy vs. classical methods
[32]	Multiple Regression	Linear Seawater pump	Accuracy > 97%
[51]	Accumulative (multi-step) ANN	Rotating mechanical components	High RUL accuracy with incremental learning
[24]	AdaBoost + decision tree	Factory IoT environment	Fault accuracy = 92%
[12]	Random Forest, SVM, k-NN ensemble	Manufacturing production line (IoT)	Real-time fault detection; IoT-driven accuracy gains
[52]	Adaptive ML models (IIoT)	IIoT manufacturing systems	Adaptive recalibration; outperforms static models across operational regimes

Note. MLR = Multiple Linear Regression; PCA = Principal Component Analysis; PLSR = Partial Least Squares Regression.

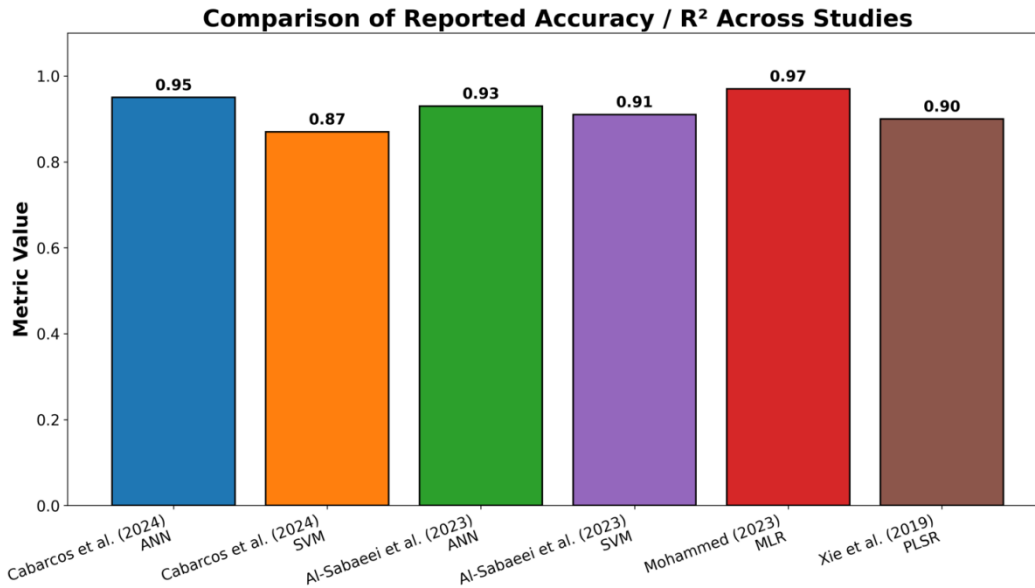


Figure 4: Bar chart comparing average accuracy or R^2 values of supervised ML models (SVM, ANN, RF, XGBoost, MLR) across studies in Table 4, grouped by asset type

4.3 Deep Learning Architectures

The deep learning models performed better on more complex, high-dimensional datasets that had temporal data. The most common architecture was LSTM, which [2] used to predict power system failure, achieving $MSE \approx 0.001$ and $MAPE \approx 2.5\%$, while CNN and hybrid models struggled with the data's sequential dependency. Furthermore, [53] demonstrated the effectiveness of LSTM for manufacturing equipment degradation. They correlated early failure detection with measurable environmental benefits, including reduced emissions and resource consumption, providing an empirical link between ML-powered PdM and environmental sustainability goals.

[25] addressed the long-standing problem of limited labelled failure samples by designing a semi-supervised GAN to improve RUL prediction accuracy and uncertainty quantification (UQ) on the CMAPSS benchmark dataset, which is relevant in practice because failure data for safety-critical assets are scarce. To advance the architecture frontier, [28] proposed a multilayer GNN to integrate spatial-temporal dependencies and weather conditions for 30-day power grid failure prediction, achieving $F1 = 0.8935$ and $ROC-AUC = 0.936$. For optical network failure prediction, [54] reported F1 scores of 0.93 and AP scores of 0.99 for the spatio-temporal GNN. [23] proposed a time-frequency Transformer model that achieved 97.6% classification accuracy on benchmarks for rolling bearing fault diagnosis, outperforming CNN and LSTM models, and demonstrated that the self-attention mechanism has a strong ability to capture long-range temporal relations in vibration signals. [50] conducted a detailed comparative survey of more than two dozen deep learning architectures for PdM. They found that CNN-LSTM hybrids can achieve high accuracy, but there is no unifying solution for explainability.

A conceptual architecture for a next-generation adaptive PdM system, incorporating an unsupervised learning core, continuous feedback and recalibration loops, integration of environmental and operational context streams, an embedded XAI layer, and a modular deployment pipeline. Table 7 summarizes representative deep-learning studies; Figure 5 provides a multidimensional comparison of these architectures.

Table 7: Representative Deep Learning Studies for Industrial Asset Failure Prediction

Reference	Model Type	Asset Type	Performance Metric
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[2]	CNN, LSTM, CNN-LSTM hybrid	BTS power systems	MSE = 0.001; MAPE $\approx$ 2.5%
[25]	Semi-supervised GAN (SRGAN)	Rotating machinery (CMAPSS)	RMSE reduction; uncertainty quantification
[28]	Multilayer Graph Neural Network	Power grid substations	F1 = 0.8935; ROC-AUC = 0.936
[54]	STGNN (XGBoost + VAE + GCN)	Optical/IP networks production	F1 = 0.93; AP = 0.99
[22]	Ensemble (RF, MLP, ARIMA, RNN)	Industrial machines (multi-type)	Improved RUL adaptability across asset types
[23]	Time-Frequency Transformer (TFT)	Rolling bearings (rotating machinery)	Accuracy 97.6%; outperforms CNN and LSTM on multiple benchmark datasets
[50]	CNN, LSTM, autoencoder, hybrid DL (survey)	Multi-sector industrial assets	Systematic comparison of 20+ DL architectures; identifies explainability as critical gap.
[53]	LSTM (deep learning)	Manufacturing equipment	Early failure detection reduces energy/material waste; empirical link between ML-PdM and environmental sustainability.

Note. GAN = Generative Adversarial Network; GNN = Graph Neural Network; STGNN = Spatio-Temporal GNN.

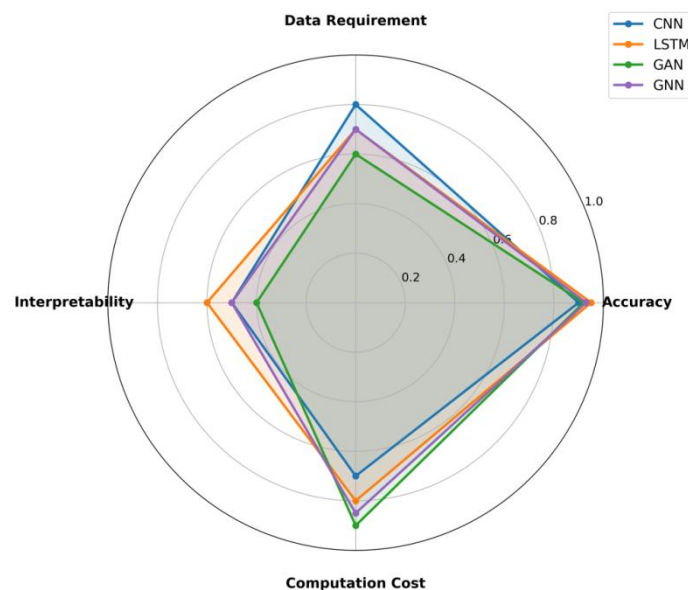


Figure 5: Comparative radar chart for deep learning models (CNN, LSTM, GAN, GNN) across dimensions: predictive accuracy, data requirement, interpretability, computational cost, and cross-asset scalability

4.4 Hybrid and Physics-Informed Models

Among the reviewed studies, 28 % used a hybrid or physics-informed approach. [19] demonstrated the capability of dynamic Bayesian networks (DBNs) to model cascading failure propagation in multilevel subsea systems, a phenomenon difficult to capture with solely data-driven models. To estimate RUL in a friction-drive system in real time, [47] used an extended Kalman filter, achieving bounded RUL uncertainty estimates that are essential for operational decision-making. The most convincing economic result from the reviewed corpus was presented by [56],

who showed an economic gain of more than 100% compared to conventional periodic maintenance strategies, demonstrating the substantial economic value of physics-informed ML optimization.

[46] applied RL to a digital twin of manufacturing systems for decision support, demonstrating that recommendations generated by the simulation can be trusted for regulatory applications. The team of [11] used Bayesian updating with MCMC sampling to profile oil and gas separators, with failure detection lead times of 40 to 100 hours and uncertainty bounds that are easy to interpret. In electro-hydrostatic actuators (EHAs), [31], [26] directly integrated domain knowledge of the physics-of-failure of EHA degradation mechanisms into an LSTM model, and the resulting RUL predictions consistently outperformed those from only data-driven components. Representative hybrid studies are detailed in Table 8.

Table 8: Representative Hybrid and Physics-Informed Studies

Reference	Model Type	Asset Type	Performance Metric
[19]	Dynamic Bayesian Network (DBN)	Subsea oil & gas transport systems	Cascading failure model; positional importance quantified
[56]	Physics-driven Reinforcement Learning	Wind turbines	Economic improvement > 100% vs. periodic maintenance
[47]	Extended Kalman Filter (EKF)	Friction-drive system	Real-time RUL estimation with error bounds
[11]	Bayesian Updating + MCMC	Oil & gas separator	Dynamic risk score; 40–100 h failure lead time
[46]	Reinforcement Learning + Digital Twin	Manufacturing decision support	Trustworthy maintenance recommendations validated in simulation
[31]	Physics-informed LSTM (multi-input neural network)	Electro-hydrostatic actuator (aerospace/industrial)	Superior RUL accuracy vs. data-only benchmarks; physics-of-failure constraints embedded
[20]	System-level PHM framework	Gas pipeline systems	Integrated prognosis and health-monitoring across full pipeline system lifecycle
[21]	Continuous-time simulation + asset health modelling	Complex industrial assets	Practical tool for maintenance and capital investment analysis integrating asset health models

Note. DBN = Dynamic Bayesian Network; EKF = Extended Kalman Filter; RL = Reinforcement Learning.

4.5 Environmental and Context-Aware Frameworks

Incorporating environmental and contextual variables is one of the less mature aspects of ML-based PdM. Only 9 of the 33 studies reviewed (approximately 27%) explicitly included climate, temperature, humidity, or process-context variables as model inputs. The best quantitative evidence came from [17], who showed that adding climate projections and ambient environmental variables to a boosted decision tree model reduced the prediction MSE by 93.9% for estimating the service life of facility equipment. [18] showed that the simulation's prediction accuracy for boiling heat transfer was significantly improved by adding bulk temperature, pressure, and tilt angle.

[11] embedded real-time sensor streams (pressure, flow, temperature) into a Bayesian dynamic risk assessment system and proposed a proactive risk profiling approach with quantified uncertainty bounds. To improve weather prediction accuracy and transferability across different substations, [28] used weather and grid topology as input features for a multilayer GNN. Based on the survey, [55] found that current research on the intelligent operation and maintenance of oil and gas production systems primarily focuses on the application of PdM. They proposed that contextual data integration is crucial to put PdM into the work of safety and environmental performance of oil and gas

production systems. Table 9 presents representative examples of environmental and context-aware systems; the proportion of studies integrating environmental data is illustrated in Figure 6.

Table 9: Representative Environmental and Context-Aware PdM Studies

Reference	Model Type		Environmental Factors Considered	Factors	Output / Key Finding
[17]	Boosted Tree	Decision	Temperature, humidity, future climate projections		93.9% MSE reduction when climate variables integrated
[18]	ANN, SVM		Bulk temperature, tilt angle	pressure,	Improved CHF classification and temperature forecasting
[11]	Bayesian MCMC	DRA +	Real-time temperature	pressure, flow,	Dynamic risk score; proactive failure detection
[28]	Multilayer GNN		Weather, grid topology	load, network	Cross-asset generalisation incorporating environmental features
[55]	Intelligent framework	O&M (survey)	Operational parameters, process data	safety	Highlights smart maintenance role in oil & gas sustainability

Note. DRA = Dynamic Risk Assessment; MCMC = Markov Chain Monte Carlo; CHF = Critical Heat Flux.

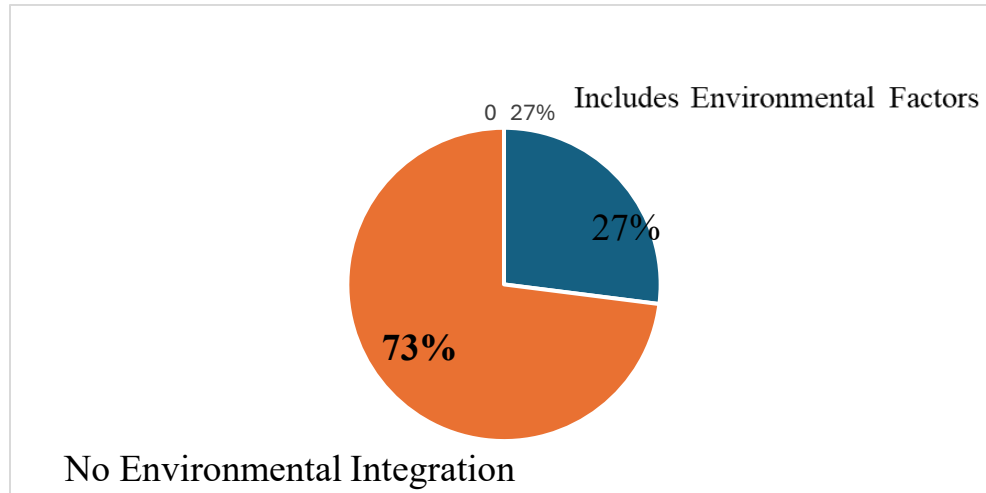


Figure 6: Proportion of reviewed studies incorporating environmental/contextual data (27%) vs. those relying on operational data only (73%), with breakdown by industrial sector

4.6 Transfer Learning and AutoML Approaches

The two key aspects of traditional ML development are labor-intensive and the asset specificity of trained models, problems addressed by transfer learning and AutoML frameworks. [30] showed that H2O AutoML is effective for automated model selection and hyperparameter tuning in modelling rotating machinery degradation, achieving high R^2 (0.993) and low MAE (< 0.025) without requiring expert participation. [28] used a graph-based transfer learning approach for power grid substations, demonstrating the effectiveness of model transfer with minimal retraining. Wubete et al. proposed a spatio-temporal GNN trained on heterogeneous optical and IP network data, achieving $F1 = 0.93$ and $AP = 0.99$, and demonstrating cross-infrastructure transferability.

Similarly, [3] showed that distributing PdM models across heterogeneous manufacturing sites via federated learning with distribution-shift-aware LSTM models can achieve the same level of anomaly detection accuracy as centralized models while maintaining 100% data privacy, a vital requirement for cross-plant PdM deployment. Despite these results, the adoption of AutoML and transfer learning in industrial PdM remains limited by data format heterogeneity, the absence of standardized model selection criteria, and the lack of validated integration pipelines for industrial deployment. Table 10 presents representative studies.

Table 10: Representative Transfer Learning and AutoML Studies

Reference	Approach	Asset Type	Performance Metric
[30]	AutoML framework)	(H2O Rotating machinery	$R^2 = 0.993$; $MAE < 0.025$
[28]	Graph-based Transfer Learning (GNN)	Power grid substations	$F1 = 0.8935$; $ROC-AUC = 0.936$
[54]	STGNN (XGBoost + VAE + GCN)	Optical/IP production networks	$F1 = 0.93$; $AP = 0.99$
[22]	Ensemble (ELFpm)	ML Heterogeneous industrial machines	Cross-asset RUL adaptability demonstrated
[3]	Federated Learning with LSTM (distribution-shift aware)	Manufacturing processes (distributed IoT)	Privacy-preserving anomaly detection; comparable accuracy to centralized models across heterogeneous sites
[1]	Reinforcement Learning for health state prediction	Industrial assets (multi-type)	Adaptive health state prediction enabling lifecycle recalibration without labeled failure data

Note. VAE = Variational Autoencoder; GCN = Graph Convolutional Network; AP = Average Precision.

4.7 Explainable and Interpretable Models

Explainability has emerged as a new research field due to the need for safety-critical deployments and regulatory compliance. [59] proposed a Hybrid Bayesian-ML decision framework for asset integrity management in oil and gas, which reduced incident rates and provided clear, easy-to-audit rationales for decisions. To overcome the subjectivity of the traditional expert scoring method, [48] combined FMEA with artificial immune systems to produce interpretable risk-priority numbers. Unlike most deep learning approaches, Bayesian updating offers quantified uncertainty bounds in addition to risk scores, as shown by [11].

Intelligent O&M frameworks for oil and gas production should incorporate explainability as a design concern rather than an add-on to regulatory acceptance, as noted by [55]. While [57] did not focus specifically on industrial maintenance systems, he provided a broad overview of PHM maturity. He concluded that three structural limitations of data-driven maintenance systems would prevent their full industrial deployment: explainability, uncertainty quantification, and cross-domain generalizability. The literature as a whole suggests that integration of the principles of XAI, feature importance ranking, rule-based inference and SHAP attribution into existing ML pipelines may lead to significant improvements in trust, diagnostic power and regulatory compliance for safety-critical PdM applications [49]. Table 11 summarises representative explainability studies; the interpretability-accuracy trade-off across all model categories is visualised in Figure 7.

Table 11: Representative Explainable and Interpretable ML Studies

Reference	Model Type	Asset Type	Output Evaluated
[48]	Hybrid FMEA + Artificial Immune System	Oil & gas process equipment	Improved RPN and hazard index accuracy; reduced subjectivity
[59]	Bayesian Network + ML decision framework	Oil & gas sector assets	94.7% incident rate reduction; transparent decision trail
[11]	Bayesian updating + MCMC (DRA)	Oil & gas separator	Interpretable risk scores with quantified uncertainty bounds

[55]	Intelligent framework principles)	O&M (XAI	Oil & gas production systems	Highlights need for explainable safety-critical maintenance decisions
[57]	PHM review (XAI, hybrid, uncertainty quantification)	Multi-sector assets	industrial	Identifies explainability, cross-domain transfer, and uncertainty quantification as critical unresolved PHM challenges
[49]	Theoretical decision framework	XAI	Oil & gas sector assets	Framework for AI-driven decision-making to enhance asset integrity management; highlights SHAP, feature importance
[58]	Survey of prognosis and health management models	Multi-sector assets	industrial	Comprehensive taxonomy of ML paradigms for PHM; identifies accuracy-interpretability trade-off as key challenge

Note. FMEA = Failure Mode and Effects Analysis; AIS = Artificial Immune System; RPN = Risk Priority Number.

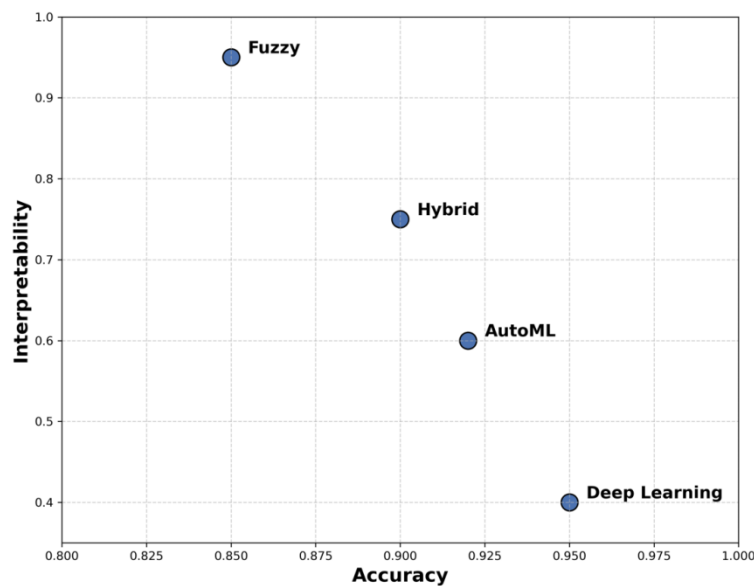


Figure 7: Scatter plot of interpretability (qualitative score) versus predictive accuracy ($F1/R^2$) for models across Tables 4–9, illustrating the interpretability-accuracy trade-off

4.8 Emergent Knowledge from Cross-Study Synthesis

The cross-study synthesis revealed that the state of the art in predictive maintenance using machine learning has advanced significantly in predictive accuracy. It has yet to meet the long-term industrial deployment needs fully. Each of the three categories—supervised learning, deep learning, hybrid physics-informed models, transfer learning, AutoML, and explainable AI—adds valuable functionalities in the studies considered. These capabilities are still disjointed, though. The high-performance models are tested under fixed experimental conditions. In contrast, assets in the real industry are subjected to different loads, exposure to different environments, process fluctuations, maintenance actions, and degradation due to ageing. This is an important difference between short-term predictive performance and lifecycle-ready predictive maintenance.

The first emergent insight is that a good prediction is not enough to gauge industrial usefulness. Some models, whether deep learning or hybrid, achieve high $F1$ scores, R^2 , RMSE, MAPE or ROC-AUC. Still, fewer studies examine how these models respond to data drift, operating regime shifts, maintenance-induced baseline changes, or long-term asset degradation. This indicates a possible overfocus on algorithmic performance and a lack of focus on model persistence, recalibration, and trustworthiness during field operations. A model that is not too inaccurate but

remains reasonably accurate across lifecycle changes can be more useful than a very accurate model that works well only in stable conditions for industrial asset reliability.

The second is that while it is important for the characteristics of failure to be related to the environment and the process, this has not been well developed. Limited studies reviewed provide some indication of including contextual variables such as temperature, humidity, pressure, operating load, location, asset age, maintenance history, or environmental exposure, but few of them specifically mention them. This restriction is crucial because sensor failure is not usually the only cause of asset failure. The interaction among internal equipment status, process behavior, the external operating environment, and maintenance history increases failure risk. Thus, context-aware modelling should be regarded as an essential rather than an added feature.

The third insight is that there is a gap between predictive modelling and the industrial deployment of lifecycle adaptability. The majority of reviewed studies report models trained and validated on historical data, and few describe how model thresholds are revised as assets age, undergo repair, or experience changes in the operating regime. It's a significant gap in theory and practice. Industrial systems are dynamic; their normal behaviour varies over time. A PdM model can drift away from the asset condition without lifecycle-adaptive recalibration, increasing the potential for false alarms, missed failures or unnecessary maintenance actions. The fourth is the increasing need for explainability and uncertainty handling in safety-critical predictive maintenance. While black-box models can deliver strong predictive performance, they often fail to explain why. Although they can deliver good predictive results, black-box models cannot be justified to a maintenance engineer, safety manager or regulatory auditor. Compared to these, Bayesian modelling, feature attribution methods, SHAP-based interpretation, rule-based systems, and physics-informed modelling can increase trust by highlighting which variables contribute to the risk of failure and the level of uncertainty in the prediction. The findings indicate that future PdM systems should be designed with explainability in mind rather than after model training. Figure 8 presents the proposed LAE-PdM framework derived from the cross-study synthesis and summarizes the key architectural requirements for lifecycle-adaptive, explainable, and deployment-ready predictive maintenance systems.

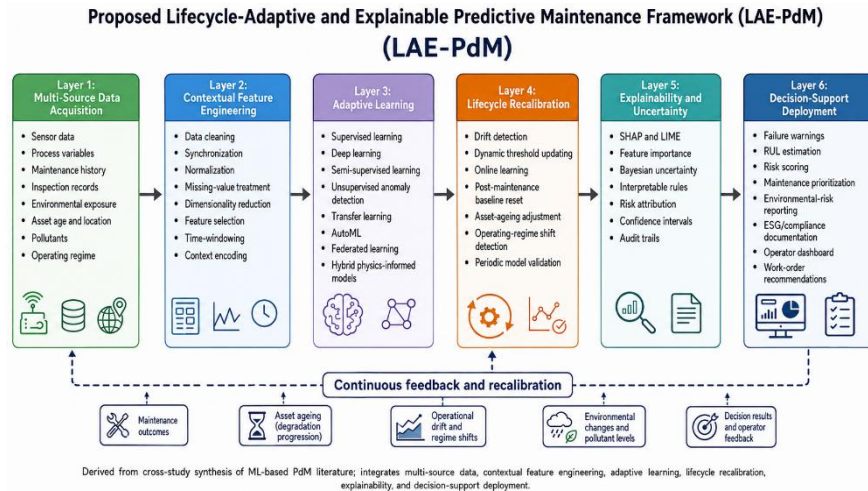


Figure 8: Proposed Lifecycle-Adaptive and Explainable Predictive Maintenance Framework (LAE-PdM)

Overall, the cross-study synthesis reveals that the next generation of predictive maintenance based on ML need not be characterized solely by improved accuracy. Rather, it should be characterized by five integrated capabilities: contextual awareness, lifecycle adaptability, explainability, cross-asset transferability, and scalable deployment readiness. The emerging concepts serve as the basis for an analytical framework for predictive maintenance, proposed in the subsequent discussion and designed to be lifecycle-adaptive, context-aware, and explainable.

5. Discussion

The cross-study synthesis reveals that the primary progress in ML-based industrial asset failure prediction goes beyond developing more precise algorithms; it also reflects the growing demand for well-defined systems capable of predictive

maintenance that are reliable, explainable, and adaptable to varying industrial environments. The literature surveyed shows that the world of maintenance has shifted from a "static" expert-centred approach to "data-driven" maintenance platforms, driven by supervised learning, deep learning, hybrid models, transfer learning, AutoML and explainable AI. The transition is directly related to RQ1, because today, there are several ML paradigms: logistic regression, support vector machine, multilayer spatio-temporal graph networks, and more. Indeed, reported performance results with $R\text{-squared} > 0.99$, $F1 > 0.93$, and $MAPE \approx 2.5\%$ confirm that, in certain experimental settings, the ML-based PdM can outperform traditional time-based and expert-scored PdM strategies [58–59]. The review, however, offers a broader perspective: "High predictive accuracy doesn't necessarily represent industrial readiness." Modelling studies conducted with fixed datasets, thresholds or asset-specific settings remain useful for only a short time, thereby limiting the long-term use of the models in dynamic industrial environments. The second insight from this review is that the need for environmental and process-context integration is among the most critical yet underdeveloped requirements of future PdM systems. When applied alongside climate variables, the impact of environmental data on improving model performance is evident in the 93.9% reduction in MSE reported by [17]. However, only about 27% of the reviewed studies include environmental or contextual inputs. The lack of evidence that context matters is not because of a lack of evidence in other sectors such as oil and gas, power systems, heat-transfer systems, or industrial operations that show that there is a relationship between degradation behaviour and parameters such as temperature, humidity, pressure, load variation, location, and process conditions [11],[18],[28]. The literature fails to address context as a fundamental design feature, however, not as a separate modelling capability. Most ML-PdM research has assumed that the behavior of internal sensors is sufficient for failure prediction. Still, in real asset degradation, it is influenced by interactions among equipment condition, process behavior, maintenance history, and environmental exposure [55]. One key theoretical finding from this review is that the ability to adapt the lifecycle has been identified as a key gap in current predictive maintenance research. Previous studies often show high model performance at a single validation event, and few provide evidence on whether the same model is effective when assets age, are repaired or inspected, have components replaced, experience seasonal load variations or change their operating regimes. This is a significant constraint as industrial assets are dynamic systems. The baseline they operate at "normally" varies over time, particularly after maintenance is performed on the system, especially if the system has been in service for long periods. There is no strong evidence from any of the reviewed studies that predictive performance improves for multiple cycles or at different stages of equipment ageing. This gap directly hinders the industrial application of a model that is reliable during validation, as it might not remain reliable when the asset's condition changes. Hence, the need for lifecycle-adaptive recalibration must be considered a theoretical necessity in future PdM frameworks, rather than merely a technical extension [1],[20],[9].

Conceptual Framework: Architecture of a Next-Generation PdM System

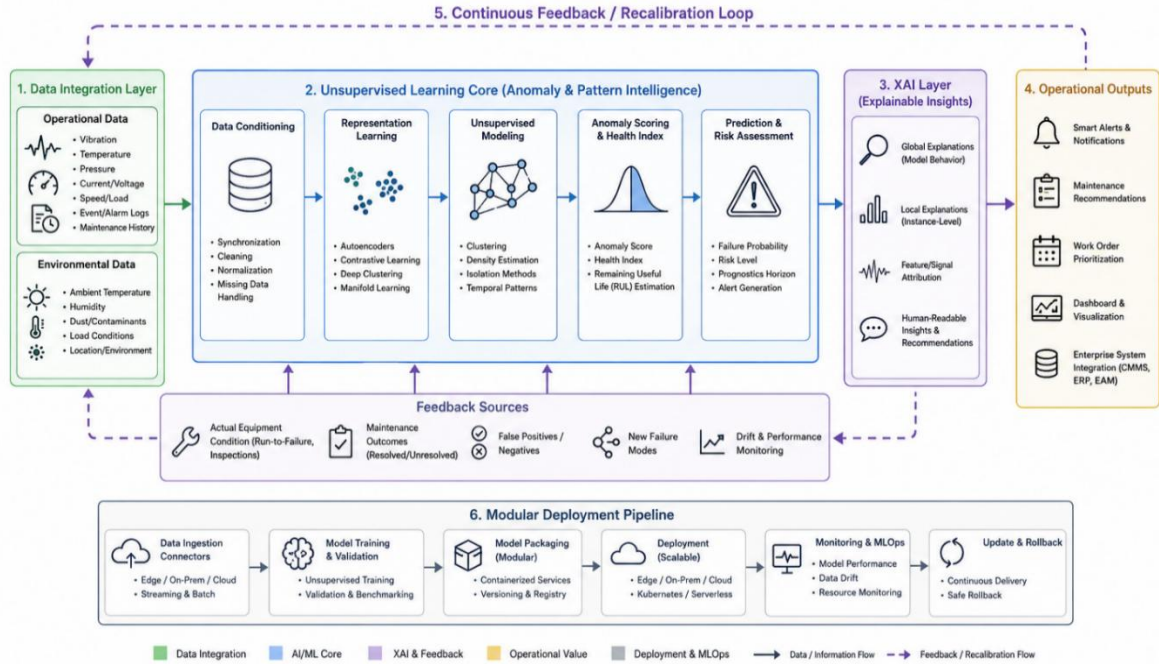


Figure 9: Conceptual architecture of a next-generation adaptive PdM system, illustrating the unsupervised learning core, continuous feedback and recalibration loops, integration of environmental and operational context streams, embedded XAI layer, and modular dep

This review also reveals that the current literature treats accuracy, explainability, transferability and scalability as disjointed concerns, but these features are interconnected and are needed for industrial deployment. Deep learning and graph-based models offer excellent predictive power, but are generally not very interpretable. On the other hand, methods such as Bayesian updating, fuzzy inference, and physics-informed methods offer more transparent reasoning and uncertainty estimation. Still, they may be more difficult to calibrate and may require more domain expertise. Thus, it remains unclear whether the accuracy-interpretability conflict identified by [58] can be resolved. Some aspects of partial solutions are evident in hybrid physics-ML methods and Bayesian ML methods, although these are not yet common across all industries. Similarly, cross-asset generalization of transfer learning and AutoML studies has shown promise. Still, existing evidence remains limited, as most demonstrations are conducted within a particular dataset, asset group, or operating site. The literature therefore lacks a common framework that integrates predictive performance, contextual learning, explanation, and scaling and deployment.

To fill these gaps, a conceptual direction for future research and industrial implementation is proposed: the Lifecycle-Adaptive and Explainable Predictive Maintenance (LAE-PdM) framework. The framework is not treated as a generic architecture introduced in the study, but it is developed from the cross-study synthesis. It breaks down the limitations identified in the literature into six design layers: multi-source data acquisition, contextual feature engineering, adaptive learning, lifecycle recalibration, explainability and uncertainty estimation, and decision-support deployment. These layers correspond directly to the key gaps highlighted in the review. Multi-source data acquisition and contextual feature engineering overcome the limitations of environmental, process, maintenance history and asset profile variables. Adaptive learning makes the flexible use of supervised, semi-supervised and unsupervised models, transfer learning, AutoML and hybrid physics-informed models. Lifecycle recalibration mitigates the core issue of recalibrating baselines, thresholds, and risk estimates as assets change over their lifecycles and move between operating regimes. Explainability and uncertainty estimation result in the auditability of safety-critical decisions.

Lastly, the review continues the discussion of PdM, shifting from an operational reliability perspective to one of sustainability and regulatory responsibility. [17] found that climate-informed maintenance planning can minimise unnecessary equipment replacement, and [53] found that early failure detection in manufacturing can

minimise energy and material waste. [56] also demonstrated significant economic benefits of physics-based reinforcement learning for wind turbine maintenance. The results support the possibility for both asset reliability and environmental performance with ML-PdM.

6. Practical Implications

The results of this review have direct applications for industrial practitioners, maintenance engineers and technology decision-makers. Asset-intensive organisations are advised to prioritise sensor coverage and IIoT connectivity to generate the multi-source data streams required by ML-based PdM frameworks. The benefits of integrating environmental data into the existing suite of predictive models, as shown by [17] in a 93.9% reduction in MSE, warrant special effort to reduce OT/IT data silos and to integrate climate and process-context variables into existing predictive models. Model selection is best approached using a portfolio strategy that accounts for asset characteristics: well-structured, data-rich assets are generally suited to supervised models, whereas safety-critical assets with limited failure records are better served by hybrid physics-ML or semi-supervised approaches. Regulatory teams are encouraged to engage proactively with XAI frameworks, particularly Bayesian and SHAP-based methods, to develop audit-ready decision documentation that is consistent with evolving safety and ESG reporting requirements. Vendors and system integrators are urged to accelerate the development of standardised, modular PdM pipelines that facilitate cross-asset transfer learning without necessitating context-specific re-engineering.

7. Future Research Directions

The three convergent future research goals should be considered. First, the development of generic unsupervised and semi-supervised ML architectures that can learn meaningful baseline models without labeled failure data and adaptively recalibrate them as operational conditions evolve, an approach demonstrated in early form through reinforcement learning-based health-state prediction and through adaptive ML models for IIoT environments. Second, the systematic embedding of environmental and climate intelligence within PdM pipelines, such as industry-standard data fusion protocols for multi-source sensor streams and industry-standard frameworks to link maintenance decisions with measurable environmental impacts consistent with net-zero and ESG goals. Third, federated and edge-deployable ML models that maintain data privacy, minimize communication requirements, and provide real-time decision support at the asset level, while also offering embedded XAI mechanisms for feature attribution and uncertainty quantification that are available for both engineers and regulatory auditors. To move from proof-of-concept demos to generalizable evidence supporting industry-wide adoption standards, extensive longitudinal validation studies are needed, with multiple comparisons of ML-PdM frameworks across multiple asset types and operating environments.

8. Limitations

This review has several limitations that must temper interpretive conclusions. Given the restriction on English-language journal articles published from 2020 to 2026, groundbreaking research and contributions in other languages from areas with significant industrial ML activity may have been overlooked. Formal meta-analysis of the 33 studies was precluded by the diversity of experimental designs, asset classes, and performance metrics reported, and the reported comparisons of performance are therefore indicative rather than statistically definitive. Publication bias, in which journals tend to publish positive results, may lead to an overrepresentation of successful models and an underrepresentation of failures when applying ML to real-world industrial settings. Lastly, the field is evolving so rapidly that architectures that seemed "state of the art" when they were first published may already have been superseded. The proposed design framework should be considered a living roadmap rather than a prescription.

9. Theoretical Contributions

This review contributes to theory in the fields of reliability engineering and predictive maintenance in several ways. First, it advances research by positioning lifecycle adaptability as a key theoretical requirement for ML-based failure prediction in industrial assets. Most studies on predictive maintenance have evaluated models using historical datasets and static validation settings. Industrial assets, however, are dynamic systems whose behaviour evolves as they age, undergo maintenance interventions and experience different process regimes and environmental exposures. The review aimed to highlight this constraint in the reviewed studies and to take predictive maintenance theory beyond short-term failure prediction towards long-term model validity throughout the asset lifecycle.

Additionally, the review advances reliability engineering by framing the prediction of asset failures as a multidimensional reliability problem rather than an algorithmic prediction task. Common evaluation metrics used in traditional ML-PdM studies include accuracy, F1 score, R2, RMSE, MAPE, and ROC-AUC. This review argues that

these are not sufficient to guarantee reliability for deployment. Besides data scarcity and changing operating conditions, environmental stressors, uncertainty, explainability, cross-asset transferability and scalability are additional factors a predictive model must take into account to support industrial reliability. The proposed multidimensional evaluation framework can thus serve as a broader theoretical basis for evaluating the feasibility of using ML-based PdM models in real industrial settings.

Moreover, by connecting the dots of disjointed research streams, the review paves the way for the development of predictive maintenance research. In previous work, supervised learning, deep learning, hybrid physics-informed modelling, transfer learning, AutoML, environmental/context-aware modelling, and explainable AI have been mentioned in isolation. This review integrates these elements and demonstrates that there is no single modelling paradigm that meets the requirements for predictive accuracy, adaptability, contextual awareness, transparency and deployment readiness. This synthesis helps to gain a higher-level understanding of how future PdM systems should be designed.

Overall, this review is a step forward, moving from assessing the performance of individual models to a lifecycle-ready predictive maintenance theory. It contends that future industrial PdM systems require not only the ability to predict failures accurately but also the flexibility to adapt over time, incorporate contextual knowledge, provide explanations of the decision-making process, generalize across assets, and facilitate reliability-centered decision-making. The review also aims to provide a theoretical backdrop for future investigations into adaptive, explainable, and scalable asset-failure prediction using the ML framework.

10. Conclusion

The reviewed literature comprises 33 peer-reviewed publications published from 2020 to 2026, and this SLR aimed to analyze the current status of ML-based approaches for predicting industrial asset failures and to determine the requirements for designing future predictive maintenance frameworks. This review demonstrates that supervised learning, deep learning, hybrid and physics-informed models, transfer learning, AutoML, and explainable AI have all enhanced failure prediction, anomaly detection, and RUL estimation. But the key conclusion of this review is that for industrial use, high predictive performance is not enough. While many studies report high accuracy, F1-score, R^2 , RMSE, MAPE, or ROC-AUC results, fewer studies have considered the broader requirements of lifecycle adaptability, environmental and process-context integration, explainability, cross-asset transferability, and scalable deployment. The review introduces new knowledge by identifying the central unresolved gap in ML-based PM research: lifecycle adaptability. Industrial assets are dynamic systems whose operating baselines evolve with changes in operating regimes, environmental exposure, maintenance interventions and with asset age. However, the available literature provides little evidence of the reliability of current predictive models across multiple maintenance cycles, at different stages of equipment ageing, or under long-term changes in operational conditions. This discovery goes beyond just algorithmic performance and presents a new approach to asset failure prediction as a lifecycle reliability issue.

The key contribution of this review is the development of the Lifecycle-Adaptive and Explainable Predictive Maintenance Framework (LAE-PdM). This framework is based on the cross-study synthesis. It comprises six intertwined layers: multi-source data acquisition, contextual feature engineering, adaptive learning, lifecycle recalibration, explainability and uncertainty estimation, and decision-support deployment. LAE-PdM moves predictive maintenance research forward by demonstrating that future frameworks should have an asset-agnostic structure and context-sensitive operation. This implies the transferability of predictive maintenance systems across different asset classes and industries, while also adapting to asset condition, process behaviour, environment, maintenance history and lifecycle stage. This review also enhances reliability engineering by proposing a multidimensional evaluation logic for ML-based PdM studies. The review is not limited to model accuracy measures but also emphasizes additional aspects, including data dependency, contextual awareness, lifecycle recalibration, explainability, transferability, scalability, and sustainability/regulatory alignment. This broader assessment is particularly crucial in asset-intensive fields like oil & gas, manufacturing, utilities, power systems, and petrochemicals, where failure prediction plays a vital role in ensuring operational continuity, environmental protection, safety standards, and compliance with audits. Future studies should therefore shift beyond proof-of-concept model development and focus on longitudinal, cross-asset, and multi-site validation. A study is needed to assess the ability of the ML-PdM models to maintain their reliability with asset ageing, maintenance interventions, seasonal variations, environmental drift and shifts in operating regimes. Practitioners should invest in OT/IT integration efforts, sensor infrastructure, environmental data capture, and modular deployment pipelines to enable lifecycle adaptive PdM implementation. An effort should be made to establish standards and regulatory acceptance criteria for explainable,

probabilistic, and automated decision-support systems in safety-critical maintenance systems. But the overarching problem in the field is bringing academic model performance to scale for industry use. The LAE-PdM framework offers a theoretical framework to tackle this challenge and to move predictive maintenance towards adaptive, explainable, sustainable and reliability-focused asset management.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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