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REVIEW

A Literature Review on Enhancing Predictive Maintenance in Smart Manufacturing Industries: Fostering Human-Technology Collaboration and Overcoming Data Scarcity Limitations with Advanced AI Models

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Abstract

Predictive maintenance (PdM) leverages artificial intelligence (AI) and data analytics to forecast equipment failures in smart manufacturing, enabling timely interventions that minimize downtime and operational costs. This literature review examines recent advancements in PdM, focusing on three interrelated dimensions: (1) data challenges and limitations, (2) role of advanced AI models, and (3) actionable decision-making with human-AI collaboration. Unlike previous studies that often address these aspects in isolation, our review synthesizes them to provide a comprehensive understanding of current capabilities and limitations. We highlight how emerging AI technologies such as generative models, large language models (LLMs), and hybrid frameworks enhance predictive accuracy, enable synthetic data generation, and support interpretable, human-centered maintenance strategies. By evaluating both strengths and gaps across existing approaches, this work offers a comprehensive foundation for developing more scalable, reliable, and adaptable PdM systems aligned with Industry 5.0 principles through the integrative data–model–human (DMH) framework.

Keywords Predictive maintenance (PDM) · Smart manufacturing industries · Artificial intelligence models · Data analytics · Human collaborations · Remaining useful life (RUL)

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1 Introduction

The manufacturing and industrial landscape has experienced a significant transformation in recent years, primarily due to the Fourth Industrial Revolution, commonly known as Industry 4.0. This revolution utilizes advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and sophisticated data analytics to create highly integrated and adaptable production environments [1, 2]. These "Smart Production Environments" facilitate seamless communication between interconnected machines and systems, optimizing processes to enhance efficiency, productivity, and flexibility [3, 4].

Within this context, predictive maintenance (PdM) has gained significant attention in research and industry as a transformative approach to equipment maintenance. Unlike traditional reactive or scheduled maintenance, PdM leverages real-time monitoring and advanced AI-driven analytics to predict potential failures before they occur [5]. By analyzing historical data and utilizing IoT-enabled sensors, PdM enables timely interventions, minimizing unplanned downtime, reducing maintenance costs, and extending equipment lifespan [6–8].

Despite these advantages, real-world implementations reveal persistent challenges. To illustrate, consider three hypothetical industrial scenarios inspired by recurring issues highlighted in the literature [9–11]. In one case, noisy sensor data could produce a 15% false-positive rate, leading to losses of around $500,000. In another, reliance on outdated AI models might result in 20% of robotic arm faults going undetected, causing unplanned downtime and damages of about $1.2 million. Finally, inadequate system integration could trigger a furnace shutdown, wasting nearly 30 tons of steel. These illustrative examples underscore how vulnerabilities at any stage of the PdM pipeline can propagate into substantial financial, operational, and safety risks.

Figure 1 illustrates this lifecycle as a sequential process in which three stages are tightly interconnected: reliable sensor data form the foundation, since poor quality inevitably leads to "garbage in, garbage out"; predictive accuracy depends on the appropriate selection and timely update of AI models, as even high-quality data cannot compensate for outdated approaches; and model outputs require expert oversight, because without contextual interpretation, accurate predictions may still fail to deliver operational value. A breakdown at any stage compromises the system, leading to financial losses, equipment damage, or safety risks. Thus, PdM must be viewed not as a purely computational task but as a systems-level challenge that requires alignment of data integrity, model robustness, and human judgment [12].

Advances in machine learning (ML) and deep learning (DL) have fueled enthusiasm for PdM. However, many models that perform well in controlled settings struggle to generalize to diverse industrial contexts due to limited validation with real-world data [13, 14]. This disconnect reduces predictive reliability and limits deployment at scale. At the same time, the transition toward Industry 5.0 shifts the emphasis from full automation to human–AI collaboration, embedding human intuition, creativity, and ethical oversight into smart manufacturing. These trends reinforce the need for PdM frameworks that balance advanced automation with human-centric decision-making [15–19].

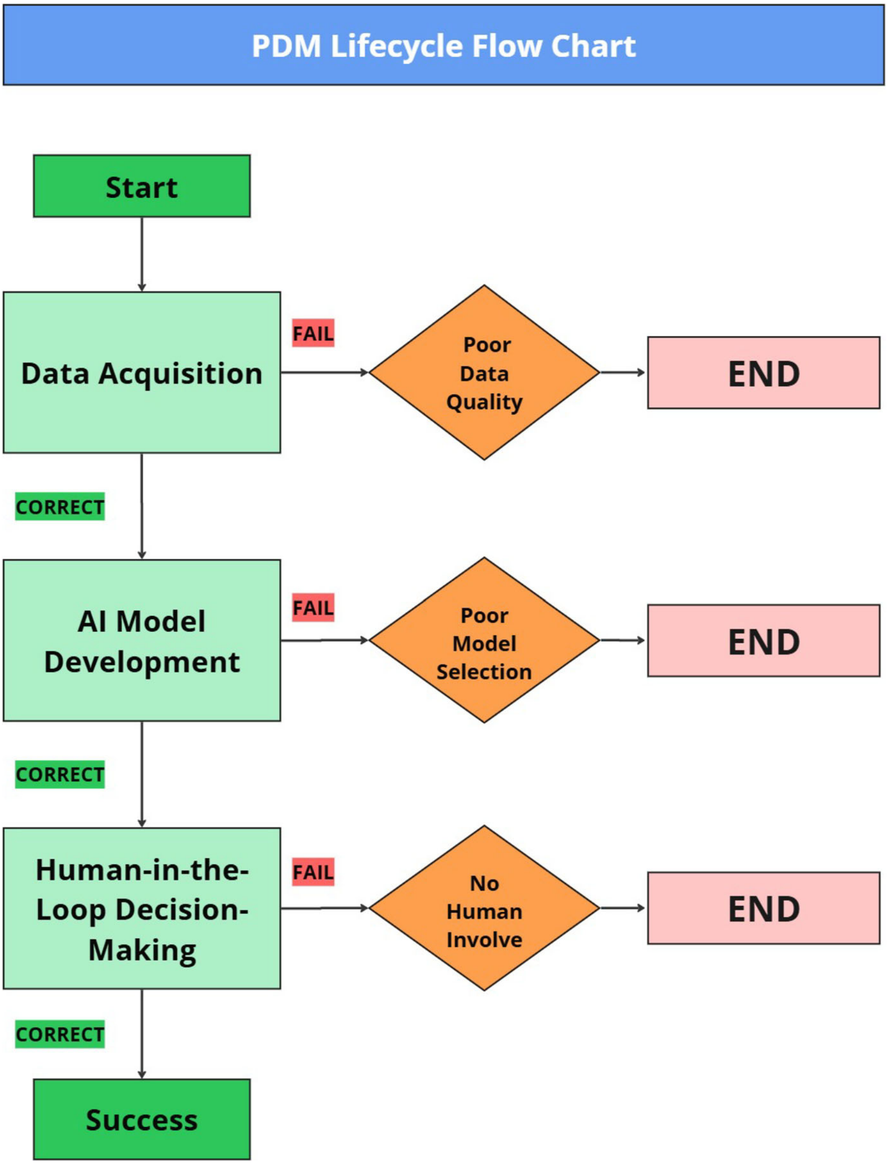

Fig. 1 Overview of the PdM lifecycle in smart manufacturing, illustrating the sequential dependencies between data acquisition, AI modeling, and human decision-making. Failure at any stage terminates the process, while integration of all three dimensions ensures successful outcomes

To contextualize our discussion, we next clarify several key terms. **Smart Industries** denote digitally enhanced production systems that leverage IoT, AI, and cyber-physical technologies for data-driven operations. Within this domain, **Industry 4.0** emphasizes automation, interconnected devices, and advanced analytics to optimize efficiency and reduce costs. In contrast, **Industry 5.0** extends these principles by focusing on human–AI collaboration, sustainability, and ethical considerations. **Human-Centric AI** refers to systems designed to support rather than replace human decision-making, prioritizing transparency, adaptability, and user control. Finally, a **Digital Twin** is a real-time virtual replica of a physical asset or system, continuously updated with sensor data to enable simulation, prediction, and performance optimization.

PdM is already applied across diverse industries, including manufacturing, aviation, energy, healthcare, and transportation, where early failure detection reduces downtime, lowers costs, and enhances safety, underscoring its combined economic and societal importance [20–27]. Still, its full potential remains constrained by recurring challenges.

To investigate this evolving landscape, our study focuses on three dimensions that critically shape PdM effectiveness:

1. **Data challenges and limitations in PDM,** where scarcity or noisy signals undermine predictive accuracy, motivating techniques such as deep generative modeling
2. **Role of advanced AI models in PDM,** including deep learning and large language models (LLMs), which offer new capabilities for analyzing high-dimensional sensor data and automating feature extraction
3. **Actionable decision-making in smart manufacturing environment,** where PdM effectiveness depends on integrating collaborative AI, IoT, big data analytics, and digital twins to ensure sustainability and human-centric oversight

Unlike previous studies [5–7, 13–18], which treat data scarcity, AI model limitations, and human-AI collaboration as separate challenges, this work is the first to explicitly emphasize their interdependencies and cascading effects on PdM effectiveness. While existing research offers valuable technical solutions to individual problems, the absence of an integrated perspective constrains their broader applicability in smart manufacturing contexts.

To overcome this gap, we critically review previous approaches and synthesize them into a unified perspective. Building upon these insights, we introduce the *data–model–human (DMH) framework* as proposed in Section 7. This high-level, integrative framework aligns scalable data practices, intelligent modeling, and human-centric deployment into a single coherent structure. Conceptually and from a research standpoint, the DMH framework reframes PdM as an interdependent system rather than a collection of isolated technical tasks, thereby demonstrating the potential for methodological rigor, theoretical significance, and practical *success of PdM* in smart manufacturing industries.

The remainder of this paper is structured as follows: Section 2 compares the contributions of this review with recent state-of-the-art advancements in PdM within smart manufacturing, highlighting its distinctive scope and approach. Section 3 details the systematic methodology used to select and analyze relevant literature. Sections 4 and 5 evaluate review and technical papers, synthesizing their strengths and limitations. Section 6 outlines the advantages and novelty of this work in addressing the interconnected aspects of data, AI models, and human collaboration. Section 7 presents a consolidated discussion of insights, proposing a strategic framework for practical implementation. Lastly, Section 8 concludes the paper and outlines directions for future research.

2 Related Work

PdM has attracted substantial research attention for its ability to reduce downtime, extend asset lifespan, and optimize operational efficiency. However, as highlighted in Section 1, the majority of studies focus on isolated segments of the PdM pipeline, neglecting the critical interplay between data quality, advanced modeling, and human involvement. This fragmented view undermines the overall robustness of PdM systems and restricts their practical applicability in real-world industrial settings.

The principle that "better data yields better results" underscores the importance of high-quality, timely information in PdM. Still, poor sensor fidelity, incomplete coverage, and limited real-time processing remain barriers to scalability [28]. Studies on digital twins and generative modeling have attempted to mitigate data scarcity; however, many approaches implicitly assume uniform sensor deployment, a condition that rarely holds in practice [5]. Similarly, anomaly detection and fault prediction methods often address data limitations as isolated technical issues, which reduces their overall reliability and applicability in real-world scenarios [29, 30].

A recent study [31] highlights key challenges in implementing generative AI (GAI) for predictive maintenance in aviation, including the limited availability of run-to-failure data due to frequent preventive maintenance, difficulties in integrating diverse models, and issues with knowledge sharing. Another study [32] discusses the challenges of obtaining high-quality annotations from weak labels and balancing annotation efforts with accuracy. It focuses on weakly supervised learning (WSL) methods that address incomplete, imprecise, and erroneous labels, while identifying open research areas in predictive maintenance.

Similarly, another study [33] demonstrates that the integration of IoT and Industry 4.0 in the nuclear industry has advanced data-driven methodologies, but challenges persist in accurately predicting maintenance needs due to the complexity of nuclear systems and the need for extensive domain knowledge and precise data. While these studies provide valuable strategies for synthetic data generation and knowledge-data hybridization, they primarily focus on the data dimension and offer limited consideration of integrating advanced AI with human expertise in line with Industry 5.0 principles.

Research on decision-making frameworks in smart manufacturing highlights the critical role of IoT-driven environments, software tools, and continuous sensor monitoring in optimizing processes. Several studies [1, 3, 17, 34] employ a variety of decision-making methodologies, such as burst analysis, systematic review, co-occurrence analysis, and cluster analysis, to identify emerging trends and challenges in PdM and Industry 4.0 technologies across multiple sectors.

While these studies offer valuable insights into PdM solutions, technological impacts, and industry trends, they share a common limitation in their reliance on existing literature, which may not fully capture cutting-edge advancements or real-world implementation challenges. For instance, some studies focus on developing decision support maps for PdM solutions, while others examine the broader implications of Industry 4.0. However, they often fail to address sector-specific challenges. Additionally, these frameworks typically overlook the essential role of human expertise, particularly in Industry 5.0 contexts, where collaboration, ethical oversight, and the integration of human judgment are crucial elements of the decision-making process [12, 18].

The role of advanced AI models in enhancing predictive accuracy and streamlining maintenance strategies has been widely studied, with evidence indicating their potential to improve predictive performance and optimize maintenance practices [6, 25, 35]. However, much of this research remains theoretical or experimental, with limited validation in resource-constrained industrial environments. More recent advancements, such as long-context language models and agent-based systems, are beginning to address this gap by facilitating intelligent data extraction, improving prediction performance, and generating actionable insights.

A systematic study [36] highlights how automated techniques like AutoML and meta-learning can reduce reliance on expert knowledge and alleviate the computational burden of manual model tuning. However, it also identifies critical gaps, including the limited application of unsupervised approaches, poor adaptability to dynamic operating conditions, and insufficient strategies for industrial deployment. These shortcomings underscore that the partial adoption of advanced AI models continues to hinder the scalability and effectiveness of PdM, slowing progress toward

Table 1 Topics comparison between our paper and the state of the art

Reference #	Data challenges and limitations	Role of advanced AI model	Actionable decision-making in smart industries
[1]			✓
[3]			✓
[5]	✓		
[6]		✓	
[13]	✓	✓	✓
[15]		✓	✓
[16]	✓		
[17]			✓
[25]		✓	
[28]	✓		
[31]	✓		
[32]	✓		
[33]	✓		
[34]			✓
[35]		✓	
[36]		✓	
Our Paper	✓	✓	✓

Industry 5.0, where adaptive, transparent, and human-centered AI is essential for trustworthy maintenance decision-making.

Among the few integrative studies, research [13] explicitly addresses data scarcity, AI modeling, and human collaboration within a unified framework. However, despite its comprehensive approach, the study offers limited guidance on scaling across heterogeneous infrastructures and fails to fully incorporate human decision-making into PdM workflows. Similarly, another study [15] combines human-centric strategies with AI modeling, but it predates recent advancements in hybrid deep learning and does not fully capture the emphasis of Industry 5.0 on collaborative, explainable, and human-AI ecosystems.

Table 1 summarizes how existing reviews address the three key dimensions of PdM: data challenges, advanced AI models, and actionable decision-making. While individual aspects have been well-studied, comprehensive syntheses remain rare. Our work builds upon this research by providing a systematic review that explicitly examines the interdependencies and cascading effects among these dimensions, offering a more holistic foundation for the success of PdM in smart manufacturing.

3 Papers Retrieval

This section outlines the methodology used to systematically identify, filter, and analyze relevant literature on our key topics in PdM. A structured search was conducted in the Scopus database on February 9, 2025, focusing on capturing essential themes in predictive maintenance. Three targeted queries were formulated to achieve this, as illustrated in Fig. 2.

The search strategy included three queries, each targeting a specific sub-theme of PdM:

- Query 1: ("Predictive Maintenance" AND ("Data Challenges" OR "Data Scarcity"))
- Query 2: ("Predictive Maintenance" AND "AI models")
- Query 3: ("Predictive Maintenance" AND "Smart Manufacturing")

All searches were conducted in titles, abstracts, and keywords for peer-reviewed articles published between 2018 and 2025, in English.

Each query was structured to maintain focus on PdM while addressing different perspectives. The first query targeted challenges related to data scarcity and limitations. The second query focused on the role of advanced AI models in PdM. The third query ensured coverage of PdM applications within smart manufacturing, a broad domain encompassing Industry 4.0 and 5.0.

The search retrieved a total of **417 studies** across the three queries:

- **26 studies** from the first query (Data Challenges and Scarcity)
- **74 studies** from the second query (AI Models in PdM)
- **317 studies** from the third query (Smart Manufacturing and PdM)

To ensure relevance and quality, we applied the following criteria during the literature screening process. We included studies explicitly focused on PdM in industrial or smart manufacturing contexts, incorporating AI, machine learning, deep learning,

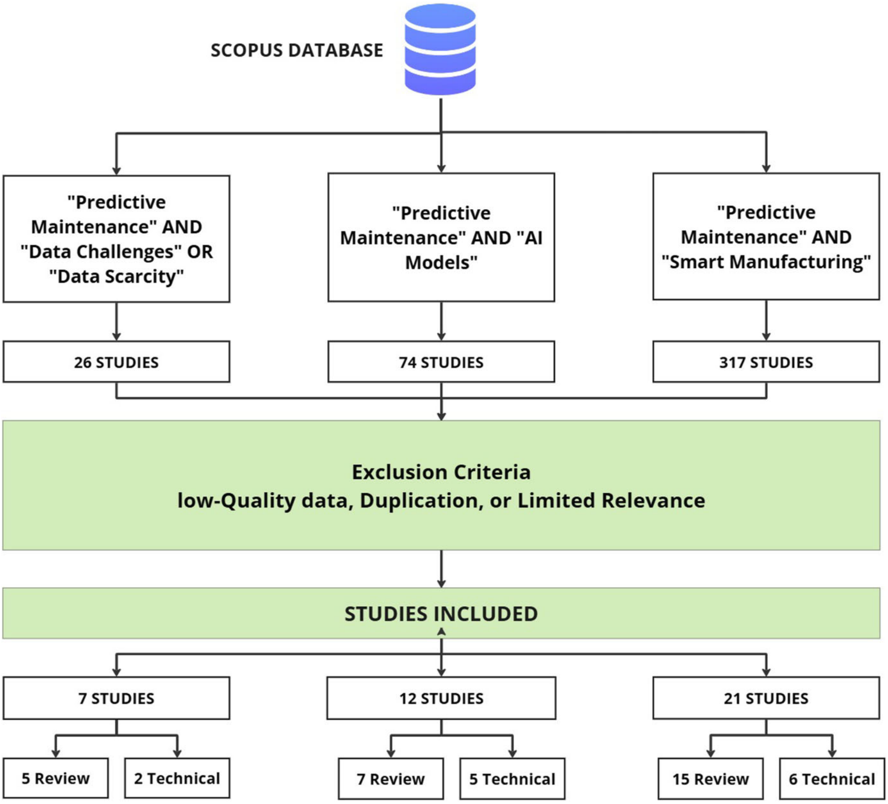

Fig. 2 Flowchart detailing the study selection process for predictive maintenance research, drawn from the Scopus database and spanning three key topics. It highlights the initial search categories, the criteria used for excluding studies, and the final set of included studies, which are classified into review and technical papers

or IoT technologies. Only peer-reviewed journal or conference articles published in English between 2018 and 2025 were considered, provided they presented empirical findings, technical frameworks, or comprehensive reviews. We excluded editorials, opinion pieces, conceptual articles without technical contributions, duplicates or papers based on the same dataset without additional insights, studies unrelated to PdM, and articles with outdated or thematically irrelevant content.

After applying these filters, we finalized **40 studies** for inclusion:

- **7 studies** from the first query (5 reviews, 2 technical)
- **12 studies** from the second query (7 reviews, 5 technical)
- **21 studies** from the third query (15 reviews, 6 technical)

The selected papers were categorized into review studies (providing theoretical insights and literature analysis) and technical studies (proposing solutions or implementations). These categories are further explored in Sections 4 and 5, where we discuss their contributions to addressing PdM challenges and advancements.

To ensure consistency in classification, we independently reviewed each article. Papers that primarily synthesized existing literature or provided conceptual discussions were classified as review papers. Studies presenting new models, experiments, simulations, or system implementations were labeled as technical papers. Disagreements between reviewers were resolved through discussion. This dual-review process aimed to enhance coding reliability and minimize subjectivity in the classification process.

4 Reviews

This section summarizes the reviewed papers, highlighting their main topics and assessing how each aligns with the three dimensions introduced in Section 1: data challenges in PdM, the role of advanced AI models, and human collaboration in decision-making. The titles of the reviewed studies are listed in Table 2.

Table 3 highlights the specific subtopics covered in the paper. These checkmarks indicate documents that discuss the corresponding subtopic in detail and are highly relevant to our study. While these papers provide valuable insights, many lack an in-depth analysis of real-world AI implementation in industrial settings. By examining existing methodologies, our work identifies their limitations and proposes solutions to these challenges, particularly in light of recent breakthroughs in AI implementation. Recent implementations that address similar challenges are discussed in detail in Section 5.

4.1 Data Challenges and Limitations in PdM

Data scarcity remains one of the most pervasive challenges in PdM, particularly within smart manufacturing environments. As illustrated in Tables 2 and 3, numerous studies acknowledge this barrier, yet few offer scalable, holistic strategies for resolving it. Most works address isolated facets such as data labeling, synthetic generation, or fault prediction, while overlooking broader integration issues, including data heterogeneity, domain adaptability, and real-world deployment constraints.

The work proposed in [37] introduces semi-supervised regression to address limited labeled data in lithium-ion battery health estimation. Although effective for its specific application, the study does not consider generalization to other domains or dynamic industrial settings. Likewise, [38] employs Recurrent Neural Networks (RNNs) for bearing prognostics using spectral data but assumes structured, clean inputs, an assumption misaligned with noisy, real-world sensor environments.

The study [39] leverages ensemble deep learning to improve remaining useful life (RUL) prediction for aircraft engines. While this method shows promising accuracy, it lacks evaluation under data corruption, missing values, or asynchronous sampling conditions common in actual factories. Another study [41] applies Elman neural networks to track degradation trends, but its simplicity and limited model flexibility undermine its effectiveness across complex PdM tasks.

Table 2 Review papers

Reference	Title
[37]	Tackling Limited Labeled Field Data Challenges for State of Health Estimation of Lithium-Ion Batteries by Advanced Semi-Supervised Regression
[38]	Bearing Failure Prognostics Using Recurrent Neural Networks: A Spectral Data Based Architecture
[39]	A Health state-related ensemble deep learning method for aircraft engine remaining useful life prediction
[40]	Utilizing TGAN and ConSinGAN for Improved Tool Wear Prediction: A Comparative Study with ED-LSTM, GRU, and CNN Models
[41]	An Elman Artificial Neural Network for Remaining Useful Life Prediction
[42]	Evaluating eXplainable artificial intelligence tools for hard disk drive predictive maintenance
[43]	Optimization of Design Parameters in LSTM Model for Predictive Maintenance
[44]	An Integrated Active Learning Framework for the Deployment of Machine Learning Models for Defect Detection in Manufacturing Environments
[45]	A Systematic Review of Artificial Intelligence Public Datasets for Railway Applications
[46]	A Surrogate Approach to Explainable AI for Predictive Maintenance: Techniques and Applications
[47]	Explainable AI in Industry: Practical Challenges and Lessons Learned
[48]	A review of artificial intelligence applications in manufacturing operations
[12]	Decision-making in predictive maintenance: Literature review and research agenda for industry 4.0
[49]	Challenges and Opportunities in the Implementation of AI in Manufacturing: A Bibliometric Analysis
[50]	AI-Enhanced Predictive Maintenance in Intelligent Systems for Industries
[51]	Artificial Intelligence in Industry 4.0: A Review of Integration Challenges for Industrial Systems
[52]	The Role of Predictive Maintenance Optimization Techniques in Enhancing Industrial Productivity
[53]	Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing
[54]	Applications and Challenges of Machine Learning Techniques for Smart Manufacturing in Industry 4.0
[55]	Artificial Intelligence in Predictive Maintenance: A Systematic Literature Review on Review Papers
[56]	Predictive Maintenance and Production Analysis in Smart Manufacturing
[57]	Industry 4.0 Technologies for the Sustainable Management of Maintenance Resources
[58]	A Semantic Model in the Context of Maintenance: A Predictive Maintenance Case Study
[59]	Industry 4.0 Technologies for Smart Manufacturing: A Systematic Review of Machine Learning Methods for Predictive Maintenance
[60]	Data Acquisition Using IoT Sensors for Smart Manufacturing Domain
[35]	Machine Learning and IoT-Based Solutions in Industrial Applications for Smart Manufacturing: A Critical Review
[61]	Deep Learning in Smart Manufacturing: Advancements, Applications, and Challenges

Table 3 Compliance of each review paper to the three subtopics from Section 1

Reference #	Data challenges and limitations	Role of advanced AI model	Actionable decision-making in smart industries
37	✓	✓	
38	✓		
39	✓		
40	✓	✓	
41	✓		
42		✓	
43		✓	
44	✓	✓	
45		✓	
46		✓	
47		✓	
48		✓	
12			✓
49			✓
50			✓
51		✓	✓
52			✓
53	✓	✓	✓
54		✓	✓
55			✓
56		✓	✓
57			✓
58			✓
59			✓
60	✓		✓
35		✓	✓
61		✓	✓

More advanced methods, such as those discussed in [40], investigate the use of generative adversarial networks (GANs), including tabular GANs (TGAN) and conditional single-image GANs (ConSinGAN), to synthetically augment tool wear datasets. While these approaches show promise, further work is needed to validate the fidelity and cross-domain transferability of the generated data to ensure their practical value for PdM reliability.

Other studies address the challenge from a system-level perspective. For example, the work by [44] proposes an active learning framework that incorporates human feedback to reduce labeling efforts. While this approach connects data acquisition with human collaboration, it falls short in addressing critical issues such as noisy labels and imbalanced failure distributions. Similarly, [53] presents an end-to-end data analytics pipeline for PdM; however, it lacks sufficient technical detail on how the proposed system handles inconsistent or incomplete sensor data, which are common challenges in real-world applications.

IoT-driven data acquisition is reviewed in [60], where issues such as sensor heterogeneity and integration bottlenecks are highlighted. While this work provides valuable insights, scalable methods for fusing multi-source data streams and standardizing inputs remain an open challenge, which is critical for effective PdM modeling across diverse systems.

While the reviewed studies each contribute valuable tools and insights, many address data scarcity as an isolated technical issue rather than as part of a broader system-level challenge. Only a limited number explicitly link data quality with model robustness or incorporate the human role in validating, augmenting, or correcting low-confidence predictions. In addition, real-world constraints such as cold start problems, data drift, instrumentation costs, and the specific challenges faced by small and medium-sized enterprises (SMEs) are often underexplored. To highlight the systemic nature of these limitations, we outline below the key data-related challenges commonly reported in PdM research.

- **Insufficient failure examples:** Since critical failures are rare, datasets are highly imbalanced, making it difficult for models to learn accurate failure patterns [37, 44].
- **Limited historical data:** Newly deployed equipment lacks long-term operational data, which is necessary for detecting slow-developing degradation trends [41].
- **Incomplete sensor coverage:** Many industrial systems suffer from blind spots due to incomplete sensor deployment, leading to undetected failures and poor diagnostic accuracy [40].
- **Data quality issues:** Noisy, inconsistent, or missing data introduces errors in predictive models, reducing their reliability and increasing the risk of incorrect maintenance actions [37, 53].
- **Lack of generalizability:** Many existing AI-driven PdM models are particular to individual machines or industries, reducing their adaptability to broader applications [39].

These challenges are not isolated technical flaws but interlinked systemic barriers that fall across the entire PdM pipeline from initial data acquisition to model deployment and human decision-making, as shown in Fig. 1. Recognizing and addressing them collectively is essential for developing resilient, real-world PdM systems capable of operating under uncertainty, evolving conditions, and diverse industrial constraints.

Section 5 explores advanced approaches such as generative models and federated learning, which create diverse synthetic datasets, preserve privacy, and enable real-time feedback. This integrative view provides a scalable alternative to traditional supervised learning, particularly in heterogeneous, resource-limited environments.

4.2 Role of Advanced AI Models in Smart Manufacturing Industries

The integration of advanced AI models, including DL, ML, and explainable AI (XAI), has significantly transformed PdM in smart manufacturing. These technologies enable the analysis of high-dimensional sensor data for early fault detection, anomaly diagnosis, and real-time decision-making, thereby improving equipment reliability and operational safety. However, despite notable progress, limitations persist across many studies highlighted in Tables 2 and 3, particularly concerning model scalability, interpretability, and practical deployment.

The study [42] examines various XAI techniques applied to PdM. While it contributes valuable insight into the interpretability of black-box models, the work reveals an unresolved tension between transparency and predictive performance. Moreover, the absence of standardized benchmarks limits cross-domain applicability. Similarly, [43] optimizes long short-term memory (LSTM) architectures by tuning hyperparameters like sequence length and learning rate, improving accuracy under static conditions. Still, the model's adaptability to dynamic industrial environments is untested, raising concerns about its robustness in practice.

To address data scarcity, [44] proposes an active learning framework that incorporates human feedback to select informative samples for labeling. This human collaboration approach reduces the dependency on fully annotated datasets but incurs significant computational costs and lacks demonstrated scalability. The systematic reviews [45, 53] provide a valuable taxonomy of public datasets used in railway PdM. However, many of the datasets are static, inconsistently labeled, and unsuitable for real-time learning, which limits their utility in real-world applications.

Study [46] examines explainability challenges in PdM through the use of surrogate models, which approximate complex black-box algorithms with simpler representations. While these approaches can enhance transparency, they may also introduce additional error or instability, particularly in high-stakes industrial environments. To address this trade-off, combining surrogates with robust XAI techniques, such as feature importance or counterfactual analysis, has been suggested as a way to balance interpretability and reliability. Likewise, [47] discusses organizational barriers to industrial AI adoption, including resistance to change, high deployment costs, and the lack of structured frameworks. Although these works raise important concerns, they provide limited actionable strategies, underscoring the continued need for practical integration approaches in real-world settings [54, 56].

Finally, study [48] outlines emerging trends such as digital twins and IoT-enhanced analytics, offering a forward-looking perspective on AI in manufacturing. However, the study remains largely conceptual and does not present empirical evidence or deployment outcomes, limiting its practical value.

While existing studies advance AI-driven PdM [35, 61], many overlook real-world challenges such as interpretability, scalability, and integration into legacy systems. This review synthesizes recent advancements that address these limitations through hybrid approaches that balance performance with transparency and human-centered design.

4.3 Human-AI Collaboration and Decision-making

The evolution from Industry 4.0 to Industry 5.0 reflects a paradigmatic shift in smart manufacturing from fully automated systems to collaborative environments that prioritize human expertise, ethical oversight, and adaptive decision-making. While Industry

4.0 focused on automation, IoT integration, and efficiency, Industry 5.0 introduces a human-centric vision, emphasizing resilience, personalization, and transparency in AI systems.

Several studies explore these transitions and their implications for PdM. For example, the study [12] highlights the need for decision-making frameworks that integrate automated AI outputs with expert human judgment. Over-reliance on AI-driven predictions, without sufficient human oversight, may undermine trust and adoption. Similarly, [49] calls for cross-sector collaboration and standardized ethical AI frameworks to overcome fragmented implementation across industrial domains.

Studies such as [50, 51, 53] address integration challenges, including interoperability between AI and legacy systems, latency in real-time decision-making, and the need for scalable, lightweight AI models. Reinforcement learning and edge computing are frequently proposed to improve real-time adaptability, but these solutions often assume uniform data quality and infrastructure, limiting their applicability in diverse settings.

A case study in [58] presents a semantic model for PdM, demonstrating how knowledge-based AI systems enhance predictive accuracy. The study notes implementation challenges related to ontology-based AI, including the requirement for extensive domain expertise, reinforcing the importance of human oversight in AI training.

The work [52] discusses PdM optimization techniques, identifying a lack of adaptive maintenance scheduling. The study supports reinforcement learning-based models that can dynamically adjust maintenance strategies based on real-time operational conditions, complementing human expertise in maintenance planning.

Efforts to align AI transparency with practical deployment are seen in [54, 55], which advocate for explainable, hybrid models and benchmark standards to guide industrial adoption. Meanwhile, [56, 57] examine the intersection of AI with enterprise resource planning (ERP) systems and sustainable energy consumption, respectively, proposing middleware and efficient model architectures to support responsible deployment [35, 60].

Table 4 presents a comparative overview of Industry 4.0 and Industry 5.0, highlighting their primary focus, key characteristics, enabling technologies, and implications for PdM. While Industry 4.0 emphasizes automation, predictive analytics, and interconnected machinery [59, 60], Industry 5.0 builds upon this foundation by prioritizing human involvement, ethical AI, and resilience [49]. In this human-centric paradigm, AI augments human expertise rather than replacing it, enabling collaborative decision-making through technologies such as cobots, XR interfaces, cognitive systems, hybrid AI, digital twins, and XAI [54–58, 61].

These solutions support real-time diagnostics, expert system recommendations, adaptive maintenance strategies, and personalized production, enhancing reliability, operational safety, and transparency in industrial environments. However, practical deployment still faces challenges, including scalability, interoperability with legacy systems, latency in real-time decision-making, and the need for domain-specific expertise to train and maintain ontology-based models. Overall, Industry 5.0 reshapes PdM practices by combining ethical, transparent AI with human-centered decision-making to achieve resilient, adaptive, and intelligent manufacturing systems.

Table 4 Key characteristics of Industry 4.0 and Industry 5.0

Industry	Primary Focus	Key characteristics	Key technologies
Industry 4.0	Machine-centric innovation, automation, operational efficiency, cost reduction, real-time optimization	Automation: AI-driven systems operate autonomously to minimize human intervention and maximize throughput [12, 51]	AI models, robotics, PLCs (programmable logic controller)
		Connectivity: IoT enables seamless machine-to-machine communication and smart factory integration [35, 60]	IoT, cloud systems, fifth-generation (5G) wireless technology
		Cyber-physical systems (CPS): integration of computational and physical processes for real-time monitoring and control [62]	CPS, ML-assisted smart production process (ML-SP2), intrusion detection system (ML-IDS), edge computing
		Digital Twin: real-time virtual replicas of physical systems used for optimization and PdM [63, 64]	Simulation, sensor fusion, virtual twins
		Predictive Maintenance: data-driven fault prediction to reduce downtime and increase operational reliability [55, 56]	AI models for prediction RUL, time-series models, forecasting tools
		Efficiency optimization: minimizing material waste and energy through automation and data analytics [54, 59]	Big data analytics, smart sensors
Industry 5.0	Human-centricity, resilience, personalization, sustainable intelligence, ethical decision-making, human-AI synergy, resource optimization	Human-AI collaboration: AI augments human expertise for safer, creative, and adaptive operations [49, 57]	Collaborative AI, XR interfaces, cognitive systems
		Personalization: custom production to suit individual consumer preferences without compromising efficiency [61]	Adaptive manufacturing, mass customization, AI recommendation engines
		Collaborative robotics: cobot systems that safely work alongside humans, enhancing safety and productivity [11, 65]	Cobot platforms, safety-aware AI, HRI interfaces (human-robot interaction)

Table 4 continued

Industry	Primary Focus	Key characteristics	Key technologies
		Sustainability: environmentally conscious production through energy optimization and waste reduction [57]	Green AI, IoT sensors, circular manufacturing tools
		Ethical and transparent AI: decision-making aligned with fairness, accountability, and explainability principles [42]	XAI, governance frameworks, ethics-by-design
		Enhanced predictive maintenance: combines AI insights with human validation for proactive and safer interventions [55, 56, 63, 64]	Hybrid AI, digital twins, human-in-the-loop systems, scheduled maintenance
		Transparency and accountability: ensures traceable and explainable AI decisions to build trust in automation [46]	SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), Trustworthy AI, interpretable ML

5 Technical Paper Analysis

This section explores recent AI-driven approaches that address PdM challenges, as discussed in earlier Sections 2 and 4. The technical solutions listed in Table 5 tackle issues such as noisy sensor data, imbalanced datasets, and limited domain-specific data, enhancing PdM system scalability and efficiency. Advancements in ML, DL, and digital twins align with Industry 5.0 principles by fostering human-AI collaboration and enabling more resilient, personalized, and transparent predictive maintenance strategies (Table 6).

5.1 Addressing Data Challenges and Limitations in Smart Manufacturing

Data-related challenges remain critical barriers to effective PdM implementation in smart manufacturing, often undermining the performance of advanced AI models. Recent progress in data augmentation and synthetic data generation offers promising solutions to address these limitations.

Recent research has increasingly targeted the critical barriers of data scarcity, imbalance, and poor data quality in PdM. Study [67] proposes a framework that integrates GANs with temporal modeling to generate synthetic failure data, thereby mitigating the scarcity and imbalance caused by the rarity of breakdown events. By combining GANs

Table 5 Technical papers

Reference	Title
[62]	Exploring the Potential Network Vulnerabilities in the Smart Manufacturing Process of Industry 5.0 via the Use of Machine Learning Methods
[63]	Digital Twin-Enabled Smart Manufacturing: Challenges and Future Directions
[64]	Digital Twin based Smart Manufacturing; From Design to Simulation and Optimization Schema
[66]	Synthetic Vibration Data Generation and Fault Classification in CNC Machines Using Transformer GANs and ConvLSTM Networks
[67]	Strategies for overcoming data scarcity, imbalance, and feature selection challenges in machine learning models for predictive maintenance
[68]	AI model factory: scaling AI for industry 4.0 applications
[69]	Methods of Decision-Making Using Artificial Intelligence for Predictive Maintenance
[70]	Deep Learning for Generating Synthetic Traffic Data
[71]	Towards big industrial data mining through explainable automated machine learning
[72]	Overview of AI-Models and Tools in Embedded IIoT Applications
[73]	Predictive Maintenance for Industrial Equipments Using ML & DL
[74]	Application of IoT and Artificial Intelligence in Smart Manufacturing Towards Industry 4.0
[75]	A Deep Learning Model for Smart Manufacturing Using Convolutional LSTM Neural Network Autoencoders
[76]	A predictive model for the maintenance of industrial machinery in the context of industry 4.0

Table 6 Comparison of AI and human-centric approaches in PdM

Reference #	Data challenges and limitations	Role of advanced AI model	Actionable decision-making in smart industries
62		✓	✓
63			✓
64			✓
66	✓	✓	
67	✓	✓	✓
68		✓	✓
69		✓	✓
70	✓	✓	
71		✓	
72		✓	
73		✓	✓
74		✓	✓
75		✓	✓
76			✓

with LSTM-based feature extraction and introducing structured failure horizons, the study improves dataset representativeness and enhances the capture of sequential degradation patterns. Reported results show notable gains in ANN models, achieving up to 89% accuracy, demonstrating the effectiveness of GAN-augmented data pipelines under challenging conditions.

In parallel, another study [66] addresses similar challenges in computer numerical control (CNC) machine maintenance by proposing a hybrid architecture that couples transformer-based GANs (TTS-GANs) with convolutional long short-term memory (ConvLSTM) networks. Their approach focuses on generating synthetic vibration signals to expand limited datasets and balance fault classes, while also improving robustness against noisy inputs. By producing realistic "good" and "bad" vibration patterns, the method reduces dependence on scarce fault data and supports more reliable fault detection. Collectively, these studies underscore the potential of GAN-driven synthetic data generation, reinforced by temporal deep learning architectures, as a powerful strategy for tackling the enduring challenges of scarcity, imbalance, and low-quality data in PdM.

Extending beyond PdM, study [70] introduces a Synthetic Traffic Data Generator (STDG) that combines deep learning with simulation tools to address data scarcity, privacy, and variability challenges in traffic datasets. Using Simulation of Urban Mobility (SUMO) generated trajectories, the model predicts internal vehicle parameters such as fuel rate, engine speed, and air pressure across different environments, achieving confidence levels of up to 90%. This approach reduces the dependence on costly real-world data collection and mitigates privacy concerns while ensuring adaptability to new domains. Taken together with the work [67] and [66], this study highlights the growing role of synthetic data generation, whether for industrial equipment, CNC machines, or traffic systems, as a scalable solution to the challenges of scarcity, imbalance, and poor-quality data in AI-driven applications.

5.2 Evaluating the Role of Advanced AI Models in PdM

The integration of advanced AI techniques has significantly enhanced the predictive capabilities of PdM in smart manufacturing. As summarized in Table 5, several studies [68–73] explore the role of ML, DL, and emerging models in tackling challenges such as failure prediction, RUL estimation, and maintenance scheduling. Collectively, these approaches improve data analysis, strengthen real-time decision-making, and enable proactive maintenance strategies.

For example, Studies [68] and [74] introduce the concept of an AI model factory, designed to scale AI applications in Industry 4.0 through standardized workflows and automation. This framework supports large-scale PdM deployment by making AI solutions more reusable and adaptable across diverse industrial assets. Similarly, study [69] investigates AI-driven decision-making methodologies, emphasizing maintenance scheduling and fault detection to reduce downtime and optimize operational costs.

A key contribution in recent years has been the use of synthetic data generation to address data scarcity and imbalance. Studies [66, 67, 70] employ GANs, ConvLSTMs, and hybrid simulation DL approaches to create artificial datasets, ranging from industrial vibration signals to traffic parameters, that enhance model robustness, reduce reliance on limited failure data, and improve generalizability. In parallel, study [71] advances explainable AutoML for industrial data mining, enabling non-experts to configure optimal models while strengthening interpretability and trust.

Complementary studies further broaden the technical landscape. For instance, [72] provides a comprehensive overview of AI models and tools for embedded IIoT systems, demonstrating their role in enabling real-time monitoring and predictive analytics. Similarly, [73] and [75] showcase the effectiveness of deep learning architectures, such as ConvLSTM autoencoders, in enhancing PdM performance under complex industrial conditions. Collectively, these contributions underscore the growing role of advanced AI models in building scalable, interpretable, and data-efficient PdM systems aligned with the principles of Industry 4.0 and Industry 5.0.

In summary, advanced AI models have become pivotal in PdM by enabling more accurate failure prediction, optimized maintenance scheduling, and longer equipment lifespan. Deep learning and hybrid approaches deliver strong performance gains, while synthetic data generation, explainable AutoML, and embedded IIoT tools enhance robustness and scalability. Although models such as LLMs and GANs offer powerful solutions, their computational demands challenge SMEs, making strategies like transfer learning, hybrid modeling, and data augmentation essential for practical adoption. Collectively, these advancements establish AI as a cornerstone of next-generation PdM, driving smarter, more resilient, and human-centric manufacturing in line with Industry 4.0 and 5.0 [62].

5.3 Enhancing Actionable Human-AI Decision-making in Smart Manufacturing

The role of AI-driven models in PdM and smart manufacturing has been extensively studied to address challenges related to data limitations, decision-making, human collaboration, and security in Industry 5.0. The papers in Table 5 present various methodologies that leverage AI, ML, and digital twins to enhance industrial efficiency, security, and predictive capabilities.

One critical aspect of Industry 5.0 is cybersecurity within smart manufacturing networks. The study [62] investigates potential vulnerabilities in connected industrial systems, applying ML techniques to detect and mitigate cyber threats. This proactive approach strengthens the integrity of AI-driven PdM systems, making them more resilient to cyberattacks and safeguarding predictive maintenance operations.

In addition to security, digital twins have emerged as a cornerstone for advancing PdM. Research [63] and [64] demonstrate how digital twins enable real-time simulation, optimization, and predictive analytics to support more reliable decision-making. Prior studies have shown that these technologies can significantly improve failure detection rates and reduce unplanned downtime, although challenges such as data synchronization, interoperability, and computational overhead remain key barriers to large-scale deployment.

Further advancements in PdM are being driven by the integration of ML and DL techniques. One study [73] proposes a framework that combines RNNs and

CNNs, achieving significant improvements in failure prediction accuracy compared to traditional models. Another work [75] applies ConvLSTM autoencoders to time-series sensor data, enhancing anomaly detection in complex industrial environments. In addition, a paper [68] introduces the concept of an AI Model Factory, providing standardized workflows to scale AI applications in Industry 4.0, while another study [69] explores AI-driven decision-making methodologies that optimize maintenance scheduling and fault detection, ultimately reducing downtime and operational costs.

Another important development is the integration of IoT with AI for real-time data acquisition and intelligent decision-making [67]. One study [74] demonstrates how automated data collection combined with AI-driven analytics can improve production efficiency, while another [76] introduces a predictive model for industrial machinery maintenance, showing how AI-powered forecasting can optimize resource allocation and reduce maintenance costs.

Finally, in the vision of Industry 5.0, human collaboration remains central to actionable decision-making. By integrating human expertise with AI-powered tools, PdM systems ensure that AI supports rather than replaces operators. This *human-in-the-loop* approach balances automation with oversight, enabling personalized, resilient, and adaptive decisions. While AI provides real-time insights, human judgment adds context, intuition, and accountability, improving both safety and efficiency [62]. Together, this collaboration fosters a human-centered Industry 5.0, where advanced technologies augment human capabilities, leading to smarter and more effective predictive maintenance.

6 Benefits

This section synthesizes the main benefits of predictive maintenance approaches as identified in the body of literature reviewed in this paper. Our analysis focuses on how AI, ML, DL, digital twins, and human–AI collaboration contribute to enhancing PdM in smart manufacturing. The benefits are grouped thematically to highlight their impact on failure prediction, data scarcity mitigation, real-time optimization, human-in-the-loop decision-making, and production efficiency. In addition, where appropriate, we complement the findings of the reviewed works with insights from external studies, which provide broader perspectives or emerging directions not yet widely covered in the PdM literature.

Enhancing Predictive Maintenance with AI and ML The integration of AI, ML, and DL has substantially advanced PdM in smart manufacturing by improving failure prediction, anomaly detection, and decision-making. Studies [67, 73, 75] demonstrate that AI-driven models enhance fault detection accuracy, reduce downtime, and increase system reliability. Hybrid frameworks that combine CNNs, RNNs, and transformers further boost prediction precision, while AI-based autoencoders improve anomaly detection in complex time-series data.

While the works in our reviewed corpus primarily demonstrate the effectiveness of hybrid AI models (e.g., CNN–RNN–transformer combinations) and autoencoders for enhancing accuracy and anomaly detection, broader research trends point toward the use of generative AI and large language models (LLMs) for extracting knowledge from unstructured maintenance logs. These approaches, though not part of our main review set, have shown promise in improving procedure recognition and supporting more efficient decision-making [77–81]. Collectively, both the reviewed and emerging studies highlight how AI-driven methods are transforming PdM into a more accurate, adaptive, and knowledge-based process, aligning with Industry 4.0 and paving the way for Industry 5.0.

Addressing Data Scarcity with Synthetic Data and Generative Models Data scarcity remains a critical challenge in PdM, particularly when historical failure data are limited. Recent studies demonstrate the effectiveness of generative models in expanding datasets and improving robustness, including TTS-GANs with ConvLSTMs [66], GANs with LSTM-based temporal modeling and failure horizons [67], and deep learning integrated with traffic simulation [70]. Beyond our selection, additional works further explore augmentation strategies with GANs and specialized architectures, reinforcing the potential of synthetic data generation in tackling imbalance and enhancing PdM robustness [82, 83].

Complementary studies beyond our reviewed corpus also reinforce these findings. For example, conditional GANs have been shown to achieve measurable improvements in RUL prediction [84], while other works report the use of GANs to generate balanced, noise-free datasets in finance [85]. Additional approaches explore adaptable synthetic data methods tailored for high-dimensional industrial datasets [86]. Together, these contributions—though outside our selected set of references—highlight the broader value of synthetic data generation in overcoming scarcity, imbalance, and noise, thereby strengthening the reliability and scalability of PdM systems.

Digital Twin Technology for Real-Time Simulation and Optimization Digital twin technology enables real-time simulation, optimization, and predictive analytics in PdM by creating virtual replicas of physical assets [63, 64]. These systems improve failure detection, reduce maintenance costs, and increase equipment uptime by allowing continuous monitoring and scenario-based analysis. Despite these benefits, challenges remain in ensuring data synchronization, interoperability, and managing computational overhead. Recent complementary works emphasize enhancing real-time data processing and leveraging edge computing to improve scalability and responsiveness, making digital twins more practical for large-scale industrial deployment [87–89].

Human-AI Collaboration in Decision-making and Industry 5.0 Industry 5.0 places human expertise at the center of AI-driven decision-making, ensuring that automation complements rather than replaces operators. Studies [62, 65] show that incorporating human judgment enhances interpretability, reduces false positives, and strengthens trust in PdM systems. Reinforcement learning approaches further enable continuous adaptation to evolving industrial conditions, keeping systems resilient and efficient. Together, these complementary works highlight the value of human-in-the-loop frameworks, where AI provides real-time insights while humans add context, intuition, and accountability, fostering safer and more adaptive predictive maintenance [11, 18].

Improving Production Speed and Efficiency with AI AI integration in PdM and smart manufacturing significantly improves production speed and operational efficiency. Automated AI-based quality control systems reduce defect rates, while edge AI frameworks support real-time analytics to minimize production delays. In addition, AI-driven predictive analytics enhance supply chain resilience by improving demand forecasting and resource allocation, thereby reducing bottlenecks and ensuring smoother operations [74, 90]; complementary studies further support this trend by highlighting applications in explainable automated machine learning and multi-sensor fusion approaches [71, 91].

7 Discussion

The literature review highlights a persistent gap: most studies treat data scarcity, AI modeling, and human–AI collaboration as isolated domains, offering valuable but fragmented solutions.

This fragmented approach overlooks their interdependencies and limits the scalability of PdM in real-world settings. Industrial evidence underscores the risks of such separation: noisy or insufficient data inflates false positives, outdated AI models miss critical failures, and poor human–AI integration undermines trust and operational continuity. These examples demonstrate that PdM requires a system-level approach rather than isolated technical fixes.

7.1 The DMH Framework: A Unified Framework

To address this gap, we propose the DMH framework, a structured three-phase methodology that organizes existing fragmented insights into a coherent and actionable process. While not a new algorithm, its novelty lies in providing a high-level systems perspective that explicitly links data quality, intelligent modeling, and human-centric deployment. This framing elevates PdM from a computational task to an interdependent socio-technical lifecycle.

Phase 1: Data Foundation and Augmentation

This first phase establishes the backbone of PdM by auditing the available data landscape and addressing gaps in coverage or quality. In data-rich contexts, historical datasets can be directly leveraged to train predictive models. In data-sparse scenarios, augmentation methods such as GANs, CGANS, or TimeGANs simulate rare but critical failure events, enriching the dataset for robust model training. In cases of data absence, physics-based simulations, expert annotation, or federated learning provide a practical means of constructing initial datasets. The outcome of this phase is a validated and resilient dataset, assessed through expert review, which ensures that subsequent modeling efforts are grounded on reliable inputs.

Phase 2: Intelligent and Explainable Modeling

Once reliable data is secured, the second phase focuses on developing models that balance predictive accuracy with interpretability and operational feasibility. Model selection is guided not only by performance metrics but also by compatibility with industrial hardware and resource constraints. Effective PdM requires navigating trade-offs between accuracy, scalability, cost, and transparency, which may involve hybrid AI–physics models, digital twins, or edge AI solutions. Equally important is explainability: tools such as SHAP, LIME, or surrogate models must be embedded into inference pipelines so that predictions remain interpretable, maintaining operator trust and enabling human experts to validate results.

Phase 3: Human-Centric Deployment and Governance

The third phase ensures that AI-generated insights translate into actionable maintenance strategies within real industrial environments. Through human-in-the-loop integration, technicians review, contextualize, and refine AI predictions, ensuring they are aligned with operational realities. Workflow integration is achieved via interfaces such as digital twins or semantic agents, which deliver interpretable insights and facilitate collaboration between humans and machines. Finally, governance mechanisms, including ethical oversight, accountability frameworks, and continuous feedback loops, safeguard responsible deployment, ensuring that PdM not only improves performance but also aligns with organizational and societal values (Table 7).

7.2 Impact and Contribution

The DMH Framework offers three core contributions:

1. **Integration:** It consolidates fragmented research on data, models, and human collaboration into a unified process, addressing interdependencies overlooked by prior studies.

Table 7 Challenge–solution–outcome mapping within the DMH Framework

Challenge	Solution/approach	Outcome
Data scarcity/noisy inputs	GANs, TimeGANs, federated learning, Physics-based simulation	Richer datasets and better generalization
Model fragility/wrong selection	Hybrid AI–physics models, Edge AI, digital twins	Robust, scalable, real-time models aligned with operational needs
Human trust gap/lack of oversight	Explainable AI (SHAP, LIME), human-in-the-loop systems, semantic agents	Transparent, trusted, and actionable decision support

2. **Practicality:** It provides a structured roadmap adaptable to industries with varying maturity levels, including those with legacy infrastructure or limited resources.
3. **Theoretical significance:** By reframing PdM as a socio-technical lifecycle, it positions reliability and adoption as outcomes of balanced data integrity, model robustness, and human oversight.

This unified framing advances PdM research beyond descriptive case analysis and toward system-level methodologies. It aligns closely with the principles of Industry 5.0, emphasizing resilience, sustainability, and human–AI synergy. By explicitly demonstrating how failures in one dimension cascade across the PdM pipeline, the DMH framework not only improves methodological clarity but also offers actionable strategies for robust, human-centric predictive maintenance in next-generation smart manufacturing. Ultimately, the effectiveness of these three stages determines the overall success of the PdM process.

8 Conclusions

This paper presents a comprehensive review of PdM in smart manufacturing, highlighting the need to move beyond fragmented approaches that treat data, modeling, and human oversight in isolation. By analyzing both review and technical papers, we show how advances such as GAN-based augmentation, LLMs for unstructured data, and hybrid models have pushed the field forward, yet challenges remain in achieving scalable, interpretable, and integrated solutions.

To address this gap, we introduce the DMH framework, a three-phase methodology that translates current insights into actionable strategies for real-world deployment. The framework emphasizes robust data readiness, intelligent and explainable modeling, and human-centric integration, ensuring that PdM systems are both technically effective and organizationally viable.

Despite its contributions, this study has limitations. As a literature-based review, the findings are constrained by the scope, quality, and domain specificity of the cited works. Many approaches remain experimental, validated only in controlled settings, and may not generalize to heterogeneous industrial environments. In addition, challenges such as computational overhead, integration in SMEs, and ethical considerations (e.g., privacy and workforce adaptation) remain insufficiently resolved.

Future research should therefore prioritize (1) lightweight, edge-compatible architectures for real-time PdM, (2) transfer learning for scalable adaptation across domains, (3) causal and self-supervised methods for deeper failure reasoning and generalization, and (4) empirical validation of PdM frameworks in diverse, real-world manufacturing ecosystems.

As industrial ecosystems evolve, PdM will be pivotal in ensuring resilience, safety, and operational excellence. Realizing this vision requires not only technical innovation but also alignment with ethical design, human collaboration, and scalable infrastructure. This review provides a strategic foundation for advancing toward intelligent, human-centric, and sustainable PdM systems.

Author Contribution F.R. wrote the manuscript D.R revised the manuscript and provided supervision and guidance

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Declarations

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