International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(9s) 2026 pp. 708-724
https://doi.org/10.70917/ijcisim-2026-3495
Article

AI-Enabled Preventive Maintenance for Industry 5.0: Advancing Equipment Reliability, Operational Resilience, and Sustainable Manufacturing

Jobin Varghese

Villa College QI Campus, Rah Dhebai Hingun, 20373 Malé, Maldives
Mail id: jobinvargheset@gmail.com

Abstract: Industry 5.0 represents a new dimension in the manufacturing industry with its focus on human-centeredness, sustainability, and resilience. The core of this change is the transformation of asset management from a reactive or purely scheduled approach to one based on artificial intelligence – proactive asset management. The purpose of this paper is to explore AIoT-based predictive and preventive maintenance within the Industry 5.0 framework and introduce the concept of Resilience-Based Maintenance (RBM). The authors propose a layered architecture that incorporates the use of DL models - namely, CNNs and Transformers – along with the high-fidelity Digital Twins within an Edge-Cloud cooperative computing environment. This enables processing high-frequency sensor data (vibration, thermal, and audio) at the edge with immediate detection of anomalies, while making long-term RUL estimation and fleet analytics in the cloud. Furthermore, the article investigates the impact of AI-based maintenance on the reliability of machinery and sustainability rates. The framework is to curtail industrial energy consumption, diminish material waste, and cut down carbon emissions by adaptive scheduling of maintenance as per energy-efficiency anomalies, and decreasing mechanical friction. In addition, the study looks into the important socio-technical challenges that hinder implementation, including the usage of Explainable AI (XAI) through SHAP frameworks to boost operators' trust, how to resolve data shortage issues through physics-informed neural networks (PINNs), and the promotion of human-in-the-loop collaboration to improve cognitive ergonomics in manufacturing.
Keywords: Industry 5.0, Predictive Maintenance, Artificial Intelligence of Things (AIoT), Resilience-Based Maintenance, Remaining Useful Life (RUL), Explainable AI (XAI), Digital Twin, Sustainable Manufacturing.

1. Introduction

Industry 5.0 is a paradigm shift from Industry 4.0 in terms of the philosophy and operations of the global manufacturing sector. Although the adoption of systems that are Cyber-Physical, automated, and that are connected to the Internet of Things (IoT) and the Industrial Internet of Things (IIoT) was an effective way to maximise throughput and operational efficiency under Industry 4.0, it often neglected the human factor and the wider ecological footprint (Breque et al., 2021; Nahavandi, 2024). The Industry 5.0 revolution directly tackles these omissions by shifting technology innovation to three key pillars: human-centric, environmental, and systemic, operational resilience (Acosta-Vargas et al., 2026; Ghobakhloo & Fathi, 2024). In this Socio-Techno-economic world, radical restructuring in asset management and machinery maintenance is needed. The traditional maintenance strategies (reactive (run-to-failure) and scheduled preventive), grouped mainly into two classes, are seriously constrained in comparison to contemporary industrial objectives. The losses associated with reactive maintenance are huge, resulting from unplanned downtime and cascading mechanical failure. On the other hand, the conventional scheduled preventive maintenance approach may lead to over maintenance, which results in premature replacement of components, higher labour cost, and higher resource usage (Bokrantz et al., 2020). To address these inefficiencies, Industry 4.0 has brought in Predictive Maintenance (PdM) and Condition Based Maintenance (CBM), which rely on real-time sensor streams to monitor and calculate Remaining Useful Life (RUL) of the asset (Gao & Wang, 2025; Li et al., 2018). However, standard Industry 4.0 PdM frameworks optimize strictly for economic and throughput variables, ignoring energy consumption, carbon footprints, and the cognitive workload of human operators (Jasiulewicz-Kaczmarek et al., 2024; van Oudenhoven et al., 2022). Industry 5.0 expands predictive analytics into a holistic framework known as Maintenance 5.0 or Resilience-Based Maintenance (RBM) (Bukowski, 2025). This next-generation approach embeds Artificial Intelligence of Things (AIoT) architectures, Digital Twins (DT), and Explainable AI (XAI) directly into shop-floor workflows (Bitam et al., 2025; Villagómez-Galindo et al., 2026). RBM ensures high equipment reliability while lowering energy waste and ensuring that automated diagnostic insights are fully transparent and supportive to human technicians (Mourtzis & Angelopoulos, 2024).

1.1 Research Gap

With the development of Industry 5.0, a growing volume of review literature focused on specific aspects of intelligent maintenance, such as predictive maintenance algorithms, Digital Twin technologies, Explainable Artificial Intelligence (XAI), Artificial Intelligence of Things (AIoT), and sustainable manufacturing, has emerged. Previous reviews, however, tend to focus on these domains separately, leaving a disjointed conceptual understanding and a need for more integration, both within and between the three technological, organisational, and human-centred domains.

The initial research focused on algorithmic developments for Remaining Useful Life (RUL) estimation and fault diagnosis, with machine learning and deep learning methods as the primary approaches of interest, an area which is particularly focused on improving prediction accuracy and maintenance scheduling (Li et al., 2018; Gao & Wang, 2025; Wu et al., 2024). While these works significantly contributed to the progress of predictive maintenance research, they tended to focus mainly on engineering performance optimisation, neglecting to fully account for human collaboration, sustainability goals, and organisational resilience. Similarly, recent studies on Digital Twin applications in maintenance have demonstrated the potential of virtual replicas to support equipment monitoring, simulation, and decision-making (Angelopoulos et al., 2025; Liu & Xu, 2025; Tao & Zhang, 2024).

Most studies focus on digital synchronisation and computational efficiency and do not discuss explainability, operator trust, or optimisation for sustainable maintenance. Industry 5.0 has been explored from a multi-dimensional, human-centric and sustainability standpoint (Breque et al., 2021; Ghobakhloo & Fathi, 2024; Nahavandi, 2024). Despite this, these efforts lay the philosophical basis of Industry 5.0, but they tend to isolate maintenance as one functional component among other components and fail to build up an integrated maintenance paradigm that can support reliability of equipment, environmental sustainability, operational resilience and human-centred decision making simultaneously. Similarly, the recent literature regarding Explainable Artificial Intelligence, human-in-the-loop maintenance, and cognitive ergonomics has led to a better understanding of operator trust and collaborative decision support (Ahangar et al., 2024; Bashir & Khan, 2024; Mourtzis & Angelopoulos, 2024).

These contributions, however, are not associated with Digital Twin ecosystems, AIoT-supported sensing architectures, or maintenance strategies aimed at sustainability, thereby limiting their applicability to fully realized Industry 5.0 environments. The overall body of literature reveals a significant conceptual division. Very few existing reviews focus on AI algorithms, Digital Twins, sustainability, operational resilience, or human-centric maintenance, despite Industry 5.0 being a socio-technical system that depends on these capabilities to operate synergistically. Currently, there is limited evidence that the state of the art provides a common conceptual model that enables the incorporation of AI-enabled predictive intelligence, Digital Twin synchronisation, Edge–Cloud synergy, explainable AI, Human-in-the-Loop maintenance, operational resilience and sustainability into a single maintenance model. To fill this gap, the authors of this paper aim to propose a complete Resilience Based Maintenance (RBM) framework that brings together these different research areas and integrates them into an overall framework for Industry 5.0. It provides a comprehensive overview of recent technological developments and critically discusses engineering and sustainability aspects as well as the human factor, laying a solid foundation for developing AI-based preventive maintenance to enable resilient and sustainable manufacturing systems.

1.2 Study Contributions

This research paper provides a comprehensive analysis of AI-enabled preventive and predictive maintenance within the Industry 5.0 ecosystem. The primary contributions of this study are threefold:

- **i.** Implements a holistic Resilience-Based Maintenance (RBM) conceptual framework connecting Artificial Intelligence-integrated Maintenance, Digital Twins, Explainable AI, Operational Resilience, Sustainability and Human-centric decision-making in the Industry 5.0 context.

ii. It combines the latest insights into AI-based preventative and predictive maintenance practices, integrating technology, operation and sustainability views on a critical basis toward a conceptual framework.

iii. It suggests a multi-layered AIoT architecture with an Edge–Cloud approach, where different types of sensing devices, deep learning, Digital Twins, and intelligent maintenance decision support are integrated.

iv. It defines the main challenges to be solved in the implementation of resilient, explainable and sustainable maintenance systems for Industry 5.0 and the future research directions.

2. Research Methodology

The method used in this study is an integrative review that aims to synthesize interdisciplinary knowledge through a critical process in the era of Industry 5.0, using it as a paradigm for preventive maintenance supported by artificial intelligence. An integrative review instead of a traditional narrative review, can systematically examine, compare, and synthesize a wide range of theoretical, technological, and application-based studies to inform the development of new knowledge relevant to the discipline (Whittemore & Knafl, 2005; Snyder, 2019). The field of Industry 5.0 presents a particular application of this methodological approach because several research domains – such as Artificial Intelligence, Manufacturing Engineering, Industrial Informatics, Sustainability, Resilience Engineering, and Human-centred Systems – are involved and have largely remained autonomous (Breque et al., 2021; Ghobakhloo & Fathi, 2024; Nahavandi, 2024). With this in mind, this review is not only aimed at describing existing developments, but also at critically synthesising the scattered knowledge and providing the proposed Resilience-Based Maintenance (RBM) as a whole conceptual view for intelligent and sustainable maintenance systems.

2.2 Literature Identification Strategy

The literature, which is part of this review, was identified by carefully conducting a structured search on major scientific databases that cover manufacturing systems, industrial engineering, artificial intelligence, predictive maintenance and sustainability research, such as Scopus, Web of Science, IEEE Xplore and ScienceDirect. The search strategy was limited to the last 6 years of publications (from 2020 to 2026) to reflect the quick developments of Industry 5.0 technologies, and to ensure the capture of seminal pieces of literature dating back before this time when they laid the theoretical foundations of predictive maintenance, Remaining Useful Life (RUL) estimation, Digital Twins and intelligent manufacturing (Li et al., 2018; Breque et al., 2021; Gao & Wang, 2025). This allowed a balance of both classic theories and recent advances in technology and was used to integrate the concepts into the conceptual synthesis.

2.3 Literature Screening and Selection

The retrieved publications were then screened following a structured approach, so as to guarantee conceptual relevance and methodological consistency. In the first step, copies and unrelated records were eliminated, using titles and abstracts. Then full-text assessments were made to determine the relevance of each publication to the goals of the present review. Studies were considered when they dealt with AI-powered predictive or preventive maintenance, Industry 5.0, smart manufacturing, intelligent production systems, enabling technologies including Artificial Intelligence of Things (AIoT), Digital Twins, Explainable Artificial Intelligence (XAI), Edge–Cloud computing, or Remaining Useful Life prediction, and sustainability, operational resilience or human-centred maintenance. On the other hand, there was research that didn't focus on AI applications and other related areas that were not AI-based, editorials, or publications that did not contain a substantive conceptual or technological contribution. The application of these criteria resulted in a solid basis for conceptual synthesis and framework development (Snyder, 2019).

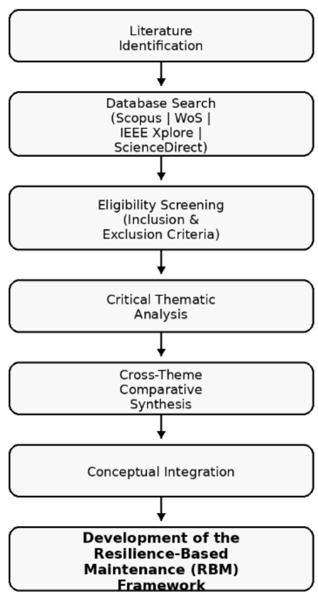
2.4 Thematic Analysis and Knowledge Synthesis

Using a thematic synthesis approach, the selected literature was comparatively examined to identify themes, emerging theories, methodological variations, implementation challenges and new avenues for research (Whittemore & Knafl, 2005). Instead of reviewing publications individually, the evidence was iteratively coded and structured into 7 interconnected themes for analysis: (i) Artificial Intelligence algorithms for predictive maintenance, (ii) technologies of Digital Twin, (iii) Artificial Intelligence of Things (AIoT) related sensing infrastructures, (iv) collaboration between edge computing and cloud computing, (v) Explainable Artificial Intelligence and human-centred maintenance, (vi) maintenance strategies based on sustainability, and (vii) operational resilience in the framework of Industry 5.0. Cross-Theme comparison helped to identify conceptual disintegration in the current studies and complementarity between technological intelligence, sustainability goals, and human-centric maintenance practices. The proposed Resilience-Based Maintenance framework was then developed based on these analytical insights.

2.5 Development of the Resilience-Based Maintenance Framework

The proposed Resilience-Based Maintenance (RBM) framework has been developed in an iterative process of conceptual integration. Thematic synthesis results were analysed systematically to determine the common constructs, the compatible theories and the unmet research needs in the current maintenance literature. These constructs were then combined in a multidimensional conceptual framework to explain the interrelationships between AI-enabled intelligence, synchronisation with a Digital Twin, Explainable Artificial Intelligence, operational resilience, sustainability optimisation and human-centred decision-making in Industry 5.0. Therefore, RBM's focus goes beyond the simple consolidation of existing maintenance concepts to the conceptual paradigm that will help to direct future empirical studies, application in the industry, and theoretical development in Maintenance 5.0 research (Bukowski, 2025; Jasiewicz-Kaczmarek et al., 2024). To enhance methodological transparency, the systematic workflow adopted for this review is presented in Figure 1. The framework illustrates the sequential process of literature identification, thematic synthesis, and conceptual integration that underpins the development of the proposed Resilience-Based Maintenance (RBM) framework. This structured approach ensures the rigour, traceability, and credibility of the review methodology (Whittemore & Knafl, 2005; Snyder, 2019)

Figure 1: Review Methodology and Conceptual Framework Development Process



Source: Developed by the authors based on the integrative review methodology proposed by Whittemore and Knafl (2005) and Snyder (2019) and adapted for AI-enabled preventive maintenance in Industry 5.0.

Figure 1 depicts the methodological process followed in this study, which involves the sequential process of literature identification, eligibility screening, thematic analysis, comparative synthesis and conceptual integration. The approach used was a structured one to ensure that the selected literature was synthesized rigorously and transparently and that the proposed Resilience-Based Maintenance (RBM) framework was developed. The workflow illustrates how information from various research fields has been consolidated and how the theoretical basis of the study has been built. Based on the above methodological approach, the next section synthesizes the selected literature in a critical manner to investigate the theoretical development of Maintenance 5.0; the technologies that enable AI-driven PM; the proposed Resilience Based Maintenance framework; and future research directions for resilient, human-centric and sustainable manufacturing ecosystems.

3. Theoretical Framework: The Evolution to Maintenance 5.0

Understanding the conceptual transition to Maintenance 5.0 requires tracing the evolutionary trajectory of maintenance philosophies relative to broader industrial revolutions.

3.1 From Industry 4.0 to Industry 5.0 Maintenance Paradigms

In early industrial models, maintenance was considered as cost of operation and an inevitable fact of life. In the era of Industry 4.0, this perception has been changed, and now maintenance data is regarded as a strategic asset. Factories began fitting vibration, thermal, and acoustic sensors onto key equipment, allowing them to detect anomalies before disaster strikes (Nagy et al., 2025). But the Industry 4.0 concept works under an automated "black-box" arrangement. Algorithms send maintenance instructions to humans (e.g., order an autonomous shutdown, send a work order) with no explanation of the reasoning (Bashir & Khan, 2024; Bousdekis et al., 2021). This lack of transparency, can lead to high cognitive stress, scepticism and decisional friction among the floor technicians (Alhaag et al., 2022). mIndustry 5.0 reintroduces a collaborative socio-technical dynamic. It moves away from fully replacing human oversight, opting instead to augment human capabilities through advanced human-machine interfaces, collaborative robots (cobots), and cognitive automation (Kaasinen et al., 2020; Romero & Stahre, 2024). Maintenance 5.0 redefines structural health monitoring by expanding optimisation models to balance mechanical reliability with ecological sustainability and operator safety (Carnero, 2025).

3.2 Conceptualisation of the Resilience-Based Maintenance (RBM) Framework

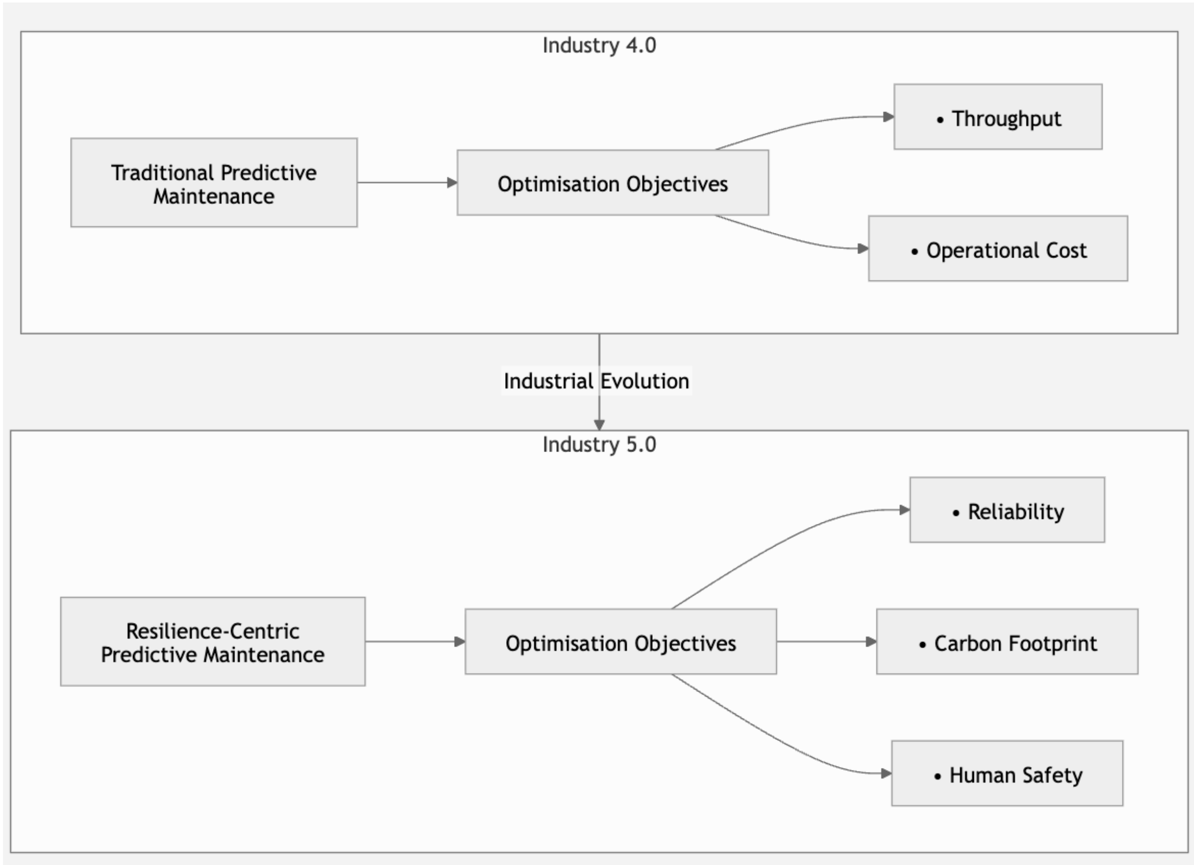
Resilience-Based Maintenance (RBM) is the main conceptual value of this work, and it is a development of Maintenance 5.0 that incorporates technological intelligence, operational resilience, sustainability and human-centric decision making in a single maintenance framework. RBM's philosophy of maintenance as a strategic organisational capability differs from traditional maintenance strategies, which focus on optimising equipment availability and maintenance costs.RBM's concept of maintenance as a strategic capability of an organisation is different from traditional maintenance approaches, which are mainly focused on optimizing equipment availability and maintenance costs. RBM is therefore not only considered a maintenance strategy but also an integrated socio-technical approach, involving the interaction between Artificial Intelligence (AI), Artificial Intelligence of Things (AIoT), Digital Twins, Explainable Artificial Intelligence (XAI) and human skills to develop resilient and sustainable manufacturing systems (Breque et al., 2021; Bukowski, 2025; Ghobakhloo & Fathi, 2024; Nahavandi, 2024).

i. **Absorptive Capacity:** The capability of an asset or production line to withstand structural degradation or sensor anomalies without experiencing immediate, catastrophic failure. AI-enabled control loops achieve this by dynamically adjusting operating parameters (e.g., dampening spindle speed or reducing thermal loads) when a micro-anomaly is identified (Angelopoulos et al., 2025). In addition to ensuring equipment performance in the event of minor disruptions, absorptive capacity is the capacity of the maintenance systems that use AI to predict equipment degradation by means of repeated condition monitoring, predictive analysis and intelligent anomaly detection. When combined with the real-time diagnostic models, the AIoT-empowered sensing infrastructures can identify early signs of degradation, thereby minimising operational risks and enhancing equipment reliability and production continuity, as seen in studies by Bitam et al. (2025) and Gao & Wang (2025).

ii. **Adaptive Capacity:** The ability of the maintenance ecosystem to alter its scheduling and resource distribution in real time based on changing asset health and supply chain constraints. Dynamic maintenance scheduling is not the only use of adaptive capacity: manufacturing systems can continuously shift maintenance priorities based on varying production requirements, supply chain events, and asset status. Adaptive maintenance, which relies on Digital Twins and Edge–Cloud collaborative intelligence, can help organisations explore various operational scenarios, make optimal maintenance decisions on time, and retain the flexibility of production and operational resilience (Angelopoulos et al., 2025; Cheng & Zhang, 2024; Liu & Xu, 2025).

iii. **Restorative Capacity:** The ease and speed with which a system can be returned to its optimal baseline state after an anomaly or component replacement occurs (Bukowski, 2025). Restorative capacity also provides emphasis on organisational learning, in that maintaining interventions provide feedback that can help to inform future maintenance decisions. AI models continuously improve the effectiveness of the maintenance system, and the outcomes of those maintenance actions, along with the data collected by new sensors, feed back into the models to continuously improve the system and enhance the organisation's resilience over time (Kaasinen et al., 2020; van Oudenhoven et al., 2022).

Figure 3: Evolution of predictive maintenance objectives from Industry 4.0 towards Industry 5.0.



The idea evolution of predictive maintenance (PdM) from the classic Industry 4.0 approach to the Industry 5.0 concept of resilience is shown in Fig. 3. In the context of Industry 5.0, the focus is expanded beyond operational efficiency (as in Industry 4.0) to sustainability and human-centric values as part of the processes of decision-making for maintenance. Predictive maintenance aims to maximize production use, while minimizing production operational and maintenance expenses within the Industry 4.0 context. Machine learning algorithms and Industrial Internet of Things (IIoT) technologies are used to predict equipment failures and schedule maintenance events to minimize asset downtime and improve its utilization.

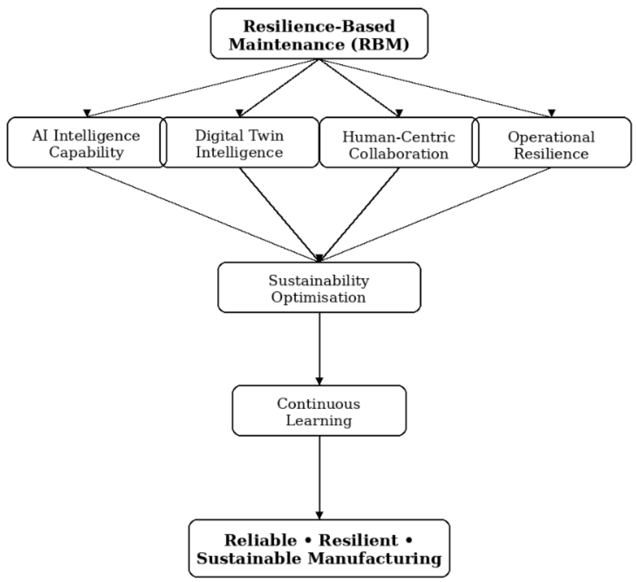
Unlike Industry 4.0, which looks at optimizing productivity, Industry 5.0 is focused on optimizing systems for reliability, environmental impacts and human safety. Operational strategies are growing carbon aware, resilience to unexpected disruption is becoming a factor in maintenance decisions, and human interactions with AI are becoming increasingly collaborative. Thus, predictive maintenance moves from being an efficiency-driven process to becoming a strategic tool that fosters sustainable manufacturing, safer workplaces, and lasting operational resilience. The illustration shows the synergies of artificial intelligence, edge computing, digital twins, and sustainability metrics in supporting the next generation of predictive maintenance solutions that are helping to ensure industrial operations are aligned with the overall goals of Industry 5.0. By combining Remaining Useful Life (RUL) tracking with carbon-accounting metrics, RBM allows to identify the machines with high mechanical friction, which consume up to 15–20% more electric current than others, for maintenance purposes, based on structural wear and energy-efficiency criteria (Jasiulewicz-Kaczmarek et al., 2024). This methodology has created the principles for sustainable manufacturing of modern days by filling the gap between the longstanding conflict between engineering reliability and corporate environmental compliance.

2.2.1 Theoretical Dimensions of the Proposed Resilience-Based Maintenance (RBM) Framework

Although the resilience capabilities mentioned in the prior segment form the theoretical basis for Resilience-Based Maintenance (RBM), they do not completely elaborate on the technological and organisational abilities necessary for enabling resilient maintenance in Industry 5.0. The studies conducted on Maintenance 5.0 have mainly concentrated on different technologies such as Artificial Intelligence (AI), Digital Twins, Explainable Artificial

Intelligence (XAI), and Artificial Intelligence of Things (AIoT), while not stressing their potential connection with a single maintenance approach (Bukowski, 2025; Jasiulewicz-Kaczmarek et al., 2024). To fill in this gap, the present research proposes its own approach that considers RBM as a multidimensional socio-technical framework that brings together predictive intelligence, operational resiliency, sustainability, and human-oriented cooperation into a unified maintenance ecosystem. This detailed approach includes several closely interrelated dimensions, such as AI Intelligence Capability, Digital Twin Intelligence, Human-Centric Collaboration, Operational Resilience, Sustainability Optimisation, and Continuous Learning. All in all, the abovementioned dimensions open possibilities for intelligent maintenance through predictive analytics, asset monitoring, explainable decision making, flexible maintenance planning, optimal resource use, and organisational learning. To illustrate the conceptual relationships among these dimensions, Figure 2 presents the proposed Resilience-Based Maintenance framework. The framework demonstrates how technological intelligence, human collaboration, resilience, and sustainability collectively contribute to reliable and adaptive manufacturing systems within the Industry 5.0 paradigm.

Figure 4: Conceptual Framework of the Proposed Resilience-Based Maintenance (RBM) Framework



Source: Developed by the authors based on the synthesis of Breque et al. (2021), Ghobakhloo and Fathi (2024), Bukowski (2025), and Jasiulewicz-Kaczmarek et al. (2024).

Figure 4 illustrates the multidimensional structure of the proposed RBM framework. It demonstrates that resilient maintenance in Industry 5.0 emerges through the integration of six complementary capabilities rather than isolated technological solutions. Collectively, these dimensions support intelligent maintenance that enhances equipment reliability, operational resilience, sustainability, and human-centred decision-making.

2.2.2 Comparative Positioning of the Proposed Resilience-Based Maintenance Framework

Feature	**Maintenance 4.0**	**Existing Maintenance 5.0**	**Proposed RBM**
AI-enabled prediction	✓	✓	✓
Digital Twins	Partial	✓	✓
Human-centric decision making	✗	Partial	✓
Sustainability integration	Limited	Partial	✓

Operational resilience	Limited	Partial	✓
Continuous organisational learning	✗	Limited	✓
Integrated socio-technical framework	✗	Partial	✓

Source: Developed by the authors based on the reviewed literature**.**

The table highlights the conceptual progression of intelligent maintenance paradigms from Maintenance 4.0 to the proposed RBM framework. While Maintenance 4.0 emphasises predictive intelligence and Maintenance 5.0 introduces greater human-centricity, RBM integrates these capabilities with operational resilience, sustainability, and continuous organisational learning into a unified socio-technical framework. This comparative perspective demonstrates the principal theoretical contribution and novelty of the proposed framework.

4. AI-Enabled Architectural Framework for Preventive Maintenance

For the effective application of Resilience-Based Maintenance (RBM), an interoperable digital architecture is vital to carry out real-time data acquisition, intelligent analytics, predictive decision-making and human-centred maintenance interventions. There have been many proposed architectures for predictive maintenance in the literature of Industry 4.0, and most of them are highly focused on the technical side with little consideration of the operational resilience, sustainability, interoperability and human-driven collaborative AI decision making (Angelopoulos et al., 2025; Bitam et al., 2025). As a response, a more advanced architecture presented in this paper combines all the preceding technologies with almost all possible components, which in turn makes a system coherent with the principles of Industry 5.0, including but not limited to heterogeneous sensing technologies, Edge-Cloud collaborative intelligence, deep learning, Digital Twins and Explainable Artificial Intelligence. To operationalise Resilience-Based Maintenance across a smart factory, a multi-tiered, interoperable computing architecture is required. This architecture bridges physical shop-floor assets with high-performance computational models via an Edge-Cloud collaborative framework.

4.1 Data Ingestion and Heterogeneous Sensing

The base layer of the architecture focuses on data acquisition from multi-modal, heterogeneous IIoT sensor networks (Bitam et al., 2025). Physical degradation manifests through diverse physical vectors, requiring a varied sensing approach:

i. **High-Frequency Vibration Sensors:** Triaxial accelerometers capture structural resonance, mechanical looseness, and rolling-element bearing degradation in the time and frequency domains.

ii. **Thermal Imaging and Infrared Thermography:** Continuous thermal arrays monitor localised friction and electrical resistance anomalies in motorised couplings and switchgear.

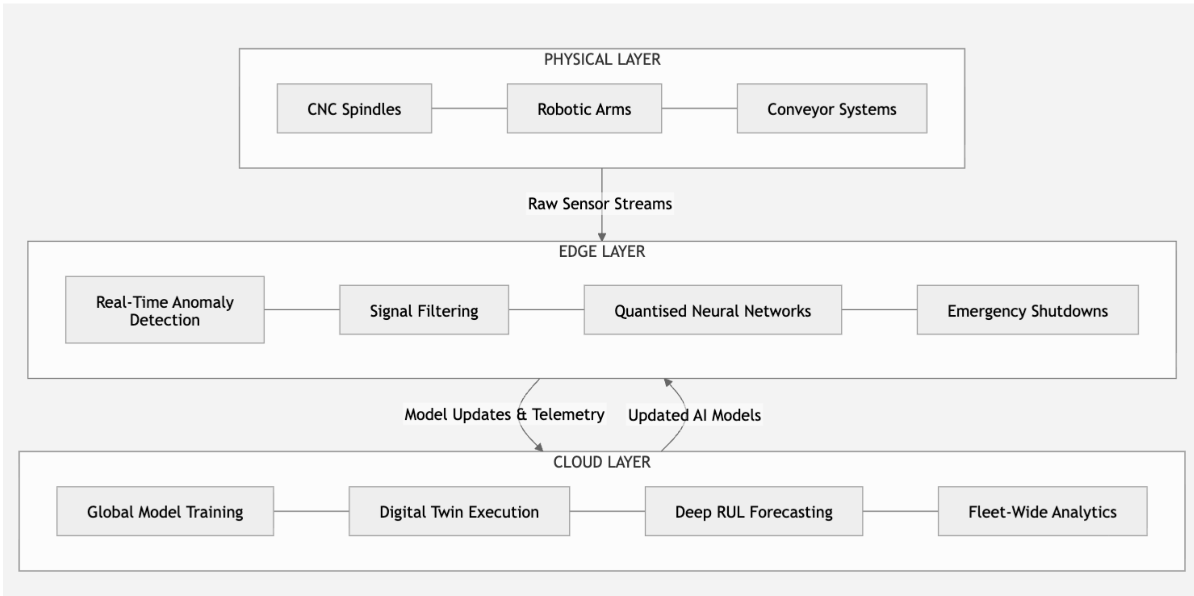
iii. **Acoustic Emission Analytics:** High-bandwidth audio sensors and microphone arrays detect high-frequency stress waves caused by micro-cracking and fluid leaks long before they manifest as detectable vibrations or temperature spikes (Kumar & Singh, 2025).

Despite significant advancements in predictive maintenance made possible through different sensing technologies, recent research has demonstrated that certain limitations persist. Almost all the monitoring systems employed today make extensive use of vibration data due to the well-established record of this type of data in the diagnosis of issues. Nevertheless, many systems that use vibration data as their main operating method are less sensitive to existing defects at the beginning phase of their development and may also be influenced by other external factors. Advantages of thermal imaging for damage detection and assessment are offset by the effect of the environment on this technology. In turn, using acoustic emission data allows for the monitoring of certain types of defects in devices before they grow larger. However, using this method imposes greater computation requirements on computers and software systems (Bitam et al., 2025; Kumar & Singh, 2025). Because of this and other reasons, researchers believe that the methodology of multimodal sensor fusion has a lot of potential. However, the number of real-world applications that integrate multimodal sensing with human-centred decision-making and sustainable maintenance practice remains low.

4.2 The Edge-Cloud Collaborative Computing Model

Processing high-frequency sensor streams creates significant data bandwidth and network latency challenges. To address this, the architecture utilises an integrated Edge-Cloud collaborative model (Cheng & Zhang, 2024).

Figure 5: Hierarchical cloud–edge–physical architecture for intelligent predictive maintenance.



The proposed architecture for the cloud–edge in the context of AI for predictive maintenance in smart manufacturing is shown in figure 5. It is composed of the Physical Layer, Edge Layer and Cloud Layer, all of which are responsible for real-time monitoring, intelligent fault detection and continual improvement of the model. Embedded sensors continuously collect operational data from industrial equipment like CNC spindles, robotic arms, conveyor systems and so on at the Physical Layer. These raw sensor streams (vibration, temperature, current, acoustical), are sent to the edge layer for immediate processing. The Edge Layer is in charge of executing latency-sensitive computations near the manufacturing gear. It performs real-time anomaly detection, signal filtering and inference based on quantised neural networks, with minimum computational load, to detect abnormal operating conditions. In case of severe faults, the edge layer can trigger emergency shutdowns to avoid damage to equipment and maintain the safety of operations. At the same time, the services that are operating pass data to the cloud via telemetry, along with diagnostic information.

The Cloud Layer gives a high-performance computing resource to edge devices that are not suited to more computationally demanding applications. These include global model training, digital twin execution, deep Remaining Useful Life (RUL) forecasting and fleet-wide analytics of multiple manufacturing assets. With aggregated historical and real-time operational data, the cloud continuously improves predictive models and pushes new AI models back to the edge layer. This bi-directional communication creates a closed-loop learning process to continuously enhance the prediction accuracy and ensure low latency decision-making at the edge. The proposed architecture is a cloud-edge architecture that integrates the advantages of cloud computing and edge intelligence to realize the large-scale, dependable and real-time predictive maintenance of equipment, thereby minimizing equipment downtime, maximizing equipment reliability and supporting the application of manufacturing systems in industry 4.0.

i. **Edge Node Processing:** Vibration and acoustic emissions are captured at frequencies often exceeding 20 kHz. Edge gateways execute real-time signal processing—including Fast Fourier Transforms (FFT) and Wavelet Transforms—to filter noise locally. Quantised, low-footprint Deep Learning models run directly on edge microcontrollers to identify immediate anomalies and initiate automated machine protection overrides within milliseconds if critical thresholds are breached (Zhang & Dynamic, 2025).

ii. **Cloud Analytics Processing:** Filtered feature vectors and event-driven data segments are transmitted asynchronously to a centralised cloud platform. The cloud layer handles computationally demanding tasks, including historical trend analysis, fleet-wide analytics, long-term RUL forecasting, and running high-fidelity Digital Twins (Liu & Xu, 2025).

The evidence from existing research shows that Edge-Cloud approaches can be more effective than purely edge-based or cloud-based solutions, as they make efficient use of computing power while ensuring real-time performance (Cheng & Zhang, 2024). However, implementations described in the existing approaches are mostly technology-driven and do not pay enough attention to such important issues as interoperability, information security, scalability, and operator-centred DSS. In addition, there is a lack of comparative assessment of the existing architectures from the perspective of sample implementation type, especially in heterogeneous production environments with diverse capabilities for computing and production processes. Overall, the above-mentioned limitations point out that future maintenance architectures should combine technological optimisation with organisational resilience and human-centred operational requirements.

4.3 Deep Learning Modelling and Remaining Useful Life (RUL) Estimation

Once data is aggregated in the cloud, deep learning models analyse machine degradation pathways to calculate accurate RUL profiles.

i. **Spatial Feature Extraction via CNNs:** 2D Convolutional Neural Networks process downsampled vibration spectrograms. The convolutional layers isolate structural fault patterns—such as outer race bearing defects—without requiring manual feature engineering (Yan & Meng, 2025).

ii. **Temporal Tracking via LSTMs and Transformers:** Extracted spatial features are passed to Long Short-Term Memory (LSTM) networks or multi-head self-attention Transformer networks. These architectures trace the progression of degradation over time, projecting the asset's health curve into the future to calculate the precise point where health metrics cross acceptable safety thresholds (Gao & Wang, 2025; Wu et al., 2024).

iii. **Digital Twin Synchronisation:** The virtual machine tool is synchronised with the physical asset and continuously updated from sensor feeds (Tao & Zhang, 2024). This Digital Twin can simulate the various stress configurations in real time, so maintenance teams can perform experiments to see how different production speeds affect the remaining life of the product before physically changing the configuration on the line (Liu & Xu, 2025).

Although deep learning has made significant advances in the field of RUL prediction, it still faces challenges related to model interpretability, computational complexity, and applicability to various industrial environments (Gao and Wang, 2025; Wu et al., 2024). The CNN can better capture the spatial degradation pattern, and the transformer can model the long-range temporal correlations well. In industries with rare failures, however, these methods are not useful, because a large number of quality labelled data are needed. The integration of Explainable Artificial Intelligence (XAI) with physics-based learning must continue to be a key priority for the research to improve the reliability and applicability of deep learning-based maintenance systems.

5. Advancing Reliability, Resilience, and Sustainable Manufacturing

AI-powered predictive maintenance explicitly fosters the performance indicators that are the cornerstone of industry 5.0. A Resilience Based Maintenance (RBM) strategy optimises uptime, structural safety and green manufacturing, not at the expense of each other.Instead of making them competing trade-offs, a Resilience Based Maintenance (RBM) approach uses real-time analytics to optimise all three of these. The literature is consistent in highlighting how AI-driven maintenance has increased the reliability of systems, but most studies focus on operational metrics like prediction accuracy, Mean Time Between Failures (MTBF) and downtime reduction, while less attention is paid to organisational resilience, team collaboration or sustainability results (Gao & Wang, 2025; Jasiulewicz-Kaczmarek et al., 2024). As a result, the existing evidence is dispersed in the engineering and sustainability fields and a need for integrated evaluation frameworks, which can assess the technological, environmental, and human-centred performances simultaneously.

5.1 Equipment Reliability Engineering via Precision Analytics

While various studies have shown the positive outcomes of AI-powered maintenance on manufacturing productivity, the results are significantly different depending on industry application, analytics tools and assessment criteria. Past studies have mostly examined specific measures, like prediction accuracy or equipment reliability, while relatively few studies assess operational resilience, sustainability or other human-centric measures. To summarise the main evidence for preventive maintenance enabled by AI and to pinpoint areas which need further exploration, a comparative synthesis of the literature reviewed is presented in Table 3. Under an AI based maintenance architecture, traditional metrics like Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) can be significantly enhanced. In contrast to traditional reliability engineering, which uses population-average bathtub curves, deep learning architectures capture the individual degradation paths of assets (Gao & Wang, 2025).

Under different stress (s), a 2D-CNN or an attention-based Transformer model identifies a rising defect signature (e.g., sub-micron spalling) and the system derives an individualised asset RUL profile (RUL=t"failure" - t"current") (Li et al., 2018; Wu et al., 2024). This precision helps minimize secondary damage in mechanical chains that include several interconnected chains. In a multi-axis CNC machine tool, for example, even a small imbalance in the spindle bearings can be mitigated early on, and this can stop destructive harmonic vibrations spreading into linear guideways and ball screws, maintaining the geometric accuracy and life of the entire asset. Preventing major breakdowns due to condition-based actions has been suggested in literature as a way of enhancing machines reliability when using AI in maintenance. Meanwhile, most evaluations are engineering-driven, e.g., focus on the Remaining Useful Life (RUL) or fault detection efficiency, while the contribution to the overall resilience and sustainability of organisations of reliability enhancement remains not sufficiently explored. It shows the necessity to develop future research using multidimensional approaches to the assessment of technical, operational and organizational indicators.

5.2 System-Level Operational Resilience

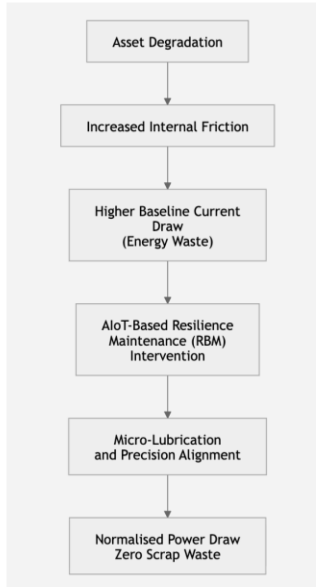
From the factory perspective, Industry 5.0 restates the idea of resilience as the ability to withstand shocks and stresses in the system, like significant variations in materials incoming, localised subsystem overload or system-wide delays, without it collapsing (Fragapane et al., 2024). This is further improved by an autonomous prescriptive adjustment and adaptive control loops, which is enabled by the AIoT based predictive framework (Angelopoulos et al., 2025; Bitam et al., 2025).

In the event an alarm signal is triggered by a cloud-synchronised Digital Twin indicating that a rapid deterioration is occurring in one of a robot's joints servo, but the system determines that there is no immediate way to perform maintenance, it doesn't just let the machine run to catastrophic failure. Rather, the internal control system of the asset performs a dynamic adjustment of its operations (Bukowski, 2025). The AI model can directly communicate with the machine's Programmable Logic Controller (PLC) to automatically adjust maximum acceleration, re-route high-torque tool paths, or modify tool paths to lower thermal and mechanical stresses on the damaged part. This mitigation allows the asset to continue to operate within the window until a scheduled maintenance window arrives to ensure the asset's continued operation without compromising overall asset system operational vulnerability.

5.3 Eco-Efficiency, Waste Reduction, and Sustainable Manufacturing

The environmental impacts of conventional industrial maintenance are substantial. With preventive maintenance scheduled out of the blue, components that still have a lot of useful life are often being scrapped, resulting in material waste and scope 3 supply chain emissions (Bokrantz et al., 2020). On the other hand, if the assets are out of tune, energy consumption is soared. The internal friction of mechanical components such as gears, pumps and bearings, which deteriorates with time, leads to the need for a higher electrical current to operate the system at normal speed (Jasiulewicz-Kaczmarek et al., 2024).

Figure 6: AIoT-enabled resilience-based maintenance workflow for mitigating energy losses caused by asset degradation



Source: Author's Compilation

AIoT-based resilience maintenance (RBM) to reduce progressive loss of energy while maintaining resilience is depicted in Figure 5. Mechanical friction rises with the age of industrial equipment because of wear, and the amount of electrical current the machine needs to run rises from that friction. An extra current draw is a wasted use of energy and is frequently a precursor to operational inefficiency and/or loss of product quality. The proposed AIoT-based RBM model continuously collects the condition of the equipment through sensors and intelligent analysis and then detects the abnormal energy usage in time. The system suggests specific maintenance measures like micro-lubrication, shaft alignment, etc., based on the detected degradation before severe failures. These are treatments that will return the equipment to normal operating conditions and will reduce the frictional losses and mechanical inefficiency.

After maintenance, the machine has normalised power consumption, reduced energy waste, and normalised production quality (no scrap waste). The figure is meant to illustrate that predictive and resilience-based maintenance is not merely about preventing failure; it's also about enhancing energy efficiency, uptime and manufacturing sustainability. By linking real-time power metrics with prognostic models, the RBM framework flags minor mechanical misalignments and lubrication starvations based on energy efficiency anomalies (Carnero, 2025). Furthermore, preventing catastrophic failures reduces material scrap. Sudden machine tool failure mid-cycle can ruin expensive, tightly toleranced workpieces, sending large volumes of raw materials to the scrap heap. AI-enabled maintenance supports circular economy objectives by allowing components to be used safely throughout their entire lifecycle and identifying precisely when sub-assemblies can be remanufactured or re-baselined rather than entirely replaced (Shin & Jun, 2025).

Even though there is growing interest in sustainability's role in Industry 5.0, current studies place a focus on environmental measures and overlook other aspects of sustainability—economic and social. Notably, there are few studies that evaluate maintenance techniques based on principles of Triple Bottom Line, Environmental, Social and Governance indicators or Sustainable Development Goals. These limitations highlight the need for research on maintenance to employ multidimensional sustainability frameworks, which would allow researchers to assess the efficiency of operations, environmental impact and creation of added value.

6. Implementation Challenges: Socio-Technical and Algorithmic Barriers

Despite the clear benefits of Maintenance 5.0, deploying enterprise-grade AI systems across heterogeneous manufacturing fleets presents complex algorithmic, technical, and human-centric challenges.

6.1 Explainable AI (XAI) and the Trust Gap

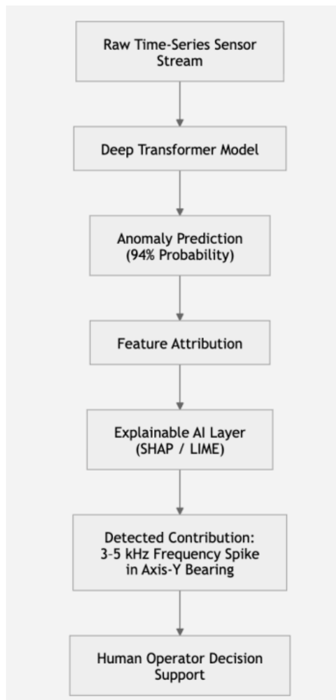
A primary barrier to deploying advanced deep learning models on the shop floor is the "black-box" problem. Standard deep neural networks, such as deep LSTMs or multi-layered CNNs, output critical degradation and failure forecasts without providing a human-interpretable rationale for their decisions (Gao & Wang, 2025). In high-stakes manufacturing environments, human operators are understandably hesitant to halt an active production line based solely on an opaque algorithmic output (Bashir & Khan, 2024).

To alleviate this mistrust, Industry 5.0 focuses on incorporating Explainable AI (XAI) frameworks (Ahangar, 2024). Technicians use post-hoc explainability methods, like SHAP (SHapley Additive exPlanations) or Integrated Gradients, to trace back black-box decisions to physical phenomena:

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i$$

where ϕ_i represents the local attribution value (SHAP value) of a specific sensor feature i To the final anomaly score or RUL prediction.

Figure 6: Explainable AI (XAI) framework for interpreting deep learning-based anomaly detection in predictive maintenance.



Source: Author's Compilation

Figure 5 shows the use of Explainable Artificial Intelligence (XAI) for a deep learning based predictive maintenance system. The raw multivariate time-series sensor data from industrial equipment are first passed through a deep learning model, based on a Transformer, to estimate the probability of equipment anomalies. Despite high predictive performance, the output of the model (e.g. 94% probability of anomaly) does not give much information about the factors that affect the model prediction, so that the result is hard for maintenance engineers to validate or believe. To overcome this drawback, the anomaly prediction is further passed to an XAI layer that uses feature attribution techniques like Shapley Additive Explanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME). These methods allow quantifying the influence of the individual input features on the model's prediction, thus identifying the mechanism behind the detected anomaly.

The XAI module gives a high anomaly score in the illustrated example mostly due to the spike in the frequency of 3–5 kHz in the Axis-Y bearing, which can be interpreted as a straightforward engineering explanation for the prediction. These interpretable insights allow maintenance staff to confirm AI-driven decisions, pinpoint the specific physical cause of degradation, and take precise maintenance measures with greater confidence. By making these predictive maintenance systems explainable, operators can better trust the information provided by the AI system, ensuring regulatory compliance, and collaborating with the AI system effectively in the context of Industry 5.0

manufacturing. Anomaly flag (Villagómez-Galindo et al., 2026) becomes visible as which sensor readings, such as a specific frequency spike between 3–5 kHz in the Y-axis bearing, were responsible for this anomaly. This transparency enables operators to make informed decisions, reducing scepticism and building an operational environment based on shared human-machine intelligence. Even though Explainable Artificial Intelligence offered a solution to the black-box problem of deep learning, the existing applications are based on the post-hoc explanation models, such as SHAP and LIME. Current works provide very limited information about the way explainability affects trust, the quality of maintenance decisions, and long-term corporate learning in industrial settings.

6.2 Algorithmic Data Scarcity and Severe Class Imbalance

In practical industrial operations, high-fidelity data representing actual machine failures is exceptionally rare. Modern industrial machinery is engineered to prevent breakdown, meaning that 99.9% of historical IIoT telemetry captures normal operating conditions (Bousdekis et al., 2021). Training supervised deep learning networks on such heavily imbalanced datasets leads to high false-negative rates, where the model fails to recognise rare, novel degradation pathways. To circumvent this challenge, modern PdM architectures deploy unsupervised and physics-informed modelling strategies (Upasane & Patel, 2024). Deep Autoencoders and Generative Adversarial Networks (GANs) are trained exclusively on healthy baseline data. During inference, the reconstruction error between the input vector () and the model's reconstructed output () serves as a robust anomaly metric: xx

$$\text{Reconstruction Error} = \|x - \hat{x}\|^2$$

If the reconstruction error exceeds a statistically determined threshold, it signals an emerging anomaly - whether it has been seen in the past or not. Furthermore, Physics-Informed Neural Networks (PINNs) incorporate the known thermodynamic and structural fatigue laws into the loss function of the neural network, which guarantees that the RUL predictions from the trained model are physically reasonable even with a sparse empirical dataset.

6.3 Human-in-the-Loop Integration and Cognitive Ergonomics

One of the key aspects of Industry 5.0 is the conscious replacement of the human worker in automation rather than the complete automation that was prevalent in the past (Nahavandi, 2024; Romero & Stahre, 2024). When it comes to maintenance, Maintenance 5.0 treats the technician as a partner instead of a subject of algorithmic orders (Kaasinen et al., 2020).

Figure 7: Human-in-the-loop cognitive maintenance framework for continuous learning in AI-enabled predictive maintenance

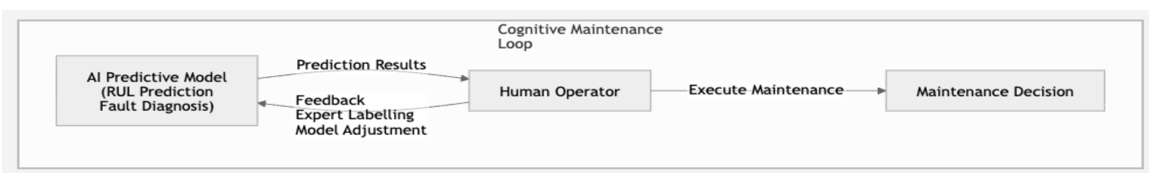


Figure 7 shows the proposed human-in-the-loop (HITL) cognitive framework for maintenance, which marries artificial intelligence with human knowledge and expertise to allow for continuous learning and resilient decision making. In comparison with traditional predictive maintenance systems that are fully automatic and are known as black-box system, the proposed one puts the maintenance engineer at the heart of the predictive maintenance process. The AI predictive model is initially designed to process the historical and real-time operational data and provide maintenance recommendations for industrial assets through Remaining Useful Life (RUL) prediction and fault diagnosis. These predictions are delivered to the human operator who utilizes his contextual understanding, operational limitations and engineering experience to either approve or alter the maintenance suggestions.

Feedback from the operator - such as corrected fault labels, maintenance results, and expert annotations - is then integrated into the learning process. This feedback helps adapt the model, enhance forecast accuracy, decrease over-allocations and enables the AI system to adjust itself to evolving equipment conditions over time. Therefore, the predictive maintenance is not just about automated inference but is an ongoing process of interaction between machine intelligence and human expertise. The cognitive maintenance loop is inspired by the principles of Industry 5.0, which emphasize the importance of putting human-centred artificial intelligence, transparency, and collaborative decision-making into practice along with automation. The framework leverages the expertise to refine the models, which helps to improve system reliability, operator trust, and long-term maintenance effectiveness, and helps to support resilient, sustainable manufacturing operations. Advanced cognitive interfaces (Mourtzis & Angelopoulos, 2024) enable the human-in-the-loop dynamics to be operationalised. If a fault is detected, the AI system sends the operator information about the fault in context using Augmented Reality (AR) headsets or mobile dashboards, thereby reducing operator cognitive fatigue (Alhaag et al., 2022). The machine's operator then checks the physical status of the machine and reenters this physical status into the system. This expert input is subsequently fed back to enhance the underlying machine-learning models, thereby continuing to improve the accuracy of the algorithm and to keep preserving a number of tacit aspects of a human-provided knowledge graph in the automated maintenance architecture (van Oudenhoven et al., 2022). Increasingly, maintenance research in the human sphere is acknowledging that maintenance workers are also part of intelligent production systems and are no longer mere recipients of automated recommendations. However, there is currently not as much empirical research that measures cognitive workload, adaptation of the workforce, skill transformation, and organizational acceptance of AI driven maintenance technologies. These human factors will increasingly play a key role in an Industry 5.0 that empowers humans and ushers in an era of collaborative intelligence rather than technological automation.

7. Synthesis, Strategic Recommendations, and Future Horizons

To successfully transition from isolated predictive maintenance pilots to an enterprise-wide Maintenance 5.0 strategy, industrial organisations must adopt a phased, cross-functional implementation roadmap.

Figure 8: Roadmap for the evolution of AI-enabled predictive maintenance towards Industry 5.0

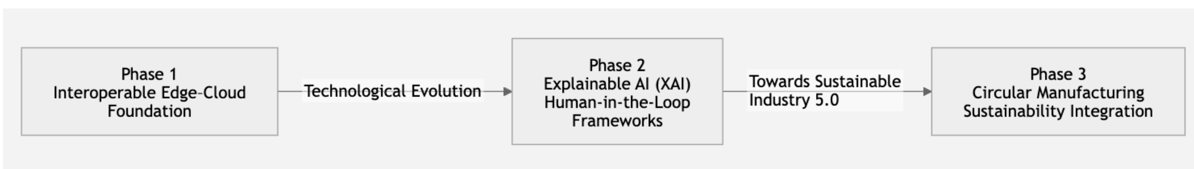


Figure 8 is a conceptual road map that shows the AI-powered predictive maintenance's evolution and the direction it will take to reach the vision for Industry 5.0. The roadmap is divided into three successive research phases, each one corresponding to a key milestone in the evolution of intelligent, resilient and sustainable maintenance systems. Phase 1 lays the groundwork for an interoperable edge–cloud foundation: Industrial Internet of Things (IIoT) devices, edge computing and cloud platforms work together to facilitate real-time data capture, low latency data analysis and scalable model deployment. This stage offers the digital backbone for the smart maintenance use cases. On top of this infrastructure, Phase 2 will introduce Explainable Artificial Intelligence (XAI) and Human-in-the-Loop (HITL) frameworks, which will enhance the transparency, interpretability, and trustworthiness of AI-driven maintenance decisions. Additive Manufacturing systems can be refined and become more adaptive, reliable, and human-centred decision making based by incorporating expert feedback for model refinement. Lastly, Phase 3 takes predictive maintenance beyond operational efficiency, addressing circular manufacturing and sustainability goals. Maintenance strategies are intended to lower energy usage, emissions of greenhouse gases, asset life cycles, and enable resource-efficient manufacturing. This is a phase that connects predictive maintenance with the wider objectives of Industry 5.0, such as sustainability, industrial resilience and responsible innovation. The roadmap highlights that predictive maintenance is not just about the future of ever more precise AI models, but also about the interoperability of digital infrastructure, explainable intelligence, collaborative human efforts, and sustainable maintenance practices.

i. **Establish an Interoperable Edge-Cloud Foundation:** Organizations need to focus on deploying open-architecture IIoT networks compatible with common communication protocols such as OPC-UA and MQTT. This foundation allows for the seamless and efficient movement of data between a variety of shop-floor resources and cloud-based systems, without any vendor lock-in (Cheng & Zhang, 2024).

ii. **Integrate Explainability and Co-Design Workflows:** AI products should have layers of explainability built in, and AI products should be chosen and configured for explainability. By engaging floor operators at the outset of the algorithm dashboard design process, metrics are broken down into intuitive, actionable and less cognitively draining measures (Bashir & Khan, 2024).

iii. **Integrate Sustainability into the Maintenance Equation:** Maintenance schedules should be dynamically co-optimised with Energy Management Systems (EMS). By treating elevated power draw and material waste as asset health indicators alongside traditional vibration metrics, factories can directly align maintenance workflows with corporate carbon-reduction mandates (Carnero, 2025; Jasiulewicz-Kaczmarek et al., 2024).

In the future, the advancement of Generative AI and Multimodal Large Language Models (LLMs) tailored for industrial use will be the next major focus in Maintenance 5.0 (Xu & Lu, 2024). Human technicians will be able to use natural language to ask the cognitive agents for more complex histories of assets, for Digital Twin simulations in real time, and for maintenance manuals, making advanced predictive insights more accessible on the shop floor.

8. Conclusion

Industry 5.0 is a paradigm shift in industrial maintenance, shifting from automation to intelligent, resilient, sustainable and human-centric manufacturing systems. This review highlights that while the use of Artificial Intelligence (AI), Digital Twins, Edge–Cloud computing, Explainable Artificial Intelligence (XAI), and AIoT has brought significant benefits to the field of predictive maintenance, current research is fragmented with few studies explicitly linking these technologies into a cohesive framework that integrates operational resilience, sustainability, and human collaboration (Breque et al., 2021; Ghobakhloo & Fathi, 2024; Jasiulewicz-Kaczmarek et al., 2024; Nahavandi, 2024). This research aimed to fill this gap, by proposing the Resilience Based Maintenance (RBM) framework, which is a multidimensional socio-technical framework that would be an extension of the Maintenance 4.0 and Maintenance 5.0 paradigm. RBM is conceptually redefining maintenance as a strategic organizational capability by combining AI intelligence, Digital Twin technologies, operational resilience, sustainability optimisation, continuous learning and human-centric collaboration. By integrating the diverse views on intelligent maintenance technology, organization, and sustainability that were previously disjointed, the framework contributes to the theoretical understanding of intelligent maintenance by providing a coherent conceptual model, which is aligned with the objectives of Industry 5.0 (Breque et al., 2021; Bukowski, 2025; Ghobakhloo & Fathi, 2024).

The review also emphasizes the role of AI in preventive maintenance, not just for maximizing equipment reliability and predictive decision-making, but for ensuring manufacturing resilience, resource optimization, and sustainable production. In this regard, the adoption of integrated maintenance architectures that integrate intelligent technologies with explainable decision support, resilient operational planning and human expertise is a requirement to achieve the full benefits of Industry 5.0. The proposed RBM framework is therefore a useful conceptual reference to researchers, practitioners and policy makers who aim to design intelligent maintenance systems which incorporate technological innovation with organisational flexibility and responsible manufacturing (Carnero, 2025; Mourtzis & Angelopoulos, 2024; Romero & Stahre, 2024). Although this knowledge has been provided, this study has a conceptual dimension and does not have an empirical validation in different industrial settings. The proposed RBM framework should be further investigated in an empirical study to explore the interactions between the different dimensions and how new technologies, like multimodal AI, federated learning and advanced Digital Twins, can be integrated into resilient maintenance ecosystems. Moreover, the standardization of resilience, sustainability and human-centric maintenance performance metrics will be crucial to enable broad-scale industrial adoption and improve the practical utility of RBM (Xu & Lu, 2024; Zhang & Dynamic, 2025). The purpose of this review is to define Resilience-Based Maintenance as a conceptual framework that enables the development of next-generation maintenance systems and to highlight that the future of industrial maintenance will be the fusion of predictive intelligence, resilience engineering, sustainability and human-centred collaboration. The study summarizes the development of knowledge and reflects the body of knowledge's evolution from Industry 4.0 to Industry 5.0, which offers a solid theoretical framework for further developments and application in intelligent manufacturing.

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