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Advancing Total Productive Maintenance in Smart Manufacturing: From Methodology to Implementation

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ABSTRACT: The rapid advancement of Industry 4.0 technologies has catalyzed the development of intelligent tools and methodologies to enhance operational efficiency, reliability, and productivity across modern industrial enterprises. Total Productive Maintenance (TPM), a foundational approach in manufacturing, traditionally improves equipment reliability, reduces downtime, and drives continuous improvement through proactive employee involvement. However, in the context of Smart Manufacturing, traditional TPM reveals significant limitations—chiefly its reliance on manual data collection, reactive maintenance, and limited real-time insight. This paper explores TPM's evolution, key innovations, and cross-industry applications while highlighting challenges in adopting Industry 4.0 technologies. It proposes a comprehensive TPM 4.0 framework integrating Lean Six Sigma's DMAIC methodology with advanced digital tools for systematic failure mode classification, risk-based maintenance prioritization, and real-time performance optimization. Leveraging IIoT-enabled condition monitoring, Digital Twin simulations, and machine learning-driven predictive analytics, the framework supports real-time anomaly detection, cognitive diagnostics, and adaptive maintenance planning—substantially improving Overall Equipment Effectiveness (OEE), cost efficiency, and system resilience. Additionally, federated learning promotes scalable, privacy-preserving AI collaboration, while blockchain enhances data security and transparency, mitigating cybersecurity risks. By merging traditional TPM with AI-driven automation and digital sustainability, TPM 4.0 establishes a foundation for self-optimizing, cyber-resilient maintenance ecosystems, accelerating the transition to autonomous manufacturing. Although conceptual, this framework offers a practical roadmap for smart manufacturing transformation, with future validation planned through case studies and pilot projects.

Keywords: Total Productive Maintenance (TPM) 4.0; DMAIC; RAMS; Predictive maintenance; Smart manufacturing

1. Introduction

In today's fast-evolving industrial landscape, effective maintenance strategies are critical for ensuring Reliability, Availability, Maintainability, and Safety (RAMS) across complex assets and infrastructure. The increasing integration of automation, digital connectivity, and data-driven decision-making has exposed the limitations of traditional maintenance approaches—ranging from reactive and preventive to predictive maintenance—in managing highly dynamic and interconnected production environments. Industries are now confronted with challenges such as unplanned downtime, inefficient resource utilization, and rising maintenance costs, necessitating the shift toward intelligent, self-optimizing maintenance frameworks. To address these challenges, organizations are embracing risk-based maintenance methodologies integrated with Industry 4.0 technologies, enabling proactive, cost-effective, and sustainable maintenance ecosystems. The convergence of Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Big Data Analytics, Digital Twin technology, cloud-edge computing, and federated learning is accelerating the transformation toward autonomous, data-driven maintenance strategies, forming the foundation of Total Productive Maintenance (TPM) 4.0. [1,2].

Total Productive Maintenance (TPM) is a holistic, organization-wide strategy designed to enhance operational excellence, asset reliability, and continuous improvement by actively engaging employees at all levels. Integrated with Total Quality Management (TQM), TPM strives for zero breakdowns, zero defects, and zero accidents, systematically eliminating inefficiencies such as downtime, equipment failures, excess inventory, and process delays. At its core, the 5S methodology fosters a structured, organized, and high-performance work environment, ensuring sustained

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productivity, efficiency, and workplace safety. The Japan Institute of Plant Maintenance (JIPM) established an eight-pillar TPM framework (Figure 1) to optimize process efficiency, asset lifecycle management, and Overall Equipment Effectiveness (OEE), empowering operators with greater equipment ownership while promoting predictive, preventive, and autonomous maintenance strategies that minimize unplanned downtime, enhance defect prevention, and optimize production workflows. Additionally, Figure 2 illustrates the Lean Six Sigma DMAIC (Define, Measure, Analyze, Improve, and Control) framework, offering a structured, data-driven methodology for achieving sustained process optimization, defect prevention, and operational excellence [3,4].

As industries advance toward Smart Manufacturing and Industry 4.0, TPM is evolving into an intelligent, data-driven system by integrating Industrial Internet of Things (IIoT), AI-powered analytics, Digital Twins, Edge AI, and Cloud Computing to facilitate real-time anomaly detection, cognitive diagnostics, and adaptive maintenance strategies, supporting self-optimizing and cyber-resilient maintenance ecosystems. As illustrated in Figure 3, Industry 4.0 is driven by a suite of advanced technologies that enable smart, interconnected, and data-driven operations. These key technologies include [1,2,5,6]:

- Internet of Things (IoT): Facilitates seamless connectivity and communication between physical devices and digital systems.
- Smart Sensors: Enable real-time data collection, monitoring, and analysis for proactive decision-making.
- Advanced Robotics: Automate complex tasks with high precision, flexibility, and efficiency.
- Artificial Intelligence (AI): Enhances decision-making through intelligent data processing, pattern recognition, and learning.
- Cyber-physical systems (CPS): These link physical assets with digital control systems to enable real-time feedback and interaction.
- Augmented Reality (AR) and Virtual Reality (VR): Provide immersive tools for design, maintenance, training, and remote collaboration.
- Cloud Computing: Supports scalable, remote access to data storage, applications, and computing resources.
- Machine Learning (ML): Enables systems to improve performance based on data insights automatically.
- Digital Twin Technology: Creates virtual models of physical assets to support monitoring, simulation, and optimization.
- Additive Manufacturing (3D Printing): Allows for rapid prototyping and customized, resource-efficient production.
- Big Data Analytics: Transforms large volumes of data into actionable insights for strategic and operational improvements.
- Cybersecurity: Protects networks, data, and systems from digital threats, ensuring resilience and trust.
- Blockchain: Ensures secure, transparent, and decentralized data management and transaction integrity.
- Location Detection Technologies: Enable real-time tracking and positioning through GPS, RFID, and related systems.

By bridging traditional maintenance principles with AI-driven automation and predictive analytics, TPM 4.0 sets the stage for the next generation of intelligent, autonomous, and highly efficient industrial operations. This transformation is embodied in TPM 4.0, a next-generation approach that integrates real-time monitoring, advanced analytics, and intelligent automation to create self-learning, adaptive maintenance frameworks. Unlike traditional TPM, which relies on manual inspections and scheduled interventions, TPM 4.0 enhances maintenance efficiency through AI-driven automation, prescriptive analytics, and Digital Twin simulations, significantly improving failure prediction accuracy, asset longevity, and downtime reduction. By leveraging Cyber-Physical Systems (CPS), machine learning, and IIoT-enabled condition monitoring, TPM 4.0 empowers industries to maximize OEE, enhance operational resilience, and achieve cost-efficient, sustainable maintenance in increasingly complex and hyperconnected production environments [5,6].

This paper introduces TPM 4.0, an advanced Industry 4.0-driven maintenance framework that enhances Total Productive Maintenance (TPM) through the integration of IIoT, Big Data Analytics, Digital Twins, Edge AI, and Cloud Computing. It enables autonomous, predictive, and prescriptive maintenance, optimizing asset reliability, lifecycle performance, and operational efficiency while reducing downtime.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive literature review that analyses existing TPM methodologies and their integration with digital technologies. Section 3 identifies the research gap, highlighting key challenges and opportunities in the implementation of TPM 4.0. Section 4 details the proposed methodology, outlining the architecture and operational mechanisms of the digital TPM 4.0 framework. Section 5 discusses results and key findings, evaluating the impact of TPM 4.0 on OEE, cost efficiency, and operational resilience. Section 6 concludes the study and explores future research directions, including advancements in 5G-powered real-time monitoring, blockchain-secured predictive maintenance, autonomous robotic maintenance, and edge AI-powered diagnostics.

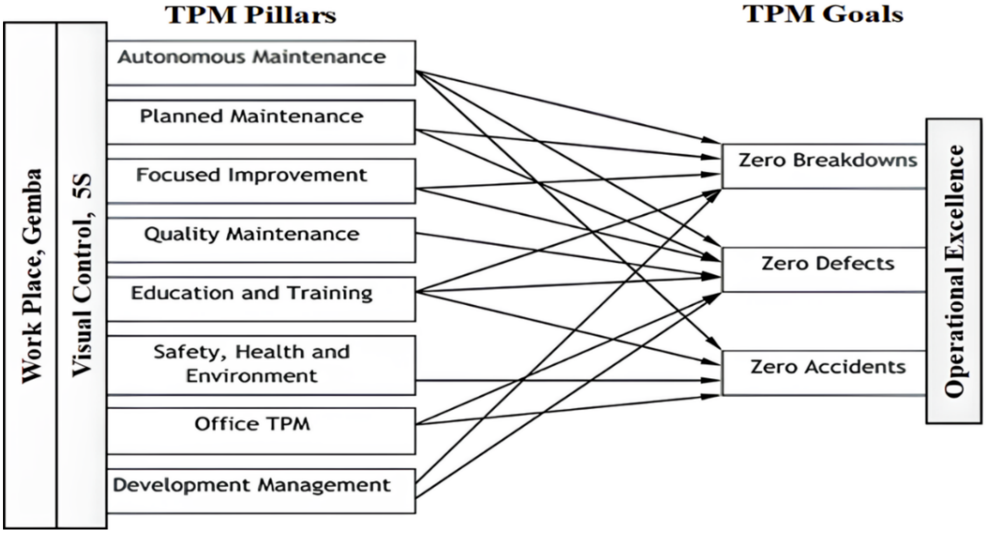

Figure 1. TPM pillars and goals.

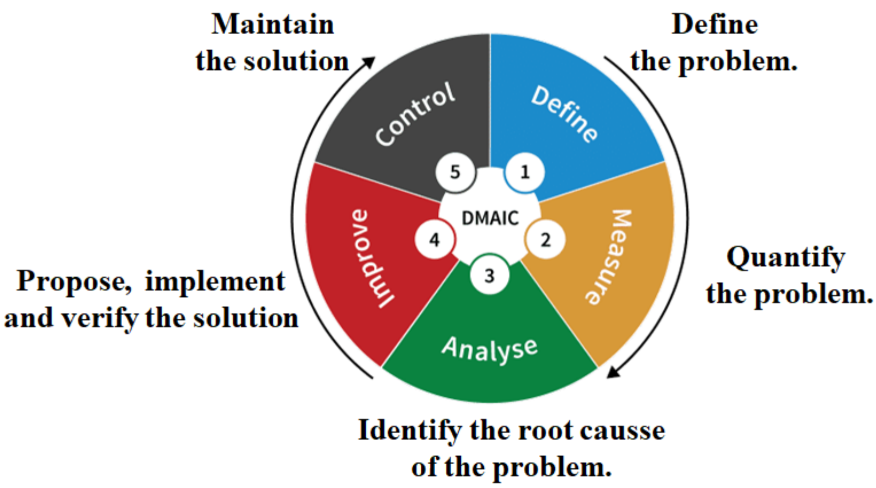

Figure 2. Lean Six Sigma DMAIC cycle.

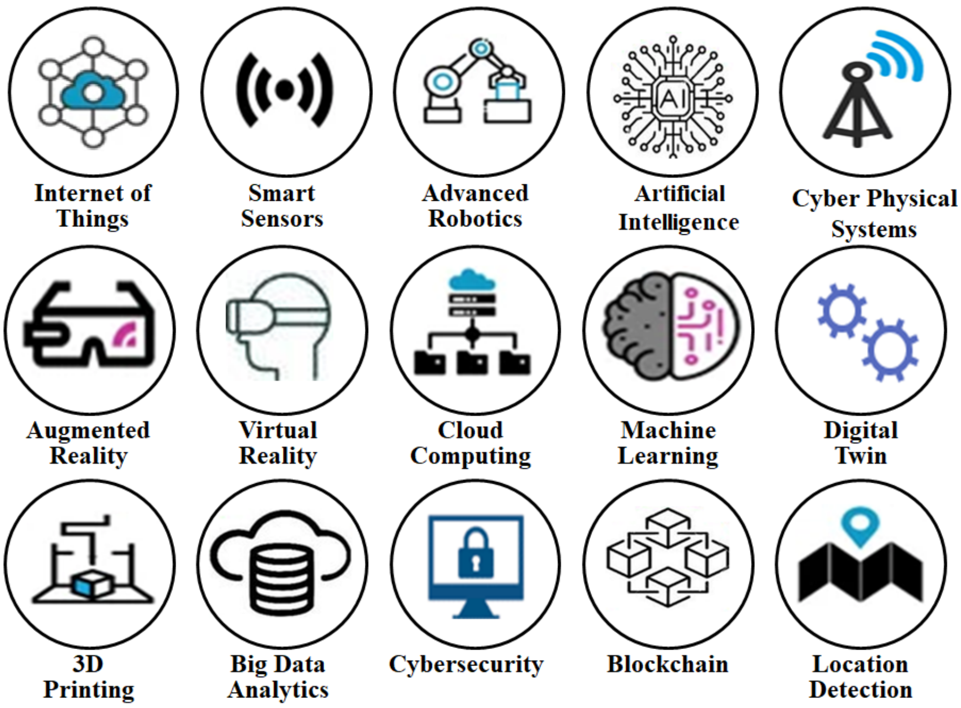

Figure 3. Main Technologies of Industry 4.0.

2. Literature Review

Continuous improvement in production enhances efficiency, quality, and cost reduction. Lean manufacturing optimizes operations by eliminating waste and increasing value. This study reviews Total Productive Maintenance (TPM), a proactive strategy for minimizing breakdowns, defects, and delays. TPM improves equipment reliability, mitigates unplanned downtime, and reduces maintenance-related losses. Its global adoption has enhanced product quality, reduced costs, and increased Overall Equipment Effectiveness (OEE). Table 1 provides a structured overview of recent studies on TPM and its integration with Lean, Six Sigma (LSS), and DMAIC methodologies across various industries. It highlights key aspects such as authors, contributions, industry applications, and main objectives, reflecting the ongoing evolution of maintenance strategies toward greater efficiency, reliability, and performance. The findings emphasize a shift toward data-driven, proactive, and continuous improvement-based maintenance approaches, aligning with modern industrial advancements. The Reference column lists the primary author(s) and publication year, providing context for each study. The Contribution column outlines the specific framework or methodology introduced, ranging from traditional TPM models to Lean, Six Sigma, and DMAIC-based maintenance approaches. The Application column identifies the industries where these frameworks were implemented, spanning manufacturing, petrochemicals, aviation, and crude oil processing, among others. The Main Objectives column defines the study's focus, such as enhancing OEE, reducing downtime, increasing machine availability, and improving reliability.

A key insight from the table is that while TPM remains a fundamental maintenance strategy, its impact is significantly enhanced when combined with Lean, Six Sigma, and DMAIC methodologies. For example, Trubetskaya (2024) [7] and Gomaa (2023) [2] developed DMAIC-based frameworks to optimize maintenance effectiveness, while Shannon (2023) [8] and West (2023) [9] integrated LSS principles to improve maintenance processes. Similarly, Al Farihi (2023) [10] and Imanov (2021) [11] introduced Lean Maintenance frameworks, focusing on waste reduction, shorter maintenance response times, and overall process efficiency. The studies span multiple industries, demonstrating the flexibility and broad applicability of TPM. While manufacturing remains a dominant focus—including pharmaceutical production, metal industries, and machining processes—TPM frameworks have also been applied in asset-heavy industries such as petrochemicals, crude oil processing, aviation, and oil services. This widespread adoption underscores TPM's role in driving maintenance excellence across diverse operational environments.

Common objectives across these studies include improving OEE, which is a central focus in research, such as Jurewicz (2024) [12], Ardi et al. (2023) [13], and Singha (2022) [14]. Reducing downtime is another critical goal, particularly in industries where unplanned failures cause significant financial losses, as seen in Trubetskaya (2024) [7], Macalinao (2024) [15], and Imanov (2021) [11]. Additionally, several studies emphasize enhancing machine reliability and availability, especially in sectors like aviation, oil services, and pharmaceutical manufacturing, where system failures can have severe operational and financial consequences.

Nardo et al. (2021) [2] present a systematic literature review on the evolution of maintenance within the Industry 4.0 paradigm, focusing on key publications from 2015 to early 2020. The study examines how digital technologies, such as smartphones and tablets, have reshaped maintenance practices in industrial environments. It categorizes contemporary maintenance management strategies and emerging trends, with an emphasis on the integration of Industry 4.0 technologies in manufacturing and maintenance operations. The paper also defines "Maintenance 4.0", outlining its principal benefits, challenges, and future directions for advancing smarter, more efficient maintenance management.

In conclusion, this literature review highlights the evolution of TPM strategies and their growing alignment with Industry 4.0 principles. The integration of Lean, Six Sigma, and data-driven maintenance frameworks is enabling more predictive, intelligent, and highly efficient maintenance practices. As industries continue to embrace digital transformation, organizations that adopt these advanced TPM methodologies will be better positioned to achieve higher operational efficiency, improved asset reliability, and long-term sustainability.

Total Productive Maintenance (TPM) plays a pivotal role in improving equipment reliability, minimizing downtime, and enhancing operational efficiency [16–18]. Its integration with Lean Management principles, Industry 4.0 technologies, and advanced statistical methods has expanded its application across various industries, including manufacturing, logistics, small and medium enterprises (SMEs), and non-production sectors such as healthcare, services, and laboratories (Okoro 2024 [19], Rathi et al. 2024 [20], Samadhiya and Agrawal 2024a [21], Tortorella et al. 2024 [22]). As shown in Table 2, numerous studies demonstrate the effectiveness of TPM across sectors.

Biswas (2024) [23] and Jurewicz et al. (2024) [12] demonstrated significant improvements in Overall Equipment Effectiveness (OEE) and reduced downtime in the steel manufacturing and automotive industries, respectively. Innovations such as integrating TPM with IoT and big data analytics (Khosroniya et al., 2024 [24]) and using the

Analytic Hierarchy Process (AHP) in cement plants (Amrina and Firda, 2024 [25]) have further enhanced TPM's adaptability. Additionally, Samadhiya and Agrawal (2024b) [26] highlighted the role of TPM in driving sustainability and accelerating the adoption of Industry 4.0.

Sector-specific studies underscore TPM's versatility. Harsanto and Yunani (2023) [27] applied TPM to power distribution systems, achieving cost reductions and enhanced efficiency, while Shannon et al. (2023) [8] reported improved OEE and reduced maintenance costs in Active Pharmaceutical Ingredient (API) plants.

Vaz et al. (2023) [28] evaluated the impact of TPM in Portuguese industries through a survey of 472 companies, emphasizing the significance of planned maintenance and training. The study found that TPM practices most significantly improved productivity, though the effect on costs was less pronounced. Similarly, Pinto et al. (2020) [29] highlighted substantial gains in machine reliability and efficiency in the machining industry.

Other notable advancements include Kose et al. (2022) [30], who developed a framework for autonomous maintenance (AM) using lean tools and axiomatic design (AD). Validated in a Turkish textile manufacturing system, the framework reduced downtime by 69.2% and increased time between failures by 65.1%. Bashar et al. (2022) [31] investigated the relationship between TPM, people management (PEM), and organizational performance in Bangladesh's apparel industry, emphasizing the importance of employee engagement in TPM practices. Flores and Vega-Alvites (2022) [32] addressed downtime in the plastics sector by incorporating Lean tools such as 5S, SMED, TPM, and Jidoka, achieving a 13% improvement in OEE and a 48% reduction in setup times.

Integrating TPM with continuous improvement tools, such as Kaizen events, further strengthens its impact on innovation performance. Habidin et al. (2018) [33] showed that while Kaizen events do not directly influence the TPM-innovation performance relationship, they enhance TPM's role in driving innovation within the Malaysian automotive industry.

While TPM has demonstrated significant benefits, its reliance on static data and traditional methods limits its potential in dynamic operational environments. To address these challenges, future advancements should focus on integrating real-time data analytics for accurate failure predictions and dynamic maintenance scheduling (Wilson et al., 2024 [34]; Wolska et al., 2023 [35]). Aligning TPM with supply chain management can optimize parts availability and improve maintenance coordination. AI-driven decision tools could empower operators to make proactive, data-driven decisions, enhancing maintenance outcomes.

Future research should prioritize the development of IoT-enabled, real-time TPM metrics, integration with supply chain systems, and AI for predictive maintenance. These innovations will make TPM a more dynamic and adaptable system, improving resource coordination, reducing downtime, and achieving more efficient decision-making across maintenance and supply chain operations.

Total Productive Maintenance (TPM) and Reliability-Centered Maintenance (RCM) are complementary strategies that enhance equipment reliability and operational efficiency. TPM emphasizes proactive and preventive maintenance by involving all employees in continuous improvement to maximize equipment effectiveness. RCM, on the other hand, is a systematic approach that prioritizes maintenance tasks based on their impact on system reliability and safety. While TPM focuses on eliminating equipment-related losses through routine inspections and operator involvement, RCM analyzes failure modes and effects to implement the most cost-effective maintenance strategies. Integrating TPM and RCM enables organizations to balance preventive and condition-based maintenance, thereby extending asset longevity, reducing downtime, and optimizing maintenance resources.

Reliability-Centered Maintenance (RCM) is a vital methodology for improving asset reliability, optimizing maintenance strategies, and minimizing unplanned downtime across various sectors (Rodríguez-Padial et al., 2024 [36]). As shown in Table 3, extensive research highlights its effectiveness in aligning maintenance practices with both operational and organizational objectives. For example, Liu et al. (2025) [37] applied RCM to high-speed rail facilities, utilizing predictive models to prevent facility deterioration while reducing maintenance costs. Ali Ahmed Qaid et al. (2024) [38] developed a fuzzy-FMECA-based framework for analyzing failure modes in manufacturing machinery, enabling data-driven, criticality-focused maintenance strategies. In the utility sector, Asghari and Jafari (2024) [39] used RCM for water treatment plant pumps, enhancing Mean Time Between Failures (MTBF) and operational efficiency, while Cahyati et al. (2024) [40] achieved a 70% reduction in maintenance costs at a processing plant. Industry-specific adaptations further emphasize RCM's flexibility, with applications ranging from boiler engines (Sembiring, 2024) [41] to cement plants (Al-Farsi and Syafiie, 2023 [42]). Additionally, RCM has been integrated with Industry 4.0 technologies to optimize performance (Introna and Santolamazza, 2024 [43]) and improve resource allocation (Jiang et al., 2024 [44]). Resende et al. (2024) [45] introduced a Fuzzy FMEA methodology for risk analysis in the aeronautical sector, improving risk prioritization and decision-making through Matlab's Fuzzy Logic Toolbox. This approach demonstrated value by addressing uncertainties and providing context-specific risk assessments for aeronautical and other industries.

Previous studies, including those by Elijaha (2021) [46] and Rosita and Rada (2021) [47], validate RCM's ability to enhance asset reliability, reduce downtime, and achieve cost-effective maintenance strategies. These findings collectively demonstrate RCM's crucial role in improving operational efficiency and optimizing maintenance across various industries.

Gomaa (2025) [48] presents Reliability-Centered Maintenance (RCM) 4.0, an AI-powered framework that integrates Artificial Intelligence, IIoT, Digital Twins, and Big Data to enhance Reliability, Availability, Maintainability, and Safety (RAMS) in smart industrial systems. By combining RCM with Lean Six Sigma's DMAIC methodology shifts maintenance from reactive to predictive and autonomous, enabling real-time anomaly detection, intelligent diagnostics, and adaptive strategies. This approach boosts operational efficiency, minimizes downtime, and optimizes asset performance. Future work will explore 5G connectivity, autonomous robotics, blockchain security, and edge AI to advance next-generation digital maintenance ecosystems further.

Despite its proven benefits, traditional RCM approaches often rely on static schedules and lack integration with real-time data, limiting their adaptability to dynamic operational environments. Key research gaps include the development of adaptive frameworks that utilize real-time data to assess and prioritize failure modes, exploring the influence of human decision-making on RCM effectiveness, and integrating continuous monitoring and predictive analytics for proactive maintenance. Future research should focus on creating flexible, real-time RCM frameworks that incorporate operational data and advanced analytics, while also addressing the role of human factors in decision-making to improve implementation. These advancements will enhance asset performance, reduce unplanned downtime, and optimize maintenance practices, further solidifying RCM's importance in modern asset management.

Table 1. Summary of TPM Studies.

#	Reference	Contribution	Application	Main Objectives
1	Jurewicz, 2024, [11]	Proposed a TPM framework	Machinery fleet	Improving OEE
2	Trubetskaya, 2024, [7]	Developed a DMAIC-based maintenance framework	Dairy industry	Reducing maintenance downtime
3	Macalinao, 2024, [15]	Described a TPM framework	Pharmaceutical manufacturing	Reducing maintenance downtime
4	Gomaa, 2023, [2]	Reported a DMAIC-based maintenance framework	Petrochemical company	Improving OEE and reliability
5	Shannon, 2023, [8]	Proposed a Lean Six Sigma (LSS) framework for maintenance	Pharmaceutical ingredient plant	Improving OEE and reliability
6	West, 2023, [9]	Developed an LSS-based maintenance framework	Oil service company	Increasing machine availability
7	Al Farihi, 2023, [10]	Developed a Lean Maintenance framework	Wiring harness production	Reducing unplanned downtime and MTTR
8	Ardi et al., 2023, [13]	Developed a TPM framework	Cut-size line machines	Improving OEE
9	Antosz, 2022, [16]	Reported an LSS-based maintenance framework	Floor coverings company	Improving machine reliability
10	Korchagin, 2022, [17]	Developed a Lean Maintenance framework	Aviation industry	Improving maintenance process efficiency
11	Drewniak, 2022, [18]	Proposed a TPM framework	Crude oil processing	Improving OEE and reliability
12	Singha, 2022, [14]	Developed a TPM framework	Metal industry	Improving OEE
13	Imanov, 2021, [11]	Proposed a Lean Maintenance framework	Aircraft maintenance	Reducing aircraft downtime

Table 2. Summary of the Review of Total Productive Maintenance.

Aspect	Details
Role of TPM	Enhances equipment reliability, minimizes downtime, and improves operational efficiency.
Applications Across Sectors	Manufacturing, logistics, SMEs, healthcare, services, laboratories, power distribution, pharmaceutical, cement, and machining industries.
Integration with Technologies	- IoT and big data analytics (Khosroniya et al., 2024 [24]). - AHP for decision-making in cement plants (Amrina and Firda, 2024 [25]). - Industry 4.0 tools to drive sustainability.
Sector-Specific Successes	- Steel manufacturing and automotive industries: Improved OEE and reduced downtime (Biswas, 2024 [23]; Jurewicz et al., 2024 [12]). - API plants: Lower maintenance costs (Shannon et al., 2023 [8]).
Key Frameworks	- Autonomous Maintenance (AM) design using lean tools and axiomatic design (Kose et al., 2022 [30]): Reduced downtime by 69.2%, increased time between failures by 65.1%.
Organizational Impacts	- Positive effects of planned maintenance and training on productivity in Portuguese industries (Vaz et al., 2023 [28]). - Role of TPM in driving innovation (Habidin et al., 2018 [33]).
Advanced Tools Used	- 5S, SMED, TPM, Jidoka in the plastics industry: Improved OEE by 13%, reduced setup times by 48% (Flores and Vega-Alvites, 2022 [32]).
Challenges	- Reliance on static data and traditional methods.

	- Limited adaptability to dynamic operational environments.
Future Directions	- Real-time data analytics for failure predictions (Gomaa, 2025a [5]; Gomaa, 2025b [6]) - AI-driven tools for dynamic maintenance scheduling and proactive decision-making. - Integration with supply chain systems.

Table 3. Summary of the Review of Reliability-Centered Maintenance.

Aspect	Details
Role of RCM	Improves asset reliability, optimizes maintenance strategies, and minimizes unplanned downtime across various sectors (Rodríguez-Padial et al., 2024 [36]).
Key Applications and Research	- High-speed Rail Facilities: Liu et al. (2025) [37] used predictive models to prevent deterioration and reduce costs.
	- Manufacturing Machinery: Ali Ahmed Qaid et al. (2024) [38] applied fuzzy-FMECA for criticality-based maintenance strategies.
	- Water Treatment Plants: Asghari and Jafari (2024) [39] improved MTBF and operational efficiency.
	- Processing Plants: Cahyati et al. (2024) [40] achieved a 70% reduction in maintenance costs.
	- Boiler Engines & Cement Plants: Applications in various industries (Sembiring, 2024 [41]; Al-Farsi and Syafiie, 2023 [42]).
	- Industry 4.0 Integration: Introna and Santolamazza (2024) [43]; Jiang et al. (2024) [44] optimized performance and resource allocation.
RCM Effectiveness	Validated by studies like Elijaha (2021) [46] and Rosita and Rada (2021) [47] for enhancing asset reliability, reducing downtime, and enabling cost-effective strategies.
Challenges and Research Gaps	- Static schedules in traditional RCM models, lack of real-time data integration.
	- Need for adaptive frameworks that incorporate real-time data and predictive analytics.
	- Exploration of human decision-making's impact on RCM effectiveness.
Future Research Directions	- Focus on flexible, real-time RCM frameworks integrating operational data and advanced analytics.
	- Addressing human factors in RCM decision-making for improved implementation.

3. Research Gap Analysis

The evolution of Total Productive Maintenance (TPM) 4.0 in the era of Industry 4.0, Smart Manufacturing, and AI-driven automation necessitates a shift from conventional preventive and predictive maintenance to autonomous, self-optimizing, and cyber-resilient maintenance ecosystems. While Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Digital Twins, Edge AI, Blockchain, and Federated Learning continue to advance, significant research gaps persist, hindering scalability, adaptability, and real-time decision-making in next-generation maintenance frameworks. As shown in Table 4, overcoming these gaps is essential to realizing zero-downtime manufacturing, cost-efficient maintenance, sustainable industrial operations, and intelligent self-healing systems. This section outlines key research gaps and future research directions.

(1) AI-Augmented TPM 4.0: From Predictive to Autonomous Maintenance: Current AI-driven predictive maintenance (PdM) frameworks remain reactive rather than proactive, lacking cognitive intelligence for self-learning and self-adapting decision-making. The Failure Mode and Effects Analysis (FMEA) model remains static and manually updated, making it inadequate for dynamic industrial environments. Future research should focus on Cognitive FMEA, integrating Bayesian networks, reinforcement learning, and explainable AI (XAI) to achieve real-time, adaptive failure classification. Additionally, existing AI models struggle with explainability and adaptability, limiting industrial trust. A significant research gap exists in hybrid AI architectures that combine deep learning, reinforcement learning, genetic algorithms, and physics-informed AI to develop self-optimizing maintenance strategies. Moving beyond predictive maintenance, AI-powered prescriptive maintenance should leverage causal inference, reinforcement learning, and cognitive decision-making to recommend and execute maintenance actions in real-time autonomously.

(2) High-Fidelity Digital Twins for Real-Time Maintenance Optimization: Despite widespread adoption, Digital Twins face limitations in real-time predictive and prescriptive maintenance. The primary challenge is latency in multi-sensor fusion, leading to delays in fault detection and diagnostics. Future research should explore neuromorphic computing, event-driven AI architectures, and edge AI processing to enhance real-time sensor fusion and anomaly detection. Moreover, most Digital Twins are static models that require manual updates, which reduces their effectiveness in dynamic environments. The next generation should be self-learning, leveraging zero-shot learning, transfer learning, and federated reinforcement learning (FRL) for continuous adaptation. Another key challenge is scalability, as integrating Digital Twins across multi-tier supply chains remains complex. Federated Digital Twin architectures should be developed to enable decentralized, AI-driven asset monitoring, enhancing resilience and adaptability across large-scale industrial networks.

(3) Federated Learning for Secure and Decentralized AI in Maintenance: Federated Learning (FL) presents a promising framework for collaborative predictive maintenance by enabling industrial plants to train AI models without sharing raw data. However, security vulnerabilities, such as adversarial attacks, model poisoning, and data leakage,

present significant risks. Future research should explore blockchain-enhanced FL frameworks incorporating differential privacy, homomorphic encryption, and zero-knowledge proofs (ZKP) to safeguard sensitive industrial data. Another critical challenge is non-IID (non-independent and identically distributed) data, which negatively impacts AI model generalizability across different industrial plants. Quantum-assisted federated learning could significantly enhance model efficiency in handling non-IID datasets. Additionally, FL models often face high computational costs and slow training times, making real-time applications infeasible. Future research should investigate energy-efficient FL architectures using neuromorphic AI and edge-compressed federated learning to optimize both processing power and scalability.

(4) Blockchain-Enabled Smart Contracts for Secure Maintenance Ecosystems: While blockchain technology enhances tamper-proof predictive maintenance and decentralized asset management, latency and computational overhead remain critical barriers to real-time applications. Traditional blockchain protocols are inefficient for AI-driven predictive maintenance, necessitating research into Directed Acyclic Graph (DAG)-based Distributed Ledger Technologies (DLTs) for high-speed, low-latency transaction processing. Moreover, AI-integrated smart contracts remain underdeveloped, limiting their potential to automate and optimize maintenance workflows. Future research should focus on self-adjusting AI-powered smart contracts that dynamically adapt to asset health conditions and autonomously trigger maintenance actions. Additionally, blockchain-based maintenance systems remain vulnerable to ransomware, quantum attacks, and Industrial IoT (IIoT) security breaches. Post-quantum cryptographic blockchain solutions will be critical in ensuring cyber-resilient, decentralized maintenance ecosystems.

(5) Autonomous Robotic Maintenance: Towards Self-Repairing Systems: Current maintenance robots lack cognitive diagnostics and adaptive intelligence, limiting their ability to manage complex repair tasks autonomously. Future TPM 4.0 systems should develop self-diagnosing robotic maintenance agents powered by Deep Reinforcement Learning (DRL), neuromorphic AI, and cognitive analytics to enable real-time self-assessment and autonomous troubleshooting. An emerging research area is swarm intelligence in robotic maintenance, where multi-agent robotic teams collaborate to optimize maintenance tasks. Future research should explore multi-agent reinforcement learning (MARL) to enable self-organizing, decentralized robotic maintenance systems. Additionally, bio-inspired robotics for extreme environments remains underexplored. Bio-mimetic, self-healing robotic systems could enhance maintenance efficiency and safety in hazardous industrial settings, such as chemical plants, offshore rigs, and nuclear facilities.

(6) 5G/6G-Powered AI-Driven Edge Intelligence for Real-Time Maintenance: The adoption of 5G/6G networks in AI-driven predictive maintenance enables ultra-low-latency, real-time asset monitoring. However, existing edge AI frameworks lack the computational efficiency required for real-time decision-making. Future research should explore AI-optimized edge intelligence, integrating spiking neural networks (SNNs), edge AI accelerators, and real-time neuromorphic processors to enable low-latency, on-device predictive analytics. Another emerging area is Quantum IoT (QIoT) for anomaly detection, where Quantum Machine Learning (QML) and next-generation IoT sensors could enable instant fault detection and enhanced predictive capabilities. Additionally, 6G-powered smart factories will require ultra-reliable low-latency communication (URLLC) to support real-time Digital Twins and AI-driven maintenance automation. Future research should focus on 6G-powered decentralized intelligence, enabling fully autonomous, real-time maintenance ecosystems with enhanced cybersecurity and operational scalability.

In conclusion, the next phase of TPM 4.0 necessitates breakthroughs in AI-augmented prescriptive maintenance, self-learning Digital Twins, federated learning, blockchain-secured predictive maintenance, autonomous robotic self-repair systems, and 5G/6G-powered edge intelligence. Addressing these research gaps will lead to zero-downtime, self-optimizing, cyber-resilient, and cost-efficient industrial maintenance ecosystems, redefining the future of AI-driven Smart Manufacturing.

Table 4. Research Gap Analysis for TPM 4.0 in Smart Manufacturing.

	Research Gap	Key Challenges	Future Research Directions
1	AI-Augmented TPM 4.0	Limited AI adaptability; Static FMEA; Lack of explainability	Cognitive FMEA with Bayesian networks and XAI; Hybrid AI with deep learning and reinforcement learning; AI-driven prescriptive maintenance
2	High-Fidelity Digital Twins	Latency in multi-sensor fusion; Static models; Scalability issues	Neuromorphic computing for real-time processing; Self-learning Digital Twins; Federated architectures for adaptive monitoring
3	Federated Learning in Maintenance	Security vulnerabilities; Non-IID data; High computational costs	Blockchain-secured FL; Quantum-assisted FL for heterogeneous datasets; Energy-efficient FL with neuromorphic AI
4	Blockchain-Enabled Smart Contracts	High latency; Limited AI integration; Cybersecurity risks	DAG-based DLTs for fast transactions; AI-driven smart contracts; Post-quantum cryptographic blockchain solutions

5	Autonomous Robotic Maintenance	Limited self-diagnosis; Inefficient collaboration; Challenges in extreme environments	DRL and neuromorphic AI for self-diagnosing robots; Multi-agent reinforcement learning; Bio-mimetic self-healing robotic systems
6	5G/6G-Powered Edge Intelligence	Inefficient real-time AI; Large-scale anomaly detection limitations; Need for ultra-reliable networks	AI-optimized edge intelligence with SNNs; Quantum IoT for real-time fault detection; 6G-powered decentralized intelligence

4. Research Methodology

This study develops a TPM 4.0 framework that integrates Total Productive Maintenance (TPM) with Lean Six Sigma's DMAIC methodology to enhance Reliability, Availability, Maintainability, and Safety (RAMS) in Smart Manufacturing. Traditional TPM relies on static failure assessments and fixed schedules, limiting adaptability in dynamic production environments. To address this, the research introduces a cyber-physical maintenance approach that leverages Industry 4.0 technologies for an intelligent, self-optimizing system. The framework integrates AI and Machine Learning for predictive maintenance, IIoT for real-time monitoring, Digital Twins for failure prediction and optimization, and Big Data Analytics for data-driven decision-making. This transforms TPM into a proactive, autonomous system that continuously refines maintenance strategies through real-time monitoring and AI-driven analytics, maximizing Overall Equipment Effectiveness (OEE) while minimizing downtime and costs. To validate TPM 4.0, the study employs a multi-method approach, combining Digital Twin simulations, industrial case studies, and statistical analysis of RAMS and OEE metrics. By merging Lean Six Sigma with Industry 4.0-driven predictive maintenance, this research pioneers a next-generation TPM paradigm, enhancing resilience, adaptability, and efficiency in Smart Manufacturing.

4.1. TPM 4.0 Pillars and Industry 4.0 Integration

Total Productive Maintenance (TPM) 4.0 represents a paradigm shift in maintenance and asset management, integrating Industry 4.0 technologies to enhance efficiency, reliability, and adaptability in Smart Manufacturing. While traditional TPM focuses on proactive maintenance strategies, TPM 4.0 leverages Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Digital Twins, and Big Data Analytics to create an autonomous, predictive, and data-driven maintenance ecosystem. Table 5 outlines the eight core TPM 4.0 pillars, detailing their objectives, implementation approaches, and the Industry 4.0 technologies that enable them. By transforming maintenance into a real-time, intelligent system, TPM 4.0 enhances Overall Equipment Effectiveness (OEE), minimizes downtime, and ensures continuous process improvement, driving operational excellence in modern manufacturing environments.

(1) Autonomous Maintenance: Traditional maintenance models rely heavily on scheduled inspections and reactive repairs, often leading to inefficiencies and unexpected downtime. TPM 4.0 enhances Autonomous Maintenance by integrating AI-powered diagnostics, IIoT-enabled condition monitoring, and smart sensor networks to detect anomalies in real-time. Edge computing and machine learning algorithms provide instant alerts and predictive insights, enabling frontline workers to take proactive measures before failures occur. This shift reduces dependency on centralized maintenance teams, minimizes downtime, extends asset lifecycles, and improves overall system reliability. Additionally, digital work instructions and augmented reality (AR)-based guidance empowers operators to perform complex maintenance tasks with precision, enhancing efficiency and reducing errors.

(2) Planned Maintenance: Conventional planned maintenance follows a fixed schedule, which can result in unnecessary servicing or unexpected breakdowns. TPM 4.0 introduces predictive and prescriptive maintenance models, leveraging AI-driven analytics, Digital Twins, and federated learning architectures. Predictive maintenance algorithms analyze sensor data to anticipate failures, while prescriptive AI models recommend optimized maintenance actions based on real-time conditions. Cloud-edge computing ensures fast and decentralized decision-making across industrial environments. This transformation from fixed schedules to dynamic, data-driven maintenance planning enhances asset utilization, reduces costs, and improves Overall Equipment Effectiveness (OEE).

(3) Quality Maintenance: Defects, process deviations, and inconsistent quality control impact productivity and profitability. TPM 4.0 enhances Quality Maintenance through machine vision, AI-powered defect detection, and blockchain-secured traceability. Smart cameras and deep learning algorithms monitor production processes in real-time, detecting defects, variations, and failures before they affect product quality. Additionally, blockchain technology ensures transparent and tamper-proof quality records, improving compliance and traceability across the supply chain. By employing self-learning quality control mechanisms, TPM 4.0 supports zero-defect manufacturing, minimal rework, and enhanced customer satisfaction.

(4) Focused Improvement (Kobetsu Kaizen): Kobetsu Kaizen focuses on structured, continuous improvement. TPM 4.0 advances this pillar with AI-driven root cause analysis, real-time process optimization, and digital lean management platforms. AI-powered predictive models analyze operational data to identify inefficiencies, suggest corrective actions, and fine-tune production parameters autonomously. Collaborative digital platforms facilitate real-time decision-making among cross-functional teams, streamlining problem-solving efforts. Robotic Process Automation (RPA) and AI-driven workflow optimization further enhance productivity by eliminating repetitive tasks, leading to sustained process excellence and increased throughput.
(5) Early Equipment Management: Designing maintenance-friendly equipment is key to minimizing lifecycle costs and downtime. TPM 4.0 integrates Digital Twins, AI-driven failure simulations, and predictive wear modeling to enhance equipment reliability during the design phase. Engineers leverage virtual prototyping and real-time structural health monitoring to detect potential failure points before mass production. Additionally, smart materials and embedded sensors provide continuous operational feedback, ensuring dynamic design improvements. These innovations reduce early-life failures, enhance maintainability, and lower total cost of ownership (TCO).
(6) Training & Skill Development: As industries transition to AI-driven, digitalized maintenance ecosystems, workforce upskilling is critical. TPM 4.0 incorporates AI-powered adaptive learning platforms, AR/VR-based training, and interactive Digital Twins to enhance skill development. Augmented Reality (AR) smart glasses provide real-time guidance, enabling technicians to execute complex tasks efficiently. Virtual simulations allow workers to practice troubleshooting scenarios in a risk-free environment, improving expertise without production downtime. Additionally, AI-driven competency mapping customizes training programs to individual learning needs, ensuring a highly skilled, future-ready workforce.
(7) Safety, Health, and Environment (SHE): TPM 4.0 integrates smart safety systems, AI-driven risk assessment models, and IoT-based real-time hazard monitoring to improve workplace safety and sustainability. Wearable safety devices, fatigue detection sensors, and AI-powered ergonomic analysis prevent injuries by monitoring worker conditions. Connected helmets and exoskeletons assist in physically demanding tasks, reducing strain and injury risks. Additionally, blockchain-enabled environmental compliance tracking and AI-driven energy optimization algorithms support eco-friendly manufacturing by reducing emissions and optimizing energy consumption. These advancements enhance workplace safety, regulatory compliance, and sustainability, fostering a zero-accident, zero-emission environment.
(8) Administrative & Support Functions: TPM 4.0 extends beyond production operations to business processes through AI-enhanced decision support systems, cloud-based Enterprise Asset Management (EAM) solutions, and blockchain-secured maintenance records. AI-driven predictive resource planning ensures optimal spare parts inventory management, minimizing shortages and excess stock. Blockchain technology enhances maintenance transparency, providing tamper-proof, auditable records that streamline compliance reporting. By integrating automated workflow management, Digital Twin-based simulations, and AI-powered procurement optimization, industries improve agility, reduce administrative costs, and enhance cross-functional collaboration.

In conclusion, TPM 4.0 represents a fundamental transformation in industrial maintenance by integrating traditional TPM principles with Industry 4.0 innovations to develop intelligent, autonomous, and self-learning maintenance ecosystems. Through AI, IIoT, Digital Twins, edge computing, and blockchain, industries shift from reactive and preventive maintenance to predictive, prescriptive, and autonomous frameworks. This evolution enhances OEE, reduces downtime, increases cost efficiency, and supports sustainable industrial operations. By implementing TPM 4.0, industries establish a data-driven maintenance strategy that ensures long-term competitiveness and aligns with the principles of Smart Manufacturing and Industry 5.0. As research and technology evolve, future advancements will include 5G-enabled real-time monitoring, autonomous robotic maintenance, and AI-driven self-healing manufacturing, further solidifying TPM 4.0 as the cornerstone of next-generation industrial maintenance.

Table 5. TPM 4.0 Pillars and Industry 4.0 Integration.

#	Pillar	Objective	Approach	Industry 4.0 Integration	Key Benefits
1	Autonomous Maintenance	Empower operators, enhance reliability	Operators perform routine maintenance, preventing failures.	IIoT sensors, AI diagnostics, AR assistance	Reduced downtime, faster issue resolution
2	Planned Maintenance	Transition to predictive strategies	Real-time data enables condition-based maintenance.	Predictive analytics, Digital Twins, AI monitoring	Lower costs, optimized asset utilization

3	Quality Maintenance	Achieve zero defects, enhance control	Automated systems ensure defect-free production.	AI defect detection, Blockchain traceability	Fewer defects, improved compliance
4	Focused Improvement	Drive continuous optimization	Structured problem-solving eliminates inefficiencies.	AI root cause analysis, RPA, Digital Lean	Increased efficiency, reduced waste
5	Early Equipment Management	Design reliable, low-maintenance assets	Embeds reliability in new equipment design.	Digital Twins, AI failure simulation, Smart sensors	Higher reliability, extended lifespan
6	Training & Skill Development	Enhance workforce digital competency	AI-driven, AR/VR-based training programs.	AI adaptive learning, AR/VR simulations	Faster skill development, fewer human errors
7	Safety, Health & Environment (SHE)	Ensure workplace safety & sustainability	Proactive safety and environmental risk management.	Smart safety systems, Wearable IoT, AI risk analysis	Fewer incidents, regulatory compliance
8	Administrative & Support Functions	Streamline processes, enhance compliance	Optimized planning, logistics, and data management.	AI-driven planning, Blockchain records, Digital Twins	Better decision-making, seamless audits

4.2. Implementing TPM 4.0: A DMAIC-Driven Intelligent Framework

Total Productive Maintenance (TPM) 4.0 marks a shift from reactive to AI-driven predictive and autonomous maintenance. By integrating Industry 4.0 technologies with Lean Six Sigma's DMAIC (Define-Measure-Analyze-Improve-Control) methodology, TPM 4.0 enhances real-time asset monitoring, predictive diagnostics, and automated interventions, ensuring maximum reliability, minimal downtime, and cost efficiency. Leveraging AI, the Industrial Internet of Things (IIoT), Digital Twins, Cloud-Edge Computing, and Advanced Analytics, TPM 4.0 replaces fixed schedules with predictive, condition-based strategies, aligning maintenance with business objectives for agile, resilient Smart Manufacturing. Table 6 outlines the DMAIC-driven TPM 4.0 framework, demonstrating how each phase integrates Industry 4.0 technologies to enhance efficiency, reliability, and cost-effectiveness.

(1) Define: Strategic Asset Prioritization & Risk Assessment: This phase establishes TPM 4.0 by identifying critical assets, maintenance objectives, and failure risks. AI-driven asset mapping, Digital Twins, and risk-based prioritization classify equipment based on failure probability and operational impact. Failure Mode and Effects Analysis (FMEA) pinpoints potential failures, while real-time data enhances decision-making. A data-driven roadmap ensures maintenance aligns with business goals, optimizing resources and proactively mitigating risks.

(2) Measure: Real-Time Data Acquisition & Condition Monitoring: IIoT sensors, edge computing, and cloud-based analytics enable continuous condition monitoring and performance tracking. Key metrics, including Overall Equipment Effectiveness (OEE), vibration analysis, thermal imaging, and AI-driven anomaly detection, are used to assess asset health. Smart sensors stream real-time data to AI-powered diagnostics, shifting maintenance from time-based to condition-based interventions for improved accuracy and efficiency.

(3) Analyze: Predictive Analytics & Failure Mode Classification: Big Data analytics, machine learning, and Digital Twin simulations predict asset degradation and optimize maintenance strategies. AI-powered failure classification enhances diagnostics, while predictive analytics forecast breakdowns before they occur. Root cause analysis through FMEA and risk-based models strengthens reliability-centered maintenance, reducing unplanned downtime and improving asset performance.

(4) Improve: AI-Driven Autonomous Maintenance & Optimization: AI-driven models, robotic maintenance systems, and adaptive automation optimize execution. Intelligent decision-making supports real-time scheduling, dynamic work orders, and autonomous robotic repairs. Cognitive automation enables self-adjusting workflows, reducing unnecessary interventions while ensuring asset reliability. AI-powered adaptive control enhances efficiency, cost reduction, and overall equipment effectiveness.

(5) Control: Continuous Optimization, Cybersecurity & Scalable Networks: The Control phase ensures TPM 4.0 remains secure, scalable, and continuously improving. Federated learning enables decentralized AI training while preserving data privacy. Blockchain-secured predictive workflows enhance data integrity, while 5G-enabled monitoring strengthens reliability and connectivity. Cyber-physical security systems and AI-driven anomaly detection safeguard assets, establishing a resilient, intelligent maintenance ecosystem.

In conclusion, TPM 4.0 revolutionizes maintenance by integrating AI-driven intelligence, predictive analytics, and autonomous interventions within the DMAIC framework. This transformation enhances asset availability, cost efficiency, and operational resilience, driving sustainable excellence in Smart Manufacturing.

Table 6. DMAIC-Driven TPM 4.0 Framework.

Phase	Objective	Key Actions	Industry 4.0 Integration	Outcomes
Define	Identify critical assets & risks	Asset classification, FMEA, risk-based prioritization	AI-driven asset mapping, Digital Twin modeling	Optimized resource allocation, reduced failure risks
Measure	Capture real-time asset health	IIoT sensor deployment, OEE tracking, condition monitoring	IIoT, AI-powered anomaly detection, Edge computing	Early failure detection, data-driven maintenance
Analyze	Predict failures & optimize strategies	RCA, predictive analytics, failure classification	Machine Learning, Big Data, Digital Twin simulations	Proactive maintenance, reduced downtime
Improve	Automate & optimize maintenance	AI-driven scheduling, robotic interventions, adaptive automation	Self-learning AI, Cognitive automation, RPA	Cost reduction, enhanced OEE, real-time optimization
Control	Ensure security & scalability	Cybersecurity measures, federated learning, blockchain	AI anomaly detection, 5G-enabled monitoring	Resilient, secure, and scalable maintenance network

4.3. Strategic Objectives and KPIs for TPM 4.0 Implementation

TPM 4.0 adoption requires a data-driven approach that integrates AI-driven predictive analytics, IoT-enabled asset monitoring, and autonomous decision-making. As industries transition to cyber-physical maintenance ecosystems, organizations must define clear strategic objectives and performance-driven KPIs to enhance reliability, cost efficiency, and resilience. This section presents a comprehensive framework for aligning TPM 4.0 objectives with real-time performance tracking, leveraging AI, Digital Twins, and predictive maintenance algorithms. Table 7 outlines key strategic objectives and KPIs, incorporating Industry 4.0 technologies such as AI, IIoT, Digital Twins, and Edge Computing to optimize maintenance performance, reduce costs, enhance sustainability, and improve workforce productivity.

(1) Maximizing asset reliability and availability is critical to reducing unplanned downtime and improving equipment performance. KPIs such as Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) measure system reliability and response efficiency. AI-driven predictive maintenance, Digital Twins, and real-time monitoring ensure failures are anticipated and prevented, resulting in higher uptime and operational stability.

(2) Optimizing maintenance costs and resource utilization focuses on reducing expenditures while maintaining efficiency. Tracking maintenance costs as a percentage of revenue ensures cost-effectiveness, while IoT-enabled condition monitoring adoption reflects the degree of smart technology deployment. AI-based inventory optimization prevents overstocking and stockouts, ensuring spare parts are available without excessive investment, thus reducing waste and unnecessary expenditures.

(3) Leveraging AI, IoT, and Edge Computing enables autonomous, self-adaptive maintenance. Edge AI response time measures how quickly AI detects and responds to anomalies, reducing reaction time. Digital Twin simulation accuracy ensures predictive models align with real-world failures. Automated work order execution and self-healing system activation improve maintenance efficiency by allowing machines to diagnose and correct issues, enhancing overall productivity autonomously.

(4) Sustainability and ESG compliance play a crucial role in maintenance strategies, aligning operations with environmental goals and regulatory requirements. KPIs such as energy efficiency improvement and carbon footprint reduction track AI-driven energy optimization and emission control. Compliance scores assess adherence to global maintenance standards, such as ISO 55000, while waste reduction KPIs measure sustainability efforts. Industry 4.0 technologies ensure maintenance operations contribute to environmental sustainability while enhancing operational efficiency.

(5) Developing autonomous, self-learning maintenance systems ensures continuous improvement. AI self-learning model accuracy evaluates how well AI adapts and refines maintenance strategies. Automated failure diagnosis rate measures AI's ability to identify and address root causes correctly. The continuous improvement index assesses AI-driven refinements, ensuring maintenance systems evolve and optimize over time without human intervention.

(6) Enhancing workforce productivity and digital skill development ensures human workers are equipped with the knowledge and tools needed for Industry 4.0-driven maintenance. AI-assisted maintenance efficiency measures AI's role in supporting human tasks, improving speed and accuracy. The adoption of Augmented Reality (AR) for training and remote troubleshooting enhances workforce capabilities. Workforce digital training completion rates ensure employees are prepared for AI-driven maintenance processes, reducing errors and improving productivity.

(7) Improving resilience and emergency maintenance preparedness is vital to minimizing disruptions and maintaining operational continuity. Emergency downtime response time measures the speed at which failures are detected and recovered. Backup system activation rates track the effectiveness of redundancy mechanisms in maintaining

uptime. AI-driven fault escalation ensures critical failures are addressed swiftly, reducing risks and enhancing emergency preparedness.

Overall, this table provides a structured framework for implementing TPM 4.0, integrating smart technologies to transform maintenance from a reactive, cost-intensive process into an intelligent, proactive, and self-optimizing system. By leveraging AI, IoT, and advanced analytics, TPM 4.0 ensures reliability, efficiency, sustainability, and resilience, driving the future of smart maintenance in manufacturing.

Table 7. Strategic Objectives & KPIs for TPM 4.0 Implementation.

#	Strategic Objective	Key Performance Indicators (KPIs)	Formula/Measurement	Industry 4.0 Relevance & Impact
1	Maximize Asset Reliability & Availability	Mean Time Between Failures (MTBF)	Total Operating Time/Number of Failures	AI-driven predictive maintenance minimizes unexpected breakdowns.
		Mean Time to Repair (MTTR)	Total Downtime/Number of Repairs	AI-powered diagnostics reduce repair time.
		Overall Equipment Effectiveness (OEE)	Availability × Performance × Quality	Real-time monitoring enhances reliability and performance.
		Failure Detection Lead Time (FDLT) (%)	(Time Before AI Prediction/Time Before Actual Failure) × 100	Measures AI's effectiveness in early failure detection.
		Predictive Maintenance Accuracy (%)	(Correct AI Predictions/Total Predictions) × 100	Evaluates AI & IoT-enabled failure forecasting precision.
2	Optimize Maintenance Costs & Resource Utilization	Maintenance Cost as % of Revenue	(Total Maintenance Cost/Total Revenue) × 100	AI-driven maintenance reduces costs and optimizes resource allocation.
		Reduction in Unplanned Downtime (%)	(Previous Downtime—Current Downtime)/Previous Downtime × 100	Quantifies the impact of predictive maintenance.
		IoT-Enabled Condition Monitoring Adoption (%)	(IoT-Monitored Assets/Total Assets) × 100	Tracks real-time predictive maintenance implementation.
		AI-Optimized Spare Parts Inventory Reduction (%)	(Previous Inventory Cost—Current Inventory Cost)/Previous Inventory Cost × 100	Reduces overstock and stockouts through AI-optimized inventory.
3	Leverage AI, IoT & Edge Computing for Smart Maintenance	Edge AI Response Time (ms)	Time from Anomaly Detection to Automated Response	Measures AI-driven maintenance automation speed.
		Digital Twin Simulation Accuracy (%)	(Predicted Failures Matched with Actual Failures)/Total Failures × 100	Assesses Digital Twin reliability in predictive maintenance.
		Automated Work Order Execution Rate (%)	(AI-Generated Work Orders/Total Work Orders) × 100	Tracks AI-driven maintenance workflow automation.
		Self-Healing System Activation Rate (%)	(Self-Corrected Failures/Total Failures) × 100	Measures AI's ability to autonomously resolve issues.
4	Enhance Sustainability & ESG Compliance	Energy Efficiency Improvement (%)	(Previous Energy Use—Current Energy Use)/Previous Energy Use × 100	AI optimizes energy consumption across industrial assets.
		Carbon Footprint Reduction (%)	(Previous CO_2 Emissions—Current CO_2 Emissions)/Previous CO_2 Emissions × 100	Aligns maintenance practices with sustainability goals.
		Regulatory Compliance Score	Compliance Rating (ISO 55000, IEC 61508, *etc.*)	Tracks adherence to industry-specific standards.
		Waste Reduction in Maintenance (%)	(Previous Waste Generated—Current Waste)/Previous Waste × 100	Measures sustainability improvements in maintenance.
5	Develop Autonomous, Self-Learning Maintenance Systems	AI Self-Learning Model Accuracy (%)	(Correct AI Model Adjustments/Total Adjustments) × 100	Evaluates AI adaptability in optimizing maintenance strategies.
		Automated Failure Diagnosis Rate (%)	(AI-Diagnosed Failures/Total Failures) × 100	Tracks AI's efficiency in identifying root causes.
		Continuous Improvement Index	Rate of AI-Optimized Maintenance Process Refinement	Measures AI-driven improvements in maintenance practices.
		Anomaly Detection Sensitivity (%)	(Detected Anomalies/Total Anomalies) × 100	Assesses AI's effectiveness in identifying complex failure patterns.
6	Enhance Workforce Productivity & Digital Skill Development	AI-Assisted Maintenance Efficiency (%)	(AI-Supported Tasks/Total Tasks) × 100	Evaluates AI's role in augmenting human maintenance capabilities.
		Augmented Reality (AR) Maintenance Adoption (%)	(AR-Guided Repairs/Total Repairs) × 100	Tracks AR's role in remote troubleshooting and training.

		Digital Workforce Training Completion Rate (%)	(Employees Trained on Digital RCM/Total Workforce) × 100	Measures workforce readiness for digital transformation.
		Maintenance Robotics Deployment Rate (%)	(Robotic Maintenance Tasks/Total Maintenance Tasks) × 100	Assesses automation in maintenance operations.
7	Improve Resilience & Emergency Maintenance Preparedness	Emergency Downtime Response Time (min)	Time from Failure Detection to Initial Recovery	Ensures rapid response to critical system failures.
		Backup System Activation Rate (%)	(Successful Backup Activations/Total Failures) × 100	Measures system redundancy and resilience.
		AI-Driven Fault Escalation Efficiency (%)	(Correct Escalations/Total Escalations) × 100	Ensures AI-driven escalation reduces response time in high-risk failures.

5. Conclusions and Future Work

This study introduces TPM 4.0, an advanced maintenance framework that redefines Total Productive Maintenance (TPM) by leveraging Industry 4.0 technologies, including IIoT, Big Data Analytics, Digital Twins, Edge AI, and Cloud Computing. By shifting from reactive and time-based maintenance to autonomous, predictive, and prescriptive strategies, TPM 4.0 enhances asset reliability, optimizes lifecycle performance, and minimizes operational disruptions. Through real-time sensor fusion, AI-driven diagnostics, and intelligent decision-support systems, this framework fosters a resilient, adaptive, and data-driven industrial ecosystem.

A key contribution of this research is the seamless integration of TPM principles with Lean Six Sigma's DMAIC methodology, offering a structured, data-driven approach to failure mode classification, risk-based prioritization, and real-time performance optimization. The incorporation of IIoT-enabled condition monitoring, Digital Twin-powered simulations, and machine learning-driven predictive analytics enable real-time anomaly detection, cognitive diagnostics, and dynamic asset management. Additionally, federated learning enhances scalability, security, and collaboration by enabling decentralized AI model training while preserving data integrity and privacy.

By positioning TPM 4.0 as a foundation for Smart Manufacturing, this research bridges the gap between traditional maintenance and AI-driven automation, cognitive analytics, and digital sustainability. AI-powered decision-making, real-time Digital Twins, and self-learning maintenance algorithms facilitate continuous asset monitoring, autonomous optimization, and proactive failure prevention. Furthermore, blockchain technology enhances data security, integrity, and transparency, mitigating cybersecurity risks in interconnected industrial environments. As industries advance toward Industry 5.0, TPM 4.0 paves the way for intelligent, cyber-resilient, and self-optimizing maintenance ecosystems, driving the future of autonomous and sustainable manufacturing.

While this study lays a strong foundation for intelligent maintenance ecosystems, future research will focus on enhancing scalability, security, and automation capabilities to improve maintenance efficiency further. Advancements in 5G-powered real-time asset monitoring will enable instantaneous condition-based monitoring and remote asset management, allowing industries to respond to maintenance needs in real-time. Blockchain-secured predictive maintenance will ensure tamper-proof maintenance records, secure data exchange, and transparent equipment performance tracking, fostering trust and security across decentralized industrial networks. Additionally, AI-driven autonomous robotic maintenance systems will be capable of self-diagnosing, repairing, and optimizing industrial assets in real-time, reducing reliance on manual intervention and significantly improving operational efficiency.

By integrating these emerging technologies, TPM 4.0 will pave the way for fully autonomous, self-healing, and cyber-resilient maintenance ecosystems, driving the next generation of smart manufacturing environments that are more efficient, adaptive, and secure.

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Declaration of Competing Interest

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