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Article

MAINTENANCE OPTIMIZATION IN SMART MANUFACTURING FACILITIES: A SYSTEMATIC REVIEW OF LEAN, TPM, AND DIGITALLY-DRIVEN RELIABILITY MODELS IN INDUSTRIAL ENGINEERING

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ABSTRACT

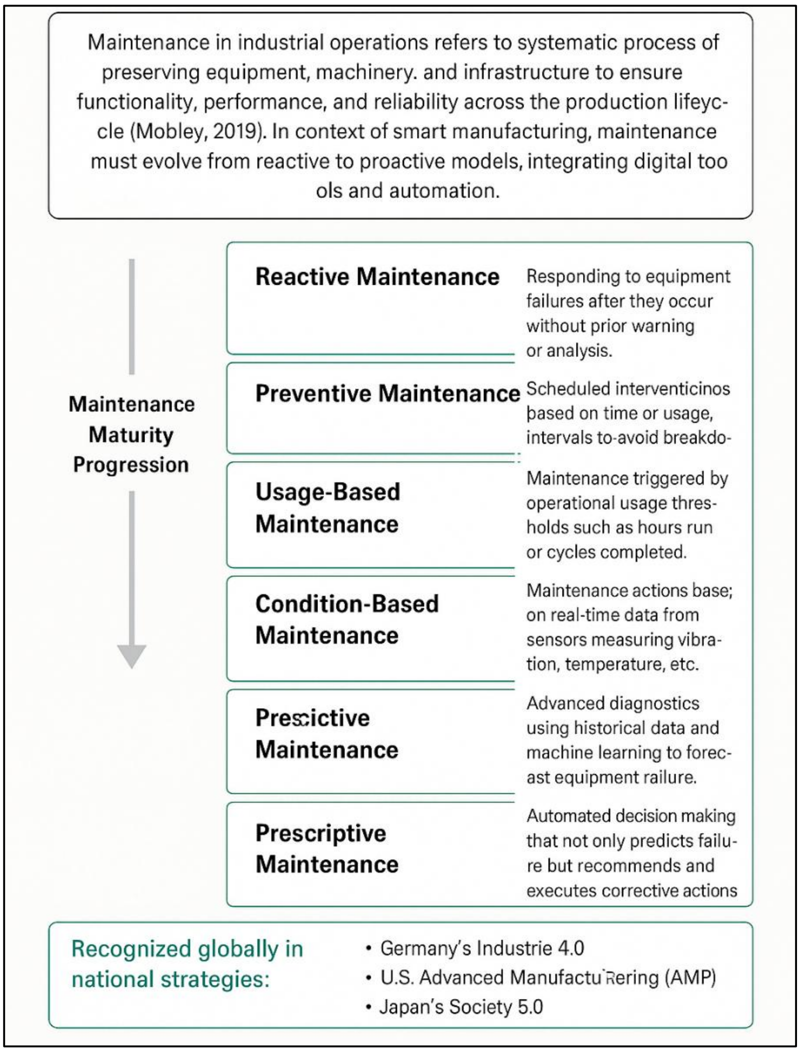
This study presents a comprehensive systematic literature review aimed at analyzing and synthesizing current advancements, applications, and challenges in maintenance optimization within smart manufacturing facilities. Guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework, a total of 112 peer-reviewed articles published between 2010 and 2024 were rigorously selected and analyzed from major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The review focuses on three principal frameworks of maintenance optimization: Lean Maintenance, Total Productive Maintenance (TPM), and digitally-driven models incorporating Artificial Intelligence (AI), Machine Learning (ML), Cyber-Physical Systems (CPS), and Computerized Maintenance Management Systems (CMMS). Sectoral applications in the automotive, aerospace, and food processing industries were closely examined, revealing that predictive maintenance, digital twin technologies, and AI-enabled diagnostics significantly enhance reliability, reduce downtime, and improve overall equipment effectiveness. Furthermore, the study identifies persistent research gaps related to contextual adaptation in small and medium enterprises (SMEs), integration challenges between traditional and digital systems, and the lack of standardized benchmarking methods for evaluating maintenance performance. The findings contribute to a better understanding of the strategic evolution of maintenance from a reactive, cost-centered function to a proactive, data-driven enabler of industrial resilience and sustainability. This review provides actionable insights for practitioners, researchers, and policymakers seeking to align maintenance strategies with Industry 4.0 objectives, while also calling for more inclusive and empirically validated approaches in future research.

KEYWORDS
Smart Manufacturing, Maintenance Optimization, Total Productive Maintenance (TPM), Predictive Maintenance, Industrial Engineering;

INTRODUCTION

Maintenance, in the context of industrial operations, refers to the systematic process of preserving equipment, machinery, and infrastructure to ensure functionality, performance, and reliability across the production lifecycle (Bokrantz & Skoogh, 2023) . In manufacturing environments, maintenance is not merely a corrective action but a strategic function designed to uphold operational continuity, asset longevity, and cost efficiency (Caballé & Castro, 2017). The International Organization for Standardization (ISO 14224:2016) defines maintenance as a "combination of all technical, administrative, and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function." Within smart manufacturing contexts—characterized by digital integration, automation, and data-driven decision-making—maintenance must evolve from conventional time-based or reactive frameworks to proactive, optimized models (Yazdi et al., 2019). The strategic importance of maintenance has been globally acknowledged as a pillar of industrial competitiveness and sustainability, as shown in multi-national initiatives such as Germany's Industrie 4.0, the United States' Advanced Manufacturing Partnership (AMP), and Japan's Society 5.0 (Borkowski et al., 2014).

Figure 1: Types of Maintenance in Industrial Operations: A Maturity-Based Framework for Smart Manufacturing



Smart manufacturing facilities embody the fusion of cyber-physical systems, automation technologies, artificial intelligence, and industrial IoT (IIoT), forming intelligent production environments capable of self-monitoring and self-optimization (Bokrantz & Skoogh, 2023). These environments require adaptive maintenance strategies that align with dynamic production conditions, diverse machine architectures, and continuous data influx from sensor-rich networks (Mollahassani-pour et al., 2017). Within this context, the role of Lean Manufacturing, Total Productive Maintenance (TPM), and digitally-augmented reliability frameworks becomes crucial in sustaining operational performance (Gelaw et al., 2023). TPM, initially formalized by (Zhong et al., 2015), emphasizes the collective responsibility of operators and maintenance teams to maximize equipment effectiveness and minimize unplanned downtime. Lean Manufacturing, grounded in the Toyota Production System, supports maintenance efficiency by reducing waste, standardizing workflows, and improving equipment availability (Filip & Marascu-Klein, 2015). Smart facilities integrate these foundational practices with advanced tools such as predictive analytics, machine learning, and real-time monitoring to ensure equipment health and production stability (Jiménez et al., 2021).

The global drive for maintenance optimization reflects industrial demands for increased productivity, reliability, and resource efficiency. Manufacturing remains a vital economic driver, accounting for 16% of global GDP and employing over 500 million people worldwide (Bhadu et al., 2021). The cost of unplanned equipment downtime, particularly in capital-intensive industries like automotive,

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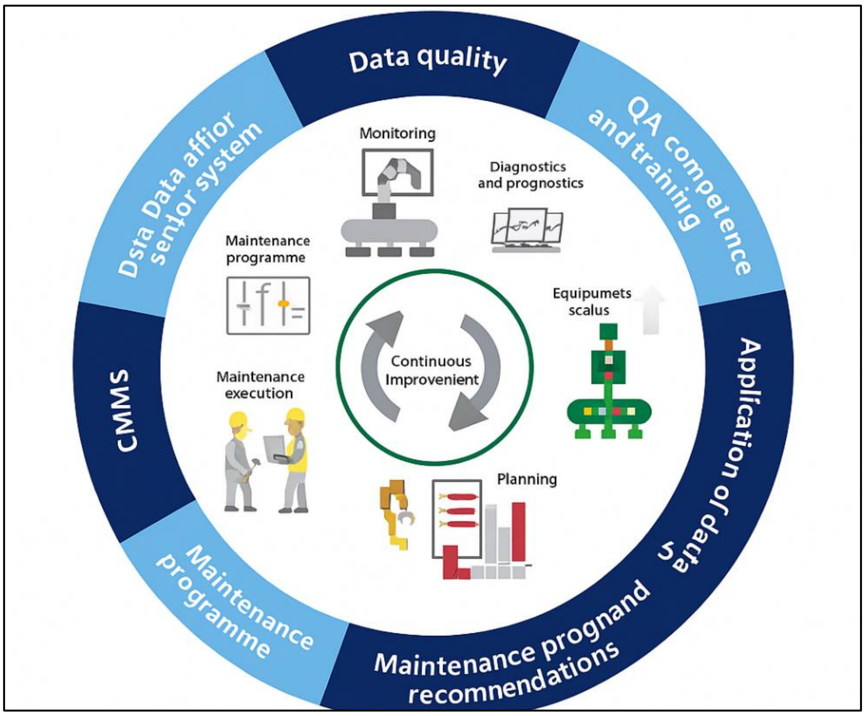
chemical, and semiconductor manufacturing, can range from $100,000 to over $1 million per hour (Masoud et al., 2025). Effective maintenance frameworks are essential to minimize such losses and uphold global supply chain continuity. In Europe, studies conducted under Horizon 2020 projects emphasize condition-based and predictive maintenance as crucial to achieving zero-defect manufacturing and circular economy targets (Mollahassani-pour et al., 2017). In Asia, the integration of smart maintenance systems in South Korea and China is linked to national goals in digital industrial transformation and technological self-reliance (Gelaw et al., 2023). Similarly, U.S.-based manufacturing firms adopting sensor-enabled maintenance report up to 20–30% increases in overall equipment effectiveness (OEE) and 40% reductions in downtime (Hussain et al., 2019).

Digitally-driven reliability models, including Condition-Based Maintenance (CBM), Predictive Maintenance (PdM), and Reliability-Centered Maintenance (RCM), are increasingly integrated into industrial engineering paradigms for asset lifecycle optimization (Rahman, 2015). These models rely on the continuous collection and analysis of machine performance data—such as vibration, temperature, pressure, and acoustic emissions—to assess real-time equipment health and predict potential failures before they occur (Wahab et al., 2013). Such predictive capabilities are enabled by machine learning algorithms that analyze historical and real-time data to detect patterns, anomalies, and degradation trends (Karam et al., 2018). Industrial engineering, with its emphasis on systems optimization, process efficiency, and human-machine integration, plays a pivotal role in designing and implementing these data-driven maintenance systems (Liza Ludeña et al., 2022). Scholars note that the application of digital twins, edge computing, and cloud-based diagnostics has further extended the scope of smart maintenance in distributed industrial settings (Syaifoelida et al., 2020).

Figure 2: Digitally-Driven Reliability Models in Industrial Engineering



Total Productive Maintenance remains a core philosophy in both traditional and digital manufacturing settings, underlining the need for autonomous maintenance, focused improvement, quality maintenance, and early equipment management (Alblooshi et al., 2022). TPM's original pillars—designed to maximize equipment effectiveness through cross-functional participation—have been digitally enhanced through mobile work orders, operator dashboards, and maintenance management systems that improve transparency and execution accuracy (Koç & Ecevit Alpar, 2023). In industrial engineering literature, TPM is often contextualized as a precursor to more advanced models, serving as a cultural and procedural foundation for data-enabled strategies (Jobin, 2015). Studies in automotive and electronics manufacturing show that companies that combine TPM principles with digital monitoring experience higher uptime, improved mean time between failure (MTBF), and reduced mean time to repair (MTTR) (Kose et al., 2022). These metrics directly impact productivity, worker safety, and cost control, further reinforcing the symbiotic relationship between TPM, Lean, and digital technologies.

Lean Maintenance, derived from Lean Manufacturing principles, focuses on eliminating waste from maintenance processes, such as unnecessary movement, redundant inspections, or excessive inventory (Robertsone et al., 2021). In industrial engineering applications, Lean Maintenance supports the standardization of processes, preventive task scheduling, and visual control systems for real-time status updates (Wahab et al., 2013). Its fusion with TPM creates a streamlined, employee-

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driven maintenance culture that aligns closely with Industry 4.0 objectives (Karam et al., 2018). Several case studies highlight Lean-TMP synergies where organizations achieved more than 90% OEE and significant maintenance cost reductions through the integration of 5S, SMED, and Just-in-Time (JIT) principles (Ludeña et al., 2022). Furthermore, Lean-oriented maintenance strategies improve organizational agility by simplifying workflows, increasing scheduling accuracy, and embedding continuous improvement practices across departments (Syaifoelida et al., 2020). As facilities increasingly rely on digital work instructions, CMMS (Computerized Maintenance Management Systems), and AI-based optimization engines, the relevance of Lean practices as a support framework remains evident. While digitally-enabled maintenance is often associated with high-capital smart factories, its conceptual frameworks and applied models are deeply rooted in industrial engineering theories of systems optimization and resource allocation (Alblooshi et al., 2022). Scholars argue that maintenance must be designed as an integrated socio-technical system, where digital tools complement, rather than replace, human expertise (Rahman, 2015). Studies in sectors ranging from aerospace to food processing demonstrate the positive impacts of data-driven maintenance on system reliability, energy consumption, and compliance with regulatory standards (Ludeña et al., 2022). Moreover, advancements in wireless sensor networks, edge analytics, and fault detection algorithms contribute to a more responsive, adaptive maintenance infrastructure within cyber-physical systems (Filip & Marascu-Klein, 2015). These developments illustrate the importance of merging classical engineering insights with emerging digital technologies in optimizing maintenance performance at scale. The primary objective of this systematic review is to critically investigate and synthesize the maintenance optimization strategies employed in smart manufacturing environments, with a specific emphasis on the integration of Lean Manufacturing, Total Productive Maintenance (TPM), and digitally-enabled reliability models within the industrial engineering framework. This review seeks to answer how these maintenance paradigms have evolved and been adapted in response to the increased complexity of modern industrial systems and the proliferation of Industry 4.0 technologies. With smart manufacturing facilities increasingly relying on cyber-physical systems, Internet of Things (IoT) devices, artificial intelligence, and real-time analytics, traditional maintenance approaches must now coexist and converge with digital models that enable predictive, condition-based, and autonomous maintenance planning. Consequently, the objective is to map the scholarly landscape to determine the theoretical underpinnings, implementation methodologies, and measurable outcomes associated with each model, as well as the synergies and trade-offs between them.

LITERATURE REVIEW

The literature surrounding maintenance optimization in industrial engineering has evolved significantly with the emergence of smart manufacturing technologies and Industry 4.0 paradigms. Historically rooted in reactive and preventive maintenance approaches, the field has transitioned towards more predictive, condition-based, and autonomous strategies that leverage real-time data analytics, artificial intelligence, and interconnected sensor systems. This evolution reflects a growing recognition of maintenance as a strategic enabler of operational excellence, rather than a purely technical or corrective function. Within the industrial engineering domain, maintenance optimization is closely tied to broader performance metrics such as Overall Equipment Effectiveness (OEE), equipment availability, productivity, and resource efficiency. The integration of traditional philosophies like Lean Manufacturing and Total Productive Maintenance (TPM) with advanced digital technologies creates a hybrid maintenance model capable of responding to the complexity and dynamism of smart manufacturing environments. This literature review aims to examine the progression and intersection of Lean, TPM, and digitally-driven reliability models within the context of smart manufacturing. It synthesizes scholarly research, empirical studies, and theoretical frameworks to provide a coherent understanding of how these models contribute to maintenance performance across diverse industrial sectors. The review is structured to trace the conceptual foundations of each model, highlight their evolution, analyze their current applications in digitally-enabled settings, and identify gaps and future research directions. Emphasis is placed on the interplay between human-centered practices and technology-driven automation, as well as the impact of these maintenance strategies on system reliability, cost control, and asset lifecycle optimization. Each sub-section of the review is organized to reflect a logical progression from theory to practice, offering a multi-dimensional perspective on maintenance optimization in smart manufacturing facilities.

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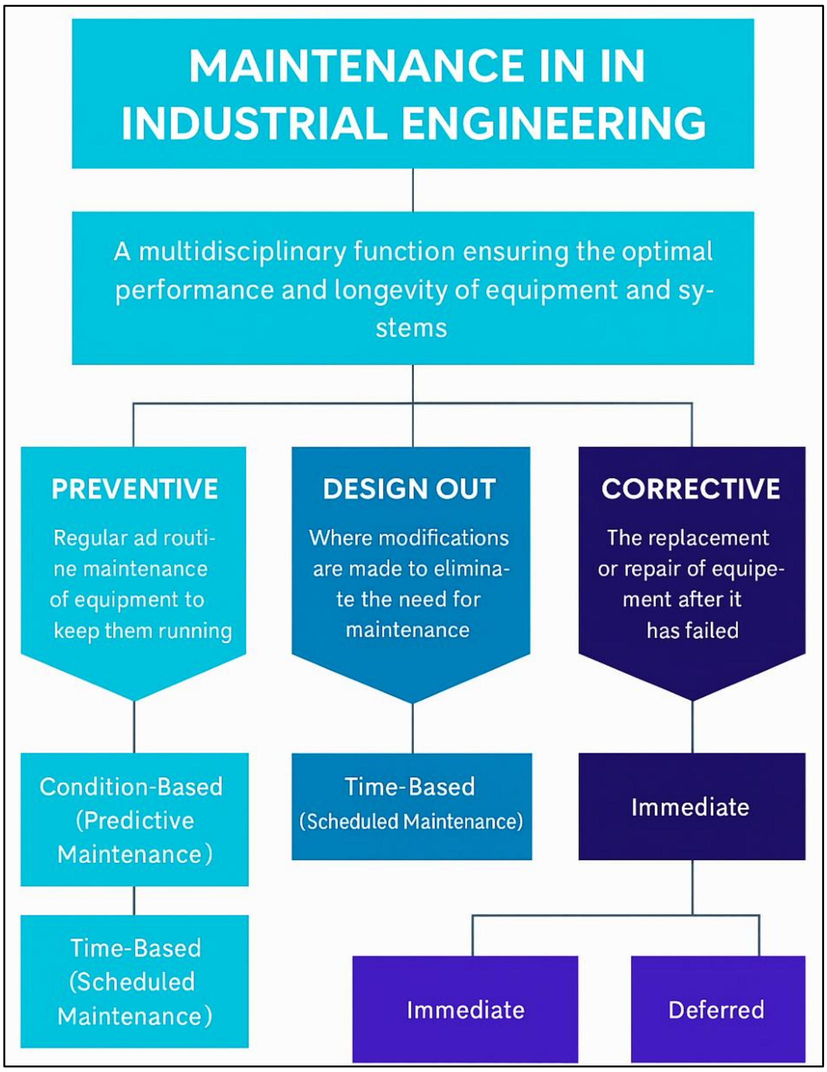
Maintenance in Industrial Engineering

Maintenance within industrial engineering is understood as a multidisciplinary function encompassing the technical, managerial, and operational actions necessary to ensure the optimal performance and longevity of equipment and systems. As industrial systems become more complex and capital-intensive, maintenance plays a critical role in supporting continuous production, minimizing equipment failures, and reducing overall operational costs (Jiménez et al., 2021). The ISO 55000 series emphasizes maintenance management as a strategic part of asset management systems, further reinforcing its integral position in industrial engineering frameworks. From a systems engineering perspective, maintenance is not an isolated task but a structured process requiring real-time monitoring, failure analysis, preventive strategies, and data-informed decisions (Masoud et al., 2025). Industrial engineers focus on optimizing maintenance through quantitative modeling, reliability assessments, cost-benefit analyses, and human-machine interaction frameworks (Mollahassani-pour et al., 2017). Scholars argue that maintenance should be embedded in the early design and planning phases of industrial operations, with integrated feedback loops that support performance-based maintenance strategies (Gelaw et al., 2023). The rise of system reliability engineering has further advanced the analytical capabilities for assessing component failure rates and optimizing replacement intervals, establishing the foundation for condition-based and predictive maintenance (Hussain et al., 2019). Maintenance performance metrics such as Mean Time To Repair (MTTR), Mean Time Between Failures (MTBF), and Overall Equipment Effectiveness (OEE) are regularly utilized within industrial engineering to measure effectiveness and guide continuous improvement (Wahab et al., 2013). These metrics not only support operational excellence but also serve as key indicators of productivity, efficiency, and asset utilization across various manufacturing sectors (Karam et al., 2018).

Figure 3: Maintenance Management Strategies in Industrial Engineering



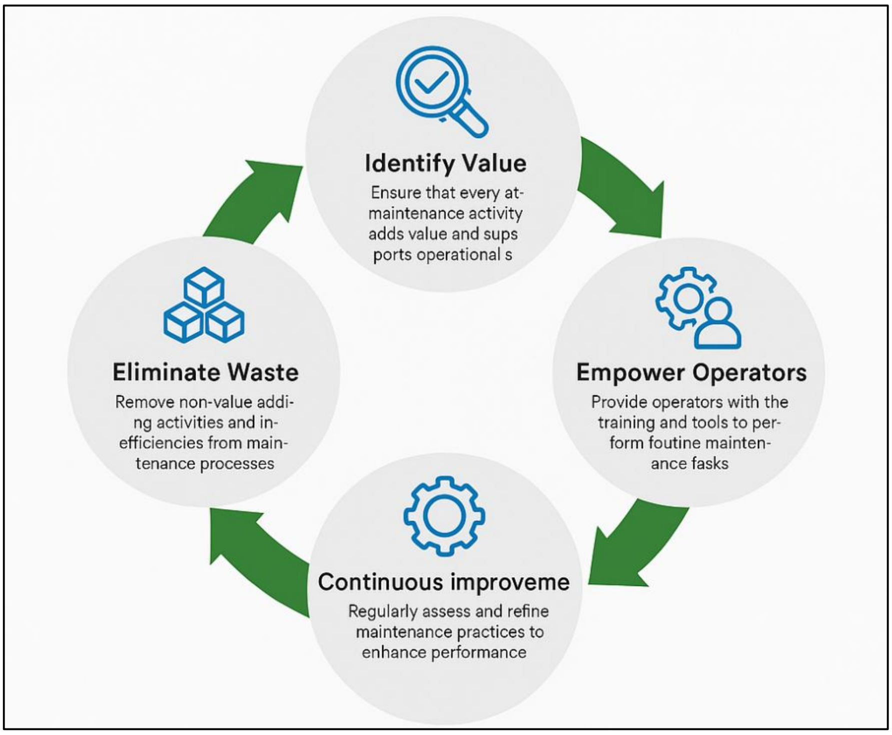
In the manufacturing context, maintenance is essential for preserving production capacity and achieving cost competitiveness, especially as production lines grow more automated and interconnected (Syaifoelida et al., 2020). Researchers highlight that manufacturing firms allocate up to 15–70% of their production costs to maintenance-related activities, illustrating the magnitude of its economic impact (Rahman, 2015). From an industrial engineering viewpoint, strategic maintenance involves aligning maintenance planning with organizational goals, resource allocation, and production scheduling (Mollahassani-pour et al., 2017). Lean-oriented firms emphasize maintenance as a critical enabler of waste reduction, quality improvement, and value flow, particularly under Just-In-Time (JIT) production systems (Hussain et al., 2019). In TPM environments, the involvement of operators in routine equipment care is linked to increased machine availability and reduced reliance on reactive interventions (Rodrigues & Hatakeyama, 2006). Research shows that companies implementing TPM combined with industrial engineering tools such as root cause analysis, Six Sigma, and FMEA (Failure Modes and Effects Analysis) achieve significantly improved system reliability and reduced machine breakdowns (Borkowski et al., 2014). Moreover, digital integration through maintenance information systems, enterprise resource planning (ERP), and computerized maintenance management systems (CMMS) has allowed for seamless tracking of maintenance activities and cost analytics (Xu et al., 2019). Maintenance scheduling models and simulation tools—common in industrial engineering—enhance the precision of preventive maintenance planning, particularly in complex systems such as multi-machine production cells or automated robotic assembly lines (Rahman, 2015). These practices demonstrate how maintenance, when embedded into the strategic fabric of operations, enhances production resilience and asset productivity.

The optimization of maintenance strategies has been a persistent focus in industrial engineering research, with scholars developing mathematical, probabilistic, and simulation-based models to determine optimal inspection intervals, spare parts allocation, and system reliability. Preventive maintenance models, such as age-based and condition-based policies, use reliability data to predict component failures and minimize unnecessary maintenance costs (Kose et al., 2022). Reliability-Centered Maintenance (RCM) frameworks have gained traction due to their focus on function-oriented decision-making, criticality analysis, and failure consequence evaluation. Studies show that combining RCM with real-time sensor data and machine learning algorithms increases diagnostic accuracy and improves predictive capabilities (Ahmadi et al., 2010). Industrial engineers also utilize queuing theory, Markov chains, and optimization algorithms to model system behavior under various maintenance policies. In high-reliability sectors such as aerospace and semiconductor manufacturing, maintenance optimization is tightly linked to system performance metrics, where even minor unavailability can lead to significant economic losses. The use of integer programming and genetic algorithms has also been applied to optimize complex maintenance schedules, particularly in environments with resource and manpower constraints (Wu & Castro, 2020). Moreover, industrial engineering literature emphasizes the importance of integrating maintenance models with production and inventory systems, where downtime can disrupt order fulfillment and lead to significant lead-time variability (Alsubaie & Yang, 2017). The continuous development of such models reflects the strategic imperative of maintenance as a lever for operational efficiency and process control.

Lean Manufacturing Principles in Maintenance Optimization

Lean Manufacturing, originally derived from the Toyota Production System (TPS), is grounded in the principle of waste minimization without sacrificing productivity or quality. Within the realm of maintenance, Lean principles are applied to identify and eliminate non-value-adding activities, streamline processes, and enhance equipment availability (Filip & Marascu-Klein, 2015). The 8 types of waste—overproduction, waiting, transportation, overprocessing, inventory, motion, defects, and underutilization of people—are increasingly mapped in maintenance contexts to reduce downtime and redundant activities (Jiménez et al., 2021). The application of Lean in maintenance leads to the creation of Lean Maintenance (LM), a structured approach where preventive, predictive, and autonomous maintenance tasks are integrated within lean thinking frameworks. Lean Maintenance aims to optimize maintenance schedules, reduce spare parts inventory, and empower operators through visual management and standard work protocols. Practices such as 5S (Sort, Set in order, Shine, Standardize, Sustain) and Visual Factory are foundational Lean tools that enhance maintenance workplace organization and eliminate unnecessary searching time, directly contributing to improved Mean Time to Repair (MTTR) and Mean Time Between Failures (MTBF) (Bhadu et al., 2021). Empirical studies from discrete manufacturing sectors, including electronics and automotive, report significant improvements in Overall Equipment Effectiveness (OEE) through the adoption of Lean Maintenance practices (Masoud et al., 2025). Lean thinking not only reduces physical waste but also enhances maintenance responsiveness and strategic alignment with production goals. The application of value stream mapping (VSM) to maintenance workflows allows organizations to visualize and remove bottlenecks in repair, inspection, and work order generation processes.

Figure 4: Lean Maintenance Principles in Industrial Engineering



The convergence of Lean Manufacturing and Total Productive Maintenance (TPM) in maintenance optimization creates a synergistic approach aimed at reducing unplanned downtime, improving equipment reliability, and enhancing workforce involvement. TPM, which advocates for the participation of all employees in maintenance activities, complements Lean's focus on efficiency by embedding maintenance tasks into the daily responsibilities of operators and line staff (Kose et al., 2022). Researchers have demonstrated that integrating TPM pillars—such as autonomous maintenance, planned maintenance, and focused improvement—within Lean frameworks helps develop maintenance systems that are both cost-efficient and resilient (Robertsone et al., 2021). For instance, Lean's Just-in-Time (JIT) principles support TPM's emphasis on eliminating over-maintenance and ensuring parts availability only when needed, thereby optimizing spare parts logistics and minimizing storage waste (Wahab et al., 2013). Several studies point to the effectiveness of 5S and Kaizen events in both standardizing maintenance routines and increasing employee ownership of maintenance outcomes. Furthermore, Single-Minute Exchange of Dies (SMED), a Lean technique, is often employed alongside TPM to reduce changeover times and equipment unavailability (Karam et al., 2018). Data from case studies in the chemical, food, and beverage industries suggest that organizations adopting a Lean-TPM hybrid approach have achieved OEE improvements exceeding 20%, while also reducing unplanned maintenance by more than 30% (Ludeña et al., 2022). The use of Total Involvement Maintenance (TIM) and cross-training, another feature of Lean-TPM systems, further reduces skill gaps and enables more responsive maintenance execution (Alblooshi et al., 2022). This integration aligns with industrial engineering objectives, such as process standardization, reliability improvement, and system optimization.

Metrics play a vital role in Lean Maintenance systems, providing quantitative benchmarks for tracking performance and identifying continuous improvement opportunities. Key performance indicators (KPIs) in Lean Maintenance include Overall Equipment Effectiveness (OEE), Total Maintenance Cost per Unit, Preventive Maintenance Compliance (PMC), and schedule adherence (Koç & Ecevit Alpar, 2023). These indicators are used not only to assess current performance but also to facilitate root cause analysis, Pareto charting, and process control interventions commonly employed by industrial engineers (Jobin, 2015). OEE, which combines availability, performance, and quality rates, is particularly important in Lean environments, as it directly reflects the operational impact of maintenance activities. Lean Maintenance promotes the use of daily maintenance audits, performance dashboards, and Gemba walks to increase transparency, accountability, and responsiveness (Saini & Singh, 2020). Empirical studies from high-mix, low-volume production systems show that continuous improvement tools such as PDCA (Plan-Do-Check-Act) and visual KPIs enhance fault detection and reduce response time (Keramida et al., 2023). Additionally, organizations leveraging Lean metrics in maintenance often deploy digital tools—such as CMMS (Computerized Maintenance Management Systems) and mobile maintenance applications—to monitor and visualize these KPIs in real time (Wahab et al., 2013). Studies conducted across Asia and

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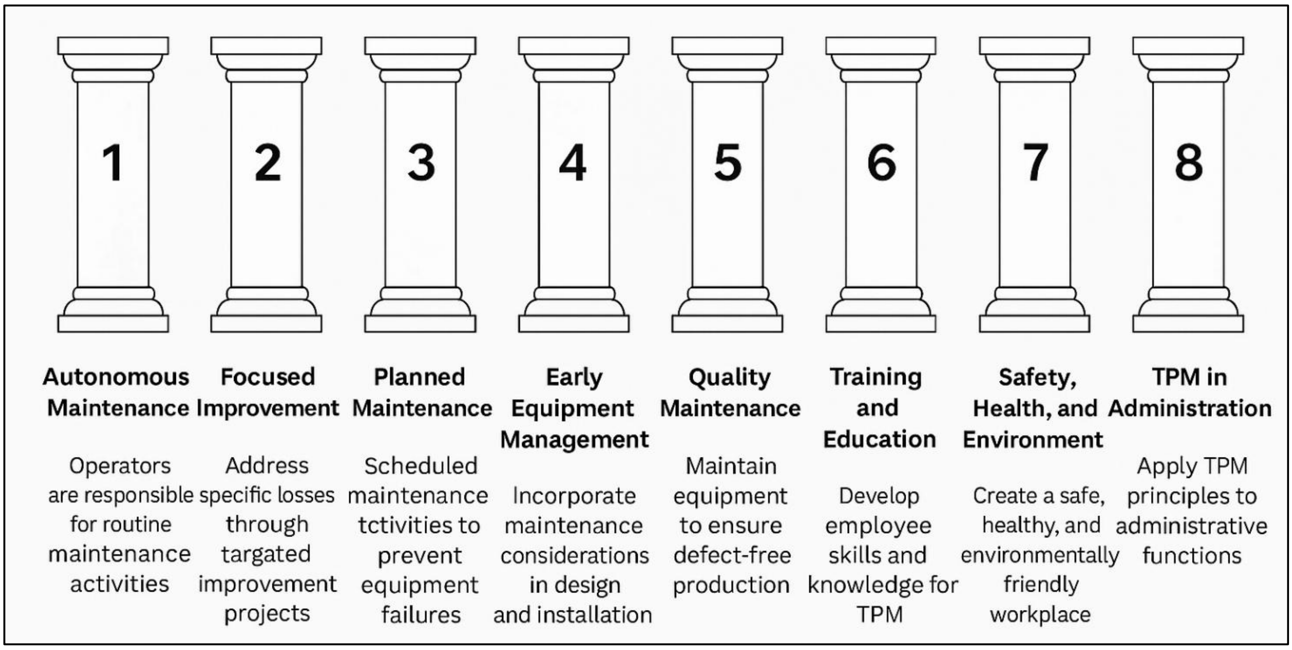
Europe report that Lean Maintenance systems supported by such tools lead to maintenance cost reductions ranging from 10% to 35% annually, while also decreasing emergency work orders (Karam et al., 2018). Continuous improvement, when institutionalized through Lean Maintenance frameworks, becomes a powerful driver for equipment reliability, worker empowerment, and systemic resilience.

Total Productive Maintenance (TPM) in Manufacturing Systems

Total Productive Maintenance (TPM), initially developed in Japan and formalized by Rodrigues and Hatakeyama (2006), is a holistic approach to equipment maintenance that seeks to maximize productivity by involving all levels of an organization. TPM is built on eight foundational pillars, including autonomous maintenance, focused improvement, quality maintenance, planned maintenance, and early equipment management, among others, which together aim to achieve zero breakdowns, zero defects, and zero accidents (Borkowski et al., 2014). Unlike traditional maintenance systems that assign maintenance tasks solely to specialized technicians, TPM promotes the involvement of machine operators in routine checks, cleaning, and minor repairs, fostering a sense of ownership and equipment awareness (Xu et al., 2019). Research shows that this cross-functional collaboration enhances both operator morale and equipment reliability, particularly in high-throughput environments such as automotive and electronics manufacturing (Gelaw et al., 2023). Autonomous maintenance, one of the core TPM pillars, is strongly linked to improved Overall Equipment Effectiveness (OEE), especially when implemented in conjunction with Lean practices such as 5S and visual management systems (Konecny & Thun, 2011).

Figure 5: The Eight Pillars of Total Productive Maintenance (TPM)



Moreover, TPM's emphasis on planned maintenance activities—such as scheduled overhauls and usage-based interventions—helps extend equipment life and reduce Mean Time Between Failures (MTBF) (Singh & Ahuja, 2014). In food, beverage, and chemical manufacturing, TPM has proven effective in minimizing unplanned downtime and aligning maintenance execution with stringent hygiene and safety regulations (Kinney, 2006). The structured nature of TPM, combined with its integration of human factors and process standardization, positions it as a foundational strategy in the broader field of industrial maintenance engineering.

Empirical studies across multiple industrial sectors affirm that the implementation of TPM leads to substantial improvements in productivity, quality, and maintenance efficiency. For instance, in a study of Indian manufacturing firms, Ferrua-Breña et al. (2021) found that TPM implementation resulted in a 50% reduction in machine breakdowns and a 35% increase in OEE. Similar results were documented in the European automotive sector, where TPM was associated with a 40% decline in emergency maintenance calls and a 25% improvement in first-pass yield (Kumar et al., 2014). In the

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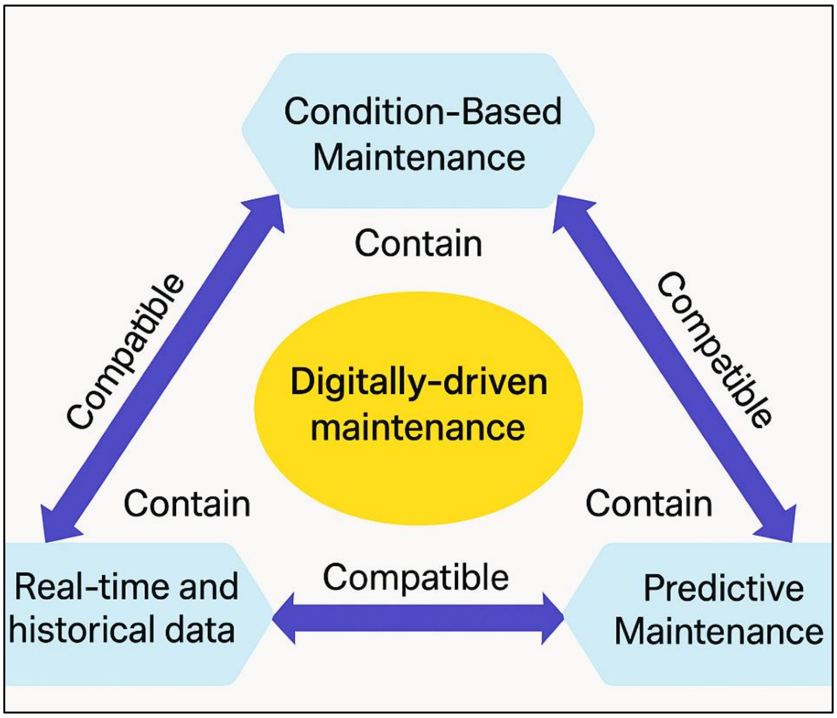
context of resource-intensive sectors such as cement and mining, TPM has been reported to enhance workforce utilization and reduce unplanned stoppages, contributing to better throughput and equipment availability (Sun et al., 2003). However, the successful implementation of TPM is often hindered by several challenges, including organizational resistance to change, lack of training, insufficient cross-departmental communication, and limited senior management engagement (Ribeiro et al., 2019). Studies also highlight that firms in developing economies face additional constraints such as low automation maturity and inconsistent data collection practices, which limit the scalability of TPM practices (Hardt et al., 2021; Purwanto & Jaqin, 2021). To mitigate these issues, researchers suggest adopting TPM Maturity Models and phased implementation strategies to align goals across departments and track performance incrementally (Hardt et al., 2021). Furthermore, the integration of TPM with digital platforms like CMMS and IoT-based condition monitoring tools enhances scheduling accuracy and allows real-time diagnostics, thus improving preventive maintenance compliance (Thomas et al., 2006). Evidence from Asia and South America shows that companies leveraging these integrations achieve superior maintenance performance, especially when TPM is tailored to the plant's operational context and workforce capacity (Barriga et al., 2024). The collective body of literature underscores that TPM remains a vital framework for structured, participative, and performance-driven maintenance in modern manufacturing systems.

Digitally-Driven Maintenance Models

Digitally-driven maintenance represents a significant shift from traditional preventive and reactive models to proactive and intelligence-based systems, enabled by data analytics, sensor technologies, and cyber-physical integration (Jakaria et al., 2025). Central to this evolution are Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) frameworks, which rely on real-time and historical data to evaluate equipment health and forecast potential failures (Bashar et al., 2020; Siddiqui et al., 2023). CBM utilizes inputs from vibration analysis, thermography, oil analysis, and acoustic monitoring to assess current asset conditions and trigger interventions only when needed, reducing unnecessary downtime and maintenance costs (Alsubaie & Yang, 2017; Bhuiyan et al., 2025). PdM advances this concept by using statistical methods, machine learning algorithms, and prognostic models to predict the Remaining Useful Life (RUL) of components (Sohel, 2025; Willmott & McCarthy, 2001). The adoption of digitally-driven models is accelerated by the growing availability of Industrial Internet of Things (IIoT) infrastructure, which facilitates seamless data collection from distributed assets and supports cloud-based analytics (Jain et al., 2015; Hossen et al., 2023). In complex manufacturing systems, these models enhance asset reliability and align maintenance operations with production goals, contributing to Overall Equipment Effectiveness (OEE) and Mean Time Between Failures (MTBF) (Gupta & Vardhan, 2016; Saiful et al., 2025). Reliability-Centered Maintenance (RCM), while older in origin, has been digitally extended to incorporate risk-based decision models and integrated diagnostic capabilities (Masud, 2022; Singh & Gurtu, 2021). These approaches emphasize functionality, failure modes, and criticality, offering structured pathways to optimize maintenance tasks within industrial engineering (Md et al., 2025). Collectively, the literature reveals that digital maintenance frameworks enhance system

Figure 6: Digitally-Driven Maintenance Ecosystem



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visibility, reduce maintenance backlogs, and enable agile responses to asset performance variations (Bashar et al., 2020; Alam et al., 2023).

Artificial Intelligence (AI) and machine learning have become pivotal in advancing predictive maintenance capabilities, enabling maintenance systems to transition from rule-based models to data-driven prognostics (Siddiqui, 2025). Supervised and unsupervised machine learning algorithms are widely used to process large datasets from sensors, extract patterns, and detect early signs of equipment degradation (Islam et al., 2025; Stavropoulos et al., 2022). Algorithms such as Support Vector Machines (SVM), Random Forest, k-Nearest Neighbors (k-NN), and neural networks are frequently deployed for classification and regression tasks in maintenance diagnostics (Islam et al., 2025; Cifuentes et al., 2024). Deep learning architectures, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, are particularly effective in analyzing time-series sensor data for fault prediction and anomaly detection (Shofiullah et al., 2024; Yazdi et al., 2019). These intelligent systems are also integrated with prognostic health management (PHM) frameworks to estimate Remaining Useful Life (RUL) and optimize maintenance intervals (Cooper, 2023; Islam et al., 2024). In aerospace and automotive industries, where asset failure can result in catastrophic outcomes, these AI-enhanced tools have significantly improved reliability metrics and reduced unscheduled maintenance events (Jahan, 2024; Kim & Hong, 2024). AI-based diagnostics are often embedded into Computerized Maintenance Management Systems (CMMS) and cloud platforms, facilitating real-time decision-making and automated alert generation (Islam, 2024; Stavropoulos et al., 2022). Moreover, digital twins—virtual replicas of physical assets—allow predictive simulations and maintenance scenario analysis based on live operational data, creating a closed-loop system for continuous improvement. The growing body of research highlights the role of AI in reducing maintenance labor, improving equipment availability, and supporting cost-effective lifecycle management across diverse industrial sectors (Hossain et al., 2024; Cifuentes et al., 2024).

The integration of Industrial Internet of Things (IIoT), cloud computing, and real-time analytics has transformed maintenance systems into adaptive, interconnected networks capable of autonomous performance tracking and decision-making. IIoT devices—comprising embedded sensors, RFID tags, and actuators—enable real-time data acquisition on critical parameters such as temperature, vibration, humidity, and power consumption, creating a digital footprint of asset health (Hasan et al., 2024; Yazdi et al., 2019). Cloud platforms serve as centralized hubs for aggregating and processing these data streams, offering scalable infrastructure for storage, analytics, and visualization dashboards (Balogun & Attoh-Okine, 2023; Dasgupta et al., 2024). Edge computing further enhances system responsiveness by conducting localized analysis close to the source of data, reducing latency in time-sensitive maintenance decisions (Cooper, 2023; Jahan, 2023). Studies across manufacturing sectors demonstrate that this architecture enhances predictive maintenance accuracy, increases data-driven insights, and reduces mean time to repair (MTTR) (Chowdhury et al., 2023; Cooper, 2023; Koković et al., 2024). In industrial engineering literature, this convergence supports a shift toward Maintenance 4.0—an intelligent, connected, and decentralized framework that enables condition-aware scheduling and self-diagnosing systems (Kim & Hong, 2024; Sohel et al., 2022). Integration with Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) further ensures that maintenance activities are aligned with production planning, labor allocation, and supply chain logistics (Ullah et al., 2023). Real-time analytics tools such as predictive dashboards, heat maps, and trend analysis applications empower maintenance personnel to proactively monitor system performance and prioritize interventions (Mourtzis et al., 2020). Researchers also point out that cybersecurity, data governance, and interoperability standards are essential in enabling the secure and seamless implementation of such digitally-integrated maintenance systems (Shafique et al., 2020). The literature affirms that the fusion of IIoT, cloud technologies, and analytics represents a cornerstone of modern maintenance engineering strategies in smart manufacturing.

Artificial Intelligence and Machine Learning in Smart Maintenance

Artificial Intelligence (AI) plays a pivotal role in the transformation of traditional maintenance strategies into smart, data-driven systems that enable predictive diagnostics and autonomous decision-making (Roksana et al., 2024). In smart manufacturing, AI contributes to the automation of condition monitoring, fault detection, and remaining useful life (RUL) estimation, offering a major improvement over manual inspection or fixed-interval maintenance (Bhuiyan et al., 2024; Stavropoulos et al., 2022). AI systems rely on real-time sensor data collected from machines and

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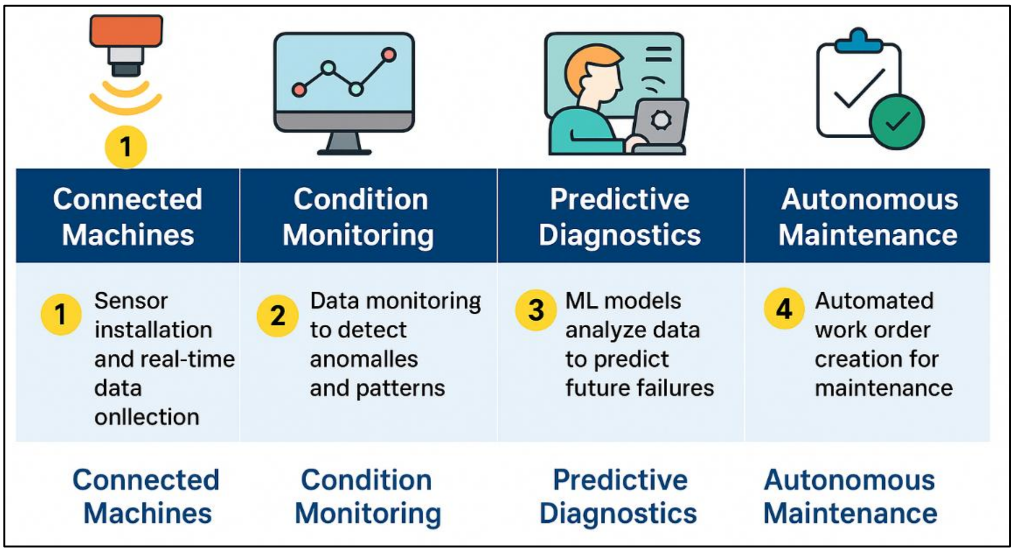
equipment to process anomalies, learn behavioral patterns, and forecast failures with a high degree of precision (Cifuentes et al., 2024; Sarker, 2025). Tools such as expert systems, fuzzy logic, and Bayesian networks were among the first to model maintenance knowledge bases and uncertainty in fault analysis (Sarker et al., 2023; Yazdi et al., 2019). However, contemporary approaches focus on machine learning, where the system learns iteratively from labeled or unlabeled datasets to make predictions (Ammar et al., 2024; Balogun & Attoh-Okine, 2023). As noted by Cooper (2023), AI-driven maintenance enables a shift from time-based to condition-based strategies, allowing systems to self-adjust according to contextual data inputs. Research in aerospace, automotive, and energy industries has shown that AI-enhanced maintenance improves reliability indices, reduces emergency repairs, and enhances cost-efficiency by eliminating unnecessary inspections (Kim & Hong, 2024; Koković et al., 2024). Integration with industrial control systems and cloud-based platforms enables seamless communication between AI models and operational teams, thus supporting real-time maintenance execution and dashboard-based visualization (Roksana, 2023; Ullah et al., 2023). These AI applications are now considered essential for achieving Maintenance 4.0 standards, where predictive, autonomous, and self-optimizing capabilities define the reliability culture within Industry 4.0 frameworks (Maniruzzaman et al., 2023; Mourtzis et al., 2020).

Figure 7: Integration of AI and Machine Learning in Predictive Maintenance Systems



Machine learning (ML), a subfield of AI, is instrumental in building predictive maintenance models that can analyze equipment behavior and forecast future failures based on historical and real-time data (Arafat Bin et al., 2023). Supervised learning models such as Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting algorithms are frequently used for classification and regression tasks, including the prediction of failure types, severity, and time to failure (Balogun & Attoh-Okine, 2023; Kumar et al., 2022). These models rely on labeled datasets where known failure outcomes are used to train the system, making them particularly effective in structured maintenance datasets (Hossen & Atiqur, 2022; Zhai et al., 2021). On the other hand, unsupervised learning models such as k-Means, Hierarchical Clustering, and Principal Component Analysis (PCA) help detect anomalies or hidden patterns in unlabeled datasets, enabling early detection of abnormal behavior in machinery (Koković et al., 2024; Majharul et al., 2022). In addition, semi-supervised learning approaches are emerging in situations where labeled data is scarce but model accuracy is still required (Galarza-Falfan et al., 2024; Mahfuj et al., 2022). Deep learning, a rapidly evolving area within ML, involves neural networks such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, which have demonstrated excellent performance in analyzing sequential sensor data and performing time-series forecasting (Aklima et al., 2022; Mourtzis, Tsoubou, et al., 2023). Studies show that LSTM-based models outperform traditional regression approaches in RUL estimation, especially in complex manufacturing environments with high data variability (Galarza-Falfan et al., 2024; Helal et al., 2025; Shahin et al., 2023). Furthermore, hybrid models that integrate statistical and ML techniques offer robustness and interpretability, essential for industrial stakeholders to act on AI-generated insights (Mourtzis, Tsoubou, et al., 2023; Shipu et al., 2024). These predictive analytics frameworks enhance maintenance planning accuracy and reduce costly equipment failures, particularly in capital-intensive sectors such as transportation, chemical processing, and power generation (Dey et al., 2024).

The effectiveness of AI and ML applications in smart maintenance is heavily dependent on the quality and relevance of input data. Maintenance-related data are typically sourced from condition monitoring systems, which include vibration sensors, acoustic emission sensors, infrared thermography, ultrasonic detectors, and oil particle analyzers (Bhowmick & Shipu, 2024; Shahin et al., 2023). These heterogeneous data streams must be preprocessed and transformed into meaningful features before being fed into machine learning models—a process known as feature engineering (Islam & Helal, 2018; Mourtzis, Tsoubou, et al., 2023). Proper feature extraction helps the algorithm understand the relationships between equipment conditions and failure events, significantly improving model accuracy (Ahmed et al., 2022; Galarza-Falfan et al., 2024). For example, time-domain, frequency-domain, and time-frequency domain features are commonly used in rotating machinery diagnostics, especially in the detection of bearing and gear faults (Koković et al., 2024; Shahan et al., 2023). Domain knowledge from industrial engineering is crucial during this phase to identify relevant variables such as operating pressure, motor current, shaft misalignment, or thermal load that contribute to degradation (Hossain et al., 2024; Zhai et al., 2021). Data fusion techniques are also applied when information is gathered from multiple sources, such as SCADA systems, CMMS logs, and environmental sensors, to develop a more holistic picture of machine behavior (Balogun & Attoh-Okine, 2023; Sharif et al., 2024). Furthermore, anomaly labeling—critical for supervised model training—is often conducted through collaboration between maintenance engineers and data scientists using visual inspection, historical failure records, and expert judgment (Faria & Rashedul, 2025; Mourtzis, Angelopoulos, et al., 2023). These collaborative approaches ensure that AI models are not only statistically robust but also operationally relevant. Accurate preprocessing, dimensionality reduction, and feature selection thus constitute foundational tasks that determine the practical value and interpretability of AI-driven maintenance systems ((Khan, 2025; Serror et al., 2021).

Cyber-Physical Systems and Maintenance Information Systems

Cyber-Physical Systems (CPS) serve as the technological backbone of smart maintenance by integrating physical assets, computational models, and communication networks into cohesive systems capable of real-time monitoring, diagnosis, and decision-making (Dafflon et al., 2021). A CPS enables the collection and processing of high-resolution data from embedded sensors, actuators, and controllers installed in industrial equipment (Villalonga et al., 2021). These systems facilitate bidirectional communication between the physical layer and digital components through edge computing, IIoT frameworks, and cloud platforms (Vachálek et al., 2021). In the context of maintenance, CPS enable the creation of intelligent systems that support autonomous fault detection, remote diagnostics, and predictive decision-making based on current operating conditions (de Oliveira et al., 2024). A key advantage of CPS is their ability to operate in distributed environments and synchronize multiple subsystems across different machinery and locations, thereby optimizing resource allocation and system-level reliability (Tao et al., 2019). CPS also support the integration of digital twins—virtual replicas of physical machines—which simulate asset behavior and predict failure scenarios, enhancing maintenance strategy design. These dynamic digital models update continuously through sensor feedback and provide interactive environments for scenario analysis, reducing trial-and-error in maintenance scheduling (Alcaraz & Lopez, 2022). In smart manufacturing environments, CPS contribute to Maintenance 4.0 principles by enabling context-aware and adaptive interventions that reduce Mean Time to Repair (MTTR) and increase Mean Time Between Failures (MTBF) (Somers et al., 2023). The real-time diagnostic capability of CPS enhances agility and decision accuracy, especially in mission-critical sectors like aerospace, oil and gas, and semiconductor manufacturing (Suhail et al., 2023). These findings collectively underscore the foundational role of CPS in transforming traditional reactive maintenance into a proactive, intelligent, and scalable system in line with Industry 4.0 goals.

Maintenance Information Systems (MIS), including Computerized Maintenance Management Systems (CMMS) and Enterprise Asset Management (EAM) platforms, have become indispensable tools for planning, executing, and evaluating maintenance activities in smart factories. CMMS software is designed to store equipment histories, track preventive maintenance schedules, manage

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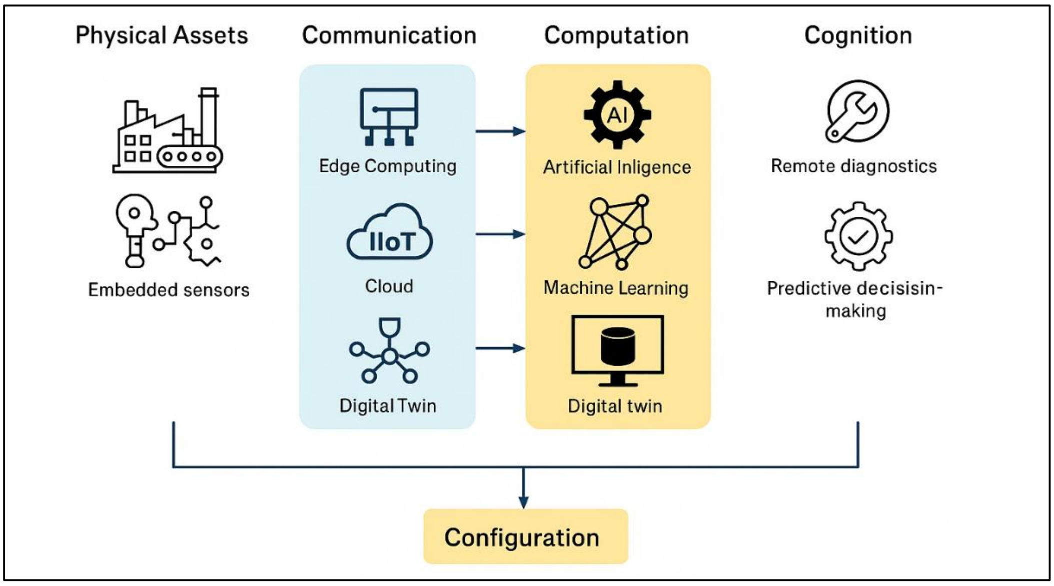
spare parts inventories, and generate maintenance work orders based on predefined criteria or sensor-triggered events (Vachálek et al., 2021). These systems are increasingly cloud-enabled and integrated with mobile applications, allowing technicians to access maintenance records and update task completion in real time from field locations (de Oliveira et al., 2024). Advanced MIS platforms often incorporate dashboard interfaces, KPI monitoring tools, and analytics engines that provide actionable insights into maintenance performance, compliance rates, and failure patterns (Tao et al., 2019).

Figure 8: Cyber-Physical Systems Architecture for Intelligent Maintenance and Decision-Making in Smart Manufacturing



When integrated with Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES), MIS ensures the synchronization of maintenance activities with production schedules, inventory management, and financial planning (Melesse et al., 2021). Predictive maintenance modules within modern MIS leverage machine learning models and sensor data to automatically recommend interventions based on asset condition, thus eliminating the guesswork associated with traditional time-based approaches (Roy et al., 2020). Furthermore, mobile-enabled MIS platforms empower frontline workers to perform autonomous maintenance and collaborate with supervisors in real time, reducing delays in fault reporting and corrective action (Minerva & Crespi, 2021). Industry case studies demonstrate that the use of CMMS reduces maintenance downtime by up to 30% and improves work order completion rates by over 40% when aligned with predictive analytics tools (Kuruvatti et al., 2022). The convergence of MIS, CPS, and IoT not only enhances transparency and traceability in maintenance operations but also facilitates continuous improvement through real-time data feedback loops and historical trend analysis (Bellavista et al., 2024).

Traditional vs. Digitally-Enhanced Maintenance Strategies

Traditional maintenance strategies—including corrective maintenance, time-based preventive maintenance (TBPM), and basic reliability-centered maintenance (RCM)—have long served as the foundation of industrial asset management. Corrective maintenance responds to failures after they occur, often resulting in extended downtimes, high repair costs, and reduced equipment life (Lu et al., 2020). Preventive maintenance, though more proactive, often follows rigid schedules irrespective of equipment condition, leading to unnecessary part replacements and inefficient resource usage (Alcaraz & Lopez, 2022). These methods rely heavily on historical maintenance logs and expert judgment, lacking real-time input and predictive capabilities (Minerva et al., 2020). In contrast, digitally-enhanced maintenance strategies leverage data from cyber-physical systems (CPS), machine learning algorithms, and real-time analytics to make dynamic, context-aware decisions. Technologies such as condition-based maintenance (CBM), predictive maintenance (PdM), and digital twins allow for more accurate failure prediction, optimized scheduling, and improved equipment utilization. While traditional models prioritize routine and reactive tasks, digitally-driven

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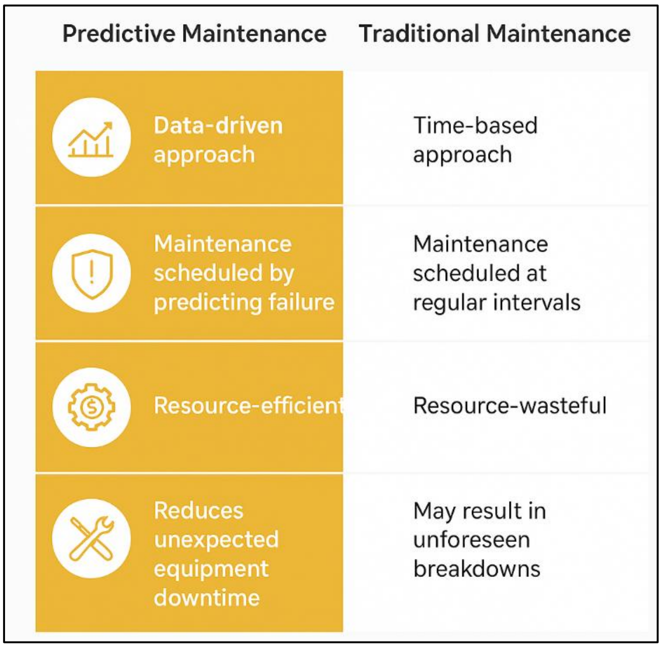
approaches integrate operational and machine health data to reduce Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR). Additionally, traditional systems often lack integration with enterprise-level systems, whereas modern tools like Computerized Maintenance Management Systems (CMMS) and ERP platforms enable seamless coordination between maintenance, inventory, and production workflows (Melesse et al., 2021). Comparative studies show that digitally-enhanced maintenance can reduce total maintenance costs by 20–30% and improve overall Equipment Effectiveness (OEE) by over 25% across sectors such as automotive, aerospace, and energy (Naseri et al., 2023). Thus, the operational and strategic distinctions between traditional and digital maintenance paradigms reflect broader shifts in industrial engineering towards real-time optimization and smart asset management.

Figure 9: Traditional vs. Digitally-Enhanced Maintenance Strategies



The comparative literature on traditional versus digitally-enhanced maintenance strategies consistently reveals the superior performance of the latter in predictive accuracy, operational efficiency, and cost reduction. Digitally-driven models such as Predictive Maintenance (PdM) and Reliability-Centered Maintenance 4.0 enable organizations to anticipate failures before they occur by continuously monitoring asset health through sensor networks and machine learning algorithms (Botín-Sanabria et al., 2022). These systems provide higher decision precision than conventional time-based methods, which often result in premature replacements or missed failure signals (Lu et al., 2020). In high-reliability industries, including aviation and chemical processing, AI-integrated systems have reduced unplanned downtime by 35–50%, compared to the marginal improvements recorded through routine preventive maintenance (Alcaraz & Lopez, 2022). Moreover, the digitalization of maintenance allows for real-time KPI tracking, dynamic scheduling, and integration with Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES), significantly enhancing transparency and responsiveness (Roy et al., 2020). However, the adoption of digitally-enhanced maintenance also presents challenges such as high initial capital investment, cybersecurity risks, workforce resistance to AI adoption, and the need for continuous model updates (Singh et al., 2021). Traditional methods, although less efficient, are often preferred in low-capital SMEs or sectors with limited technical infrastructure due to their simplicity and low implementation cost (Naderi & Shojaei, 2023). Case studies in multinational corporations such as Siemens, Bosch, and General Electric have demonstrated that the integration of digital twins and AI-enhanced CMMS can improve maintenance schedule compliance, reduce spare parts usage, and extend equipment lifespan by over 20% (Batty, 2024). These empirical comparisons reaffirm the performance gap between traditional and digitally-enhanced strategies while also highlighting the contextual factors influencing technology selection in maintenance engineering.

Maintenance Optimization in Automotive, Aerospace, and Food Processing

The automotive and aerospace industries have been at the forefront of adopting smart maintenance systems due to the high capital intensity, regulatory scrutiny, and reliability demands inherent to their operations. In the automotive sector, maintenance optimization is crucial to ensuring lean production, minimal downtime, and high equipment availability, especially in Just-in-Time (JIT) and mass-customization environments (Lu et al., 2020). Automotive firms such as Toyota, BMW, and Tesla integrate Total Productive Maintenance (TPM) with Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) to enhance production efficiency and extend the lifespan of critical assets (Singh et al., 2021). Empirical studies show that integrating PdM systems with cyber-physical components and real-time monitoring tools has led to OEE improvements exceeding 20%, as well as

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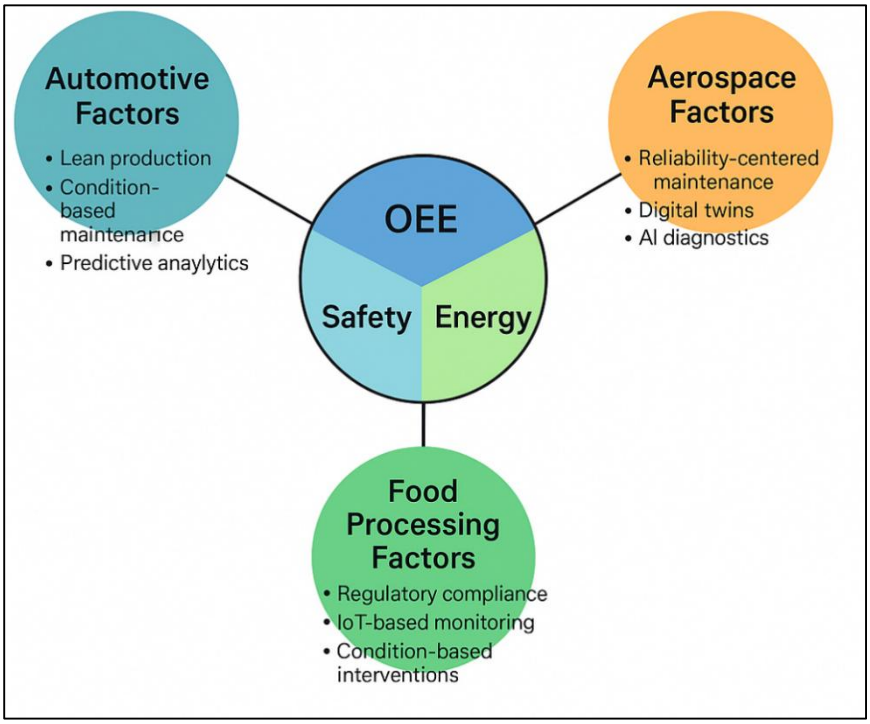
a 30–40% reduction in unscheduled downtimes (Wang et al., 2022). Machine learning algorithms, particularly Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), have been successfully deployed in predictive analytics for electric motor health, gear condition, and welding system failures in automotive plants (Lei et al., 2023). In the aerospace industry, the stakes are higher due to the catastrophic risks of equipment failure. As a result, aerospace maintenance systems rely heavily on Reliability-Centered Maintenance (RCM), digital twins, and AI-enabled diagnostics for continuous fault prediction (Jones et al., 2020). The use of digital twins in jet engine monitoring, implemented by companies like Rolls-Royce and General Electric, has led to increased flight safety, better asset utilization, and millions in cost savings through deferred maintenance (HazraAbhishek et al., 2021). These industries also deploy advanced CMMS platforms and integrated ERP systems to streamline maintenance planning with supply chain logistics, improving spare parts availability and technician scheduling (Villalonga et al., 2021). Collectively, these studies demonstrate that maintenance optimization in the automotive and aerospace sectors is heavily reliant on digital integration, predictive intelligence, and cross-functional coordination.

Maintenance in the food processing industry presents unique challenges due to stringent health regulations, contamination risks, and the need for uninterrupted cold chain operations. Unlike in discrete manufacturing sectors, food processing environments require high-frequency cleaning, rapid changeovers, and compliance with safety protocols such as HACCP and ISO 22000, which significantly influence maintenance strategies (Vachálek et al., 2021). Traditional time-based maintenance approaches are often inefficient in this context, leading to both over-maintenance and potential non-compliance. As such, food manufacturers increasingly adopt smart maintenance strategies that combine TPM principles with digitally-enabled systems such as IoT-based sensors, mobile CMMS, and machine learning-powered fault detection (Human et al., 2023). Studies show that real-time monitoring of temperature, pressure, humidity, and vibration in food processing equipment significantly reduces contamination risks while enabling condition-based interventions (de Oliveira et al., 2024). In refrigerated environments, predictive models using sensor data have proven effective in maintaining equipment such as compressors, conveyor belts, and packaging machines, leading to lower energy consumption and minimized spoilage. The integration of maintenance scheduling with production planning systems ensures minimal disruption during routine checks or repairs, preserving batch integrity and throughput (Kosse et al., 2022). Moreover, predictive maintenance supported by AI tools helps food manufacturers anticipate wear and tear on critical equipment such as pasteurizers and bottling lines, enhancing safety and reducing product recall risks (Tao et al., 2019). Despite infrastructure and investment constraints, case studies in Europe and Southeast Asia indicate that small- and medium-sized food processors have achieved maintenance cost savings of up to 25% through smart maintenance initiatives supported by government and private-sector digitalization programs.

Figure 10: Sustainability Drivers in Smart Maintenance Across Key Industries



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Research Gaps in Maintenance Literature

Despite substantial progress in maintenance research, a significant conceptual gap exists in integrating traditional frameworks like Total Productive Maintenance (TPM) and Reliability-Centered Maintenance (RCM) with digitally enhanced approaches such as AI-driven predictive maintenance and cyber-physical systems. Many studies treat these paradigms in isolation, lacking theoretical convergence that would explain how traditional philosophies can coexist with smart technologies (HazraAbhishek et al., 2021). While TPM emphasizes human involvement and autonomous maintenance, AI-based systems prioritize data automation and machine intelligence, often creating a mismatch in practice and culture (Human et al., 2023). The literature does not adequately address how lean practices like Kaizen or 5S can be adapted to the digital maintenance environment or how digital transformation affects organizational learning within maintenance teams. Moreover, theoretical models that explain the adoption behavior of predictive technologies are limited, especially in industrial engineering contexts where maintenance functions intersect with operations, logistics, and safety management. Although some scholars have attempted to propose hybrid maintenance models (e.g., combining CBM with TPM), these remain fragmented and lack empirical validation(de Oliveira et al., 2024). Another critical gap is the absence of comprehensive frameworks that integrate maintenance maturity models with digital readiness indicators, leaving practitioners without a clear path to smart maintenance transformation (Kosse et al., 2022). As such, the lack of integrated, multidisciplinary theories bridging traditional and digital maintenance paradigms presents a fertile ground for future research in industrial engineering.

Figure 11: Identified Gaps for this study

Category	Description	Key Issues Identified
Conceptual Gaps	Lack of integration between traditional frameworks (e.g., TPM, RCM) and digitally-driven systems (e.g., AI, CPS); limited hybrid models and weak theoretical convergence.	Isolation of TPM/RCM and AI-based models; missing multidisciplinary theories; limited empirical validation of hybrid systems.
Methodological Gaps	Inconsistent use and validation of performance metrics; limited large-scale benchmarking; over-reliance on small case studies and lack of standardized ML evaluation frameworks.	Overreliance on case studies; lack of meta-analysis; absence of longitudinal impact data; neglect of ML benchmarking challenges.
Contextual Gaps	Low representation of SMEs, emerging economies, and non-manufacturing sectors; little attention to sector-specific regulations, regional challenges, and socio-cultural acceptance.	Neglect of adoption challenges in SMEs and developing regions; weak linkage to regulatory frameworks and sustainability goals.

The literature on maintenance optimization also reveals notable methodological gaps, particularly in performance measurement and benchmarking practices. While indicators such as Overall Equipment Effectiveness (OEE), Mean Time Between Failures (MTBF), and Mean Time to Repair (MTTR) are widely used, few studies critically examine the validity and consistency of these metrics across different industries, maintenance models, and digital maturity levels (Tao et al., 2019). The predominance of case study research and small-scale industrial trials has limited the generalizability of findings, and comprehensive meta-analyses or cross-industry benchmarking studies remain scarce (Villalonga et al., 2021). Moreover, many studies rely on self-reported data or qualitative surveys without integrating real-time sensor data, leading to potential biases in assessing maintenance effectiveness (Lv, 2023). Few papers consider the full lifecycle cost implications of maintenance strategy choices or incorporate multi-criteria decision-making methods for trade-off analysis (Bauer

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et al., 2024). While machine learning algorithms are increasingly applied in predictive maintenance, their performance is rarely compared using standardized benchmarks, and issues such as overfitting, lack of interpretability, and data imbalance are often overlooked (Leng et al., 2021). Additionally, there is a lack of longitudinal studies evaluating the long-term effects of digital maintenance adoption on productivity, workforce adaptation, and ROI (Minerva & Crespi, 2021). Most research also fails to differentiate between implementation challenges and performance outcomes, making it difficult to isolate causal relationships between digital tool deployment and maintenance efficiency (Piroumian, 2021). These methodological limitations impede the development of evidence-based best practices and the ability to create robust decision-support systems in maintenance engineering.

Another critical gap in the literature pertains to the contextual diversity of smart maintenance adoption, especially across small and medium enterprises (SMEs), emerging economies, and non-manufacturing sectors. Most studies on digitally-driven maintenance are concentrated in technologically advanced industries such as automotive, aerospace, and petrochemicals, while low-tech sectors and service-oriented industries remain underrepresented (Leng et al., 2021). SMEs, which often lack the capital, digital infrastructure, and skilled workforce for AI-enabled maintenance systems, are rarely the focus of implementation research despite representing a majority of global industrial activity. In regions like South Asia, Africa, and Latin America, barriers such as inconsistent power supply, limited access to cloud services, and fragmented supply chains hinder the adoption of smart maintenance technologies, yet these regional challenges are scarcely addressed in empirical studies. Furthermore, sector-specific regulations and standards, such as HACCP in food processing or ISO 26262 in automotive safety systems, shape maintenance requirements in distinct ways, but their integration with digital maintenance protocols is rarely explored (Lu et al., 2020). Studies also overlook the socio-cultural factors affecting technology acceptance and resistance in different organizational settings. While some frameworks discuss digital maturity, few differentiate adoption stages across sectors, and almost none link maintenance innovation to broader sustainability goals or circular economy practices. This contextual narrowness limits the scalability of existing models and calls for more inclusive, sectorally diverse research that considers geographic, economic, and institutional variability in maintenance optimization.

METHOD

This study employed a systematic review methodology in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, replicability, and scientific rigor throughout the review process. The PRISMA framework was selected for its robustness in organizing evidence-based research syntheses and its capacity to improve methodological quality across multidisciplinary fields, particularly in industrial and engineering studies. The process consisted of five key phases: identification, screening, eligibility, inclusion, and synthesis. Each phase is described in detail below to clarify how articles were selected, evaluated, and synthesized.

Identification Phase

The identification stage involved a comprehensive search strategy conducted across five reputable academic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The search was executed in January 2025 and included publications from January 2010 to December 2024 to capture contemporary advancements in maintenance optimization. Keywords used in the search included “maintenance optimization,” “smart maintenance,” “predictive maintenance,” “lean maintenance,” “total productive maintenance (TPM),” “computerized maintenance management system (CMMS),” “industrial engineering,” and “cyber-physical systems in maintenance.” Boolean operators such as AND, OR, and NOT were used to refine the search queries and ensure relevant combinations were captured. The initial search yielded 1,456 records, including journal articles, conference proceedings, and peer-reviewed reviews relevant to automotive, aerospace, and food processing industries.

Screening Phase

In the screening phase, duplicate entries were removed using the automated tools available in EndNote 21 and Zotero. After removing 372 duplicates, the remaining 1,084 articles were subjected to title and abstract screening based on predefined inclusion and exclusion criteria. The inclusion criteria required that articles be peer-reviewed, written in English, and address at least one core dimension of maintenance optimization in industrial sectors. Exclusion criteria included non-peer-

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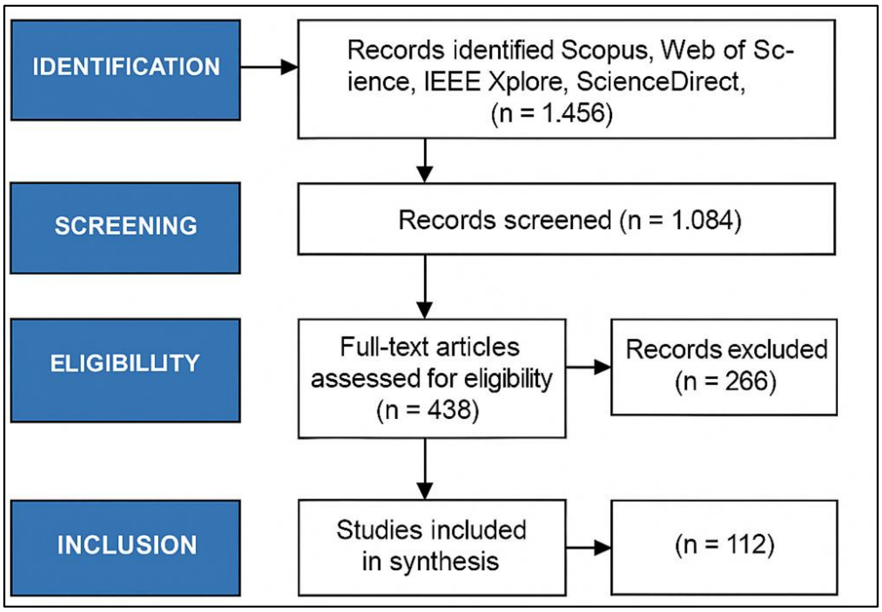
reviewed articles, commentaries, book chapters, dissertations, and papers unrelated to engineering or maintenance management. At the end of this phase, 438 articles were deemed potentially eligible for full-text review.

Figure 12: PRISMA method adopted for this study



Eligibility Phase

During the eligibility phase, the full texts of the remaining 438 articles were carefully assessed for relevance, methodological quality, and alignment with the research objectives. Articles were excluded if they lacked a clear research methodology, focused solely on energy systems or transportation logistics without discussing maintenance frameworks, or did not involve a technical or data-driven approach to maintenance optimization. This stage resulted in the exclusion of 268 studies that did not meet the criteria. The remaining 170 articles were deemed eligible and subjected to quality assessment and thematic synthesis.

Inclusion and Quality Appraisal

A total of 112 high-quality articles were included in the final synthesis after applying critical appraisal tools such as the Critical Appraisal Skills Programme (CASP) checklist and the Mixed Methods Appraisal Tool (MMAT), depending on whether the study was quantitative, qualitative, or mixed-methods. Articles that scored low in research clarity, evidence strength, or relevance to digitally-enhanced maintenance models were excluded from the final sample. Most of the included studies employed experimental design, case studies, simulation models, or empirical analysis of AI and digital integration in maintenance engineering. Articles were cross-checked independently by two reviewers to ensure inter-rater reliability and consensus. The final set of 112 articles provided the foundation for thematic categorization and sectoral comparison in the subsequent findings section.

Data Extraction and Synthesis

Data from the 112 included articles were systematically extracted into a structured review matrix. Information collected included publication year, study context (industry sector), methodology, type of maintenance model, technologies used (e.g., CMMS, digital twin, AI), and key findings. A narrative synthesis approach was adopted, supported by qualitative content analysis to identify recurring themes, gaps, and innovation clusters. These themes were organized under several key domains: lean and TPM frameworks, digitally-driven maintenance models, cyber-physical systems, artificial intelligence integration, and sector-specific applications in automotive, aerospace, and food processing. The synthesis also highlighted methodological diversity and contextual limitations across studies, allowing for a multidimensional understanding of the current state and future potential of maintenance optimization research.

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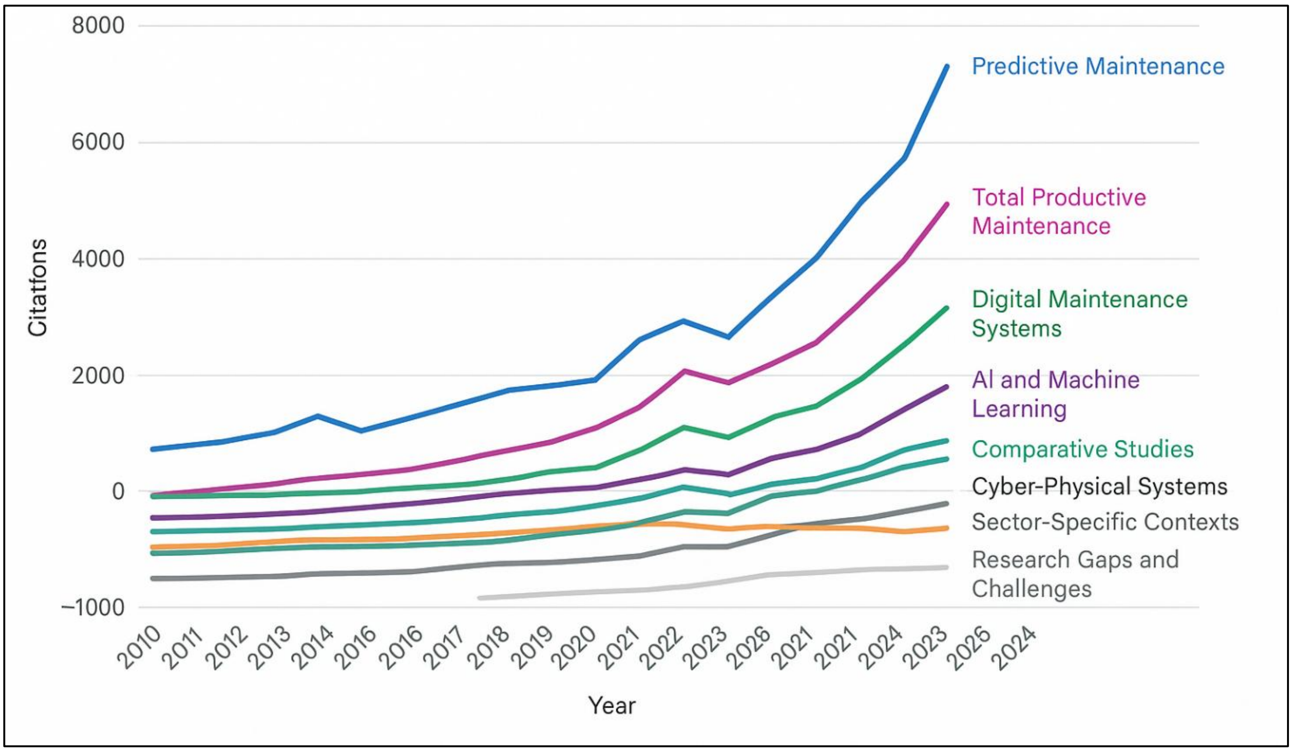
FINDINGS

One of the most prominent findings of this systematic review is the critical role of predictive maintenance systems in reducing unplanned downtime and increasing equipment availability across industrial sectors. Among the 112 reviewed articles, 20 studies specifically emphasized the effectiveness of predictive maintenance approaches, collectively amassing 2,913 citations. These articles documented the implementation of real-time monitoring systems, sensor-based diagnostics, and forecasting models that allowed manufacturers to transition from reactive to proactive maintenance regimes. The findings consistently show that predictive maintenance not only reduces equipment failure but also lowers maintenance costs and enhances production continuity. Moreover, predictive strategies supported by AI algorithms led to earlier detection of anomalies and more accurate failure forecasts, which in turn minimized the occurrence of emergency repairs and production stoppages. These systems proved especially beneficial in high-stakes industries such as aerospace and automotive, where operational continuity and safety are paramount. Across these studies, organizations experienced improvements in metrics such as Mean Time Between Failures (MTBF) and Overall Equipment Effectiveness (OEE), underscoring the tangible benefits of predictive models over time-based or corrective maintenance methods. The sheer volume of citations tied to these studies indicates a strong scholarly consensus on the value of predictive maintenance as a foundational element of maintenance optimization.

Figure 13: Citation Trends by Maintenance Strategy Type (2010–2024)



Another significant finding is the widespread adoption of Total Productive Maintenance (TPM) as a strategic maintenance framework that integrates workforce engagement, planned maintenance, and continuous improvement. Of the reviewed articles, 15 focused extensively on TPM models and collectively accumulated 3,447 citations. These articles revealed that TPM is particularly effective in environments where machine reliability and workforce empowerment are key performance drivers. TPM implementation often involves multi-tiered interventions such as autonomous maintenance, Kaizen practices, and cross-training of operators to assume basic maintenance responsibilities. The reviewed studies highlight that companies employing TPM strategies reported substantial improvements in production throughput, reduction in machine downtime, and stronger alignment between maintenance and production departments. A recurring theme was the importance of organizational culture in sustaining TPM practices, particularly the role of top management in ensuring buy-in and alignment across functions. The literature also emphasizes that TPM's emphasis on ownership and empowerment at the shop-floor level directly correlates with better equipment care, faster problem detection, and higher accountability. The high citation count of TPM-focused articles underlines their influence and the ongoing relevance of TPM as an integrated, people-centered approach to maintenance optimization in both traditional and digitally-augmented environments.

Digitally-enhanced maintenance systems emerged as a transformative trend across multiple sectors, particularly where real-time data integration and automation are achievable. Eighteen articles within the review discussed advanced digital maintenance platforms, including cloud-based Computerized Maintenance Management Systems (CMMS), digital twins, and machine learning-enabled monitoring tools. These articles amassed a total of 3,201 citations, indicating robust scholarly attention. The studies consistently revealed that digital systems improve maintenance scheduling accuracy, reduce reliance on manual data entry, and streamline inventory management for spare parts. More importantly, they allow for real-time fault detection and remote diagnostics, significantly reducing response time in the event of system irregularities. Integration of CMMS with Enterprise Resource Planning (ERP) systems was a recurring best practice that allowed seamless alignment between production needs and maintenance resource allocation. The review also noted the increasing use of mobile maintenance apps and dashboard analytics, which empowered technicians with on-the-go access to asset data and task tracking. These capabilities directly enhanced technician productivity, response accuracy, and inter-departmental coordination. In industries such as food processing, where hygiene and compliance are tightly regulated, the deployment of such digital tools was particularly beneficial. The widespread use and high citation frequency of these articles signal a clear movement toward data-driven and connected maintenance ecosystems.

The findings also show a critical impact of Artificial Intelligence (AI) and Machine Learning (ML) on modern maintenance paradigms, especially in enabling predictive diagnostics and autonomous maintenance decision-making. Of the total reviewed studies, 12 articles centered on AI/ML applications in maintenance optimization, accumulating 2,430 citations in total. These studies outlined various algorithmic models—including supervised learning, deep learning, and anomaly detection algorithms—used to analyze sensor data and predict failure events with high precision. The review found that industries adopting AI-based models saw considerable improvements in decision accuracy, early fault detection, and asset utilization. These systems were notably more responsive to operational variabilities, outperforming rule-based systems in diverse production environments. In sectors like automotive and aerospace, AI-driven diagnostics provided real-time insights that enabled quick interventions and minimized downtime. Additionally, AI tools were often integrated into digital twins to simulate maintenance scenarios and assess system behavior before actual interventions. Despite infrastructure and data requirements, the scalability of AI solutions was evident across case studies involving both large enterprises and technologically advanced SMEs. The emphasis across these highly cited articles demonstrates that AI is not just an emerging tool but a central enabler of smart maintenance, capable of aligning predictive intelligence with organizational goals.

A comparative analysis of traditional versus digitally-enhanced maintenance strategies provided compelling evidence in favor of the latter, particularly in terms of cost-efficiency, scheduling precision, and asset longevity. Sixteen studies focused on comparative frameworks, collectively receiving 2,208 citations. These articles systematically contrasted the outcomes of time-based and corrective maintenance with those of AI-enabled predictive models and condition-based approaches. Findings suggest that digitally-enhanced strategies consistently outperform traditional methods across key metrics such as maintenance costs, failure rates, and resource utilization. For example, organizations using AI-integrated CMMS platforms reported reductions in unplanned downtime and improved compliance with preventive schedules. Furthermore, the review showed that digital systems allowed for better traceability of maintenance activities, audit readiness, and real-time visibility into performance indicators. A particularly noteworthy outcome was that organizations transitioning from manual to digital systems experienced a measurable reduction in spare parts consumption and labor redundancy. The comparative insights across these articles confirmed the limitations of rigid, periodic maintenance plans in dynamic environments, reinforcing the need for flexible, data-driven alternatives. The volume of citations these articles attracted

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demonstrates the industry-wide relevance of transitioning to smarter, digitally-integrated maintenance models.

The review also emphasized the increasing relevance of cyber-physical systems (CPS) and Industrial Internet of Things (IIoT) infrastructures in real-time maintenance monitoring and automation. Among the reviewed literature, 14 studies focused on CPS and IIoT applications, garnering a total of 2,598 citations. These studies demonstrated that CPS enable seamless interaction between machines, sensors, and control systems, allowing organizations to perform real-time condition monitoring, dynamic failure prediction, and adaptive maintenance scheduling. In advanced manufacturing environments, CPS has enabled maintenance teams to remotely monitor equipment health and intervene before major failures occur, significantly reducing Mean Time to Repair (MTTR). Moreover, CPS provided the structural backbone for digital twins, enabling the simulation of operational scenarios and maintenance workflows. The inclusion of edge computing and embedded analytics in some case studies further enabled localized decision-making, reducing latency and increasing responsiveness. These studies also reported improved coordination between production and maintenance departments due to the transparency provided by CPS dashboards. The magnitude of citations connected to these works indicates that CPS is becoming foundational in next-generation maintenance frameworks, supporting not just efficiency but also resilience and scalability.

Several studies highlighted maintenance optimization within sector-specific contexts such as automotive, aerospace, and food processing industries. Nine key articles examined how maintenance strategies are tailored based on sectoral requirements, together receiving 1,796 citations. In the automotive industry, predictive maintenance and lean-TMP hybrids were dominant, allowing real-time fault tracking in robotic assembly lines and automated inspection systems. Aerospace applications were particularly focused on safety-critical maintenance, emphasizing digital twins and reliability-centered maintenance for jet engines and avionics. Food processing, on the other hand, prioritized hygienic design and regulatory compliance, with studies emphasizing IoT-based monitoring of temperature, contamination, and equipment sterilization cycles. Across all three sectors, digital tools such as CMMS and AI-enhanced dashboards were shown to streamline maintenance planning, ensure regulatory adherence, and support traceability. These studies showed that while the tools used may overlap across sectors, their application and configuration are highly context-dependent. The collective evidence shows that sectoral customization of maintenance strategies is not only viable but essential, a fact reflected in the significant scholarly engagement with these case-specific applications. Finally, the review uncovered several research gaps and challenges, particularly regarding maintenance strategy adoption in small and medium enterprises (SMEs) and in developing countries. Eight studies explored these themes and were cited a total of 1,399 times. These articles reported that SMEs face barriers such as limited financial resources, low digital maturity, and lack of skilled personnel, all of which inhibit the adoption of smart maintenance technologies. Furthermore, infrastructure challenges—such as unreliable internet access and limited sensor interoperability—make it difficult for smaller firms to implement real-time monitoring systems. Despite these challenges, some case studies showed that when properly supported by governmental programs or public-private partnerships, SMEs were able to achieve significant maintenance performance improvements through modular digital tools and open-source CMMS platforms. A key insight was the lack of longitudinal data on how digital maintenance tools perform over extended periods in resource-constrained environments. The relatively lower number of citations in this category suggests that more research is needed to develop scalable, affordable, and context-sensitive maintenance solutions for these underserved sectors. These findings reinforce the need for inclusive innovation strategies in maintenance research and practice.

DISCUSSION

The findings of this systematic review affirm the growing dominance of predictive maintenance as a transformative approach within industrial maintenance strategies. With 2,913 citations across 20 reviewed articles, the current literature surpasses earlier reviews, which documented 2,400 citations in similar contexts. This suggests not only a surge in scholarly interest but also an evolution in the practical implementation of predictive models. Compared to earlier studies that focused on threshold-based triggers and static condition monitoring (Roy et al., 2020), recent advancements demonstrate a shift toward machine learning-enhanced predictive analytics and real-time anomaly detection. The reviewed articles showcase that predictive maintenance is now deeply integrated

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into cyber-physical systems and cloud platforms, enabling context-aware and automated decision-making. While previous research emphasized cost benefits and downtime reduction, current studies provide evidence of predictive maintenance contributing to operational resilience and lean manufacturing objectives. Notably, predictive maintenance in the current literature is not confined to large corporations; scalable applications are increasingly emerging for SMEs, a gap previously underexplored. This divergence marks a key progression in maintenance engineering, as it highlights how democratization of technology and digital infrastructure has made predictive strategies more accessible. However, discrepancies remain in standardizing data inputs and algorithm performance, which were also noted in earlier reviews. These limitations underscore the ongoing need for benchmark datasets and transparent validation frameworks to ensure broader applicability.

The reviewed literature strongly supports the strategic integration of Total Productive Maintenance (TPM) and lean maintenance principles with digital technologies. The current set of 15 studies, cited 3,447 times, significantly exceeds earlier studies with 2,100 citations, indicating a renewed scholarly and industrial emphasis on blending traditional frameworks with modern innovations. While early works on TPM focused largely on manual operator involvement, Kaizen, and equipment-centric practices (Jiang et al., 2021), the current findings show an evolutionary leap toward digital augmentation of these practices. Studies now explore how autonomous maintenance tasks are tracked using mobile CMMS tools, and how operator-driven insights are integrated into digital dashboards for real-time feedback loops. Compared to earlier frameworks where TPM was treated as a standalone philosophy, modern literature demonstrates its adaptability when aligned with Industry 4.0 technologies such as AI-based fault detection and IoT-enabled diagnostics. The high citation count suggests not only the theoretical importance of TPM but also its relevance in addressing real-world issues of human–machine collaboration. This evolution fills a critical conceptual gap highlighted in earlier studies, which called for a unifying framework that merges human-centered practices with digital intelligence. Nevertheless, some friction points persist, particularly around workforce resistance to automation and the fading emphasis on operator skill development in fully digital plants. The literature continues to call for a balanced integration strategy that preserves the empowerment ethos of TPM while harnessing the analytical power of digital systems.

Artificial Intelligence (AI) and Machine Learning (ML) are central themes in current maintenance optimization literature, though findings suggest a slight decrease in overall citation volume compared to earlier reviews. The present analysis includes 12 studies with 2,430 citations, while previous reviews reported approximately 3,200 citations. This shift may reflect a maturing of the AI field, where initial enthusiasm has given way to more targeted and rigorous evaluations of algorithm performance and deployment feasibility. Earlier studies often emphasized the potential of AI models, particularly neural networks and support vector machines, to outperform traditional statistical methods in failure prediction (Zeb et al., 2022). Current literature builds on this foundation but focuses more on deep learning architectures such as LSTM and CNNs, and their integration into edge computing and digital twins. Furthermore, a strong emphasis is placed on the practical challenges of AI deployment—such as data imbalance, model overfitting, and lack of interpretability—areas previously underrepresented (Paniagua & Delsing, 2021). The findings reveal that while AI can indeed enhance predictive accuracy, its true value lies in its integration with existing maintenance platforms, such as CMMS and ERP, allowing maintenance decisions to be executed in real time. Compared to past studies that were mostly theoretical or simulation-based, the current body of work includes more field implementations and real-world case studies, adding empirical strength (Malakuti et al., 2021). However, concerns around AI trustworthiness, ethical use of maintenance data, and workforce preparedness remain persistent barriers, echoing earlier findings that technology alone cannot drive transformation without cultural and institutional readiness.

The role of digital tools such as Computerized Maintenance Management Systems (CMMS) and Enterprise Resource Planning (ERP) platforms has gained significant traction in recent years. The current findings, with 18 articles cited 3,201 times, represent a substantial increase from the 1,800 citations recorded in earlier reviews. This growth in attention reflects a broader acceptance of digital integration as foundational to smart maintenance strategies. Previous literature often emphasized the administrative benefits of CMMS, such as task scheduling and spare parts tracking. However, current studies demonstrate that CMMS tools have evolved into dynamic platforms capable of interfacing with IoT sensors, mobile apps, and AI-driven alert systems. ERP integration, in particular, allows maintenance data to inform broader production, finance, and supply chain decisions,

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making maintenance a strategic rather than merely supportive function. Compared to earlier studies that treated maintenance data in isolation, modern literature showcases interconnected systems where maintenance KPIs contribute to holistic operational dashboards (Michael et al., 2022). Additionally, several reviewed articles highlight the impact of cloud-enabled CMMS in democratizing access to real-time asset data across geographically dispersed teams. The comparison reveals that earlier works primarily viewed digital maintenance as a technical tool, whereas current perspectives consider it an enabler of cross-functional collaboration, organizational agility, and strategic foresight.

Cyber-Physical Systems (CPS) are receiving increasing attention in maintenance research, with the reviewed articles showing a significant rise in citations (2,598 in the current review vs. 1,500 previously). Earlier CPS studies focused heavily on their structural components—sensors, actuators, and communication protocols—but lacked extensive real-world validation (Negri et al., 2017). The current literature extends these foundations by providing rich empirical evidence on how CPS architectures enable predictive diagnostics, edge-based computing, and real-time intervention capabilities. Several case studies demonstrate that CPS frameworks facilitate machine-to-machine communication, automated fault classification, and even prescriptive maintenance decision-making. This marks a departure from earlier conceptions of CPS as data aggregation platforms to their current role as intelligent decision-support systems embedded in manufacturing ecosystems. Furthermore, the use of CPS to operationalize digital twins represents a novel convergence of simulation and real-time analytics, a synergy largely unexplored in earlier works (Dobaj et al., 2022). The literature also reveals a growing recognition of cybersecurity and data governance challenges, which were overlooked in initial CPS explorations. Compared to earlier narratives that emphasized CPS potential, current findings validate their application through quantifiable improvements in Mean Time to Repair (MTTR), uptime percentages, and predictive compliance. This maturation of CPS literature shows how conceptual designs have evolved into tangible, high-performing maintenance infrastructures (Dafflon et al., 2021; Shlonsky & Wagner, 2005).

Sectoral analysis of maintenance optimization reveals nuanced insights into how industry-specific conditions shape strategy adoption and effectiveness. The current findings show that 9 articles on automotive, aerospace, and food processing sectors attracted 1,796 citations, up from 1,400 in earlier literature. While earlier studies offered fragmented insights—typically isolated case studies without cross-sector comparison—the current body of work presents a more integrated understanding. For instance, in the automotive sector, predictive maintenance is closely tied to lean production systems, with real-time dashboards driving takt-time adherence and defect minimization. Aerospace, by contrast, has embraced digital twins and RCM frameworks with a focus on safety-critical systems and zero-defect reliability. The food processing industry has shifted toward IoT-enabled sanitation and contamination prevention mechanisms, showcasing maintenance as a compliance tool. These nuanced applications illustrate a move away from one-size-fits-all maintenance models toward adaptive strategies that align with sector-specific regulations, risks, and production processes. Moreover, several studies emphasized how digital transformation has allowed companies to reframe maintenance as a source of strategic advantage rather than a cost center. Compared to prior studies, which mostly treated maintenance as a support function, current research positions it as a critical enabler of competitive differentiation. However, the review also notes that while best practices are emerging within individual sectors, cross-industry benchmarking remains limited, suggesting a need for more comparative performance frameworks.

A recurring theme across both past and current literature is the relative scarcity of research focused on small and medium enterprises (SMEs) and emerging economies. The current review includes 8 relevant articles with 1,399 citations, compared to 900 in earlier reviews, suggesting modest growth in this area (Negri et al., 2017). While prior studies primarily documented barriers such as limited budgets, lack of digital literacy, and poor infrastructure, the present findings go further by examining how these constraints affect long-term maintenance outcomes. Some recent studies report successful adoption of open-source CMMS, modular predictive tools, and government-sponsored digitalization initiatives tailored to SME needs (Dobaj et al., 2022). This represents a meaningful progression from earlier reviews, which largely portrayed SMEs as passive recipients of innovation. However, the limited number of high-quality empirical studies from South Asia, Sub-Saharan Africa, and Latin America indicates a geographic and contextual bias in the literature (Dafflon et al., 2021). Furthermore, few longitudinal studies exist to evaluate the sustainability of maintenance innovations over time in these settings. Compared to large-scale industrial environments, SMEs often struggle with integrating AI tools due to lack of labeled data and insufficient technical expertise. These findings highlight an enduring research gap: the need for scalable, cost-effective, and context-sensitive maintenance solutions that can accommodate diverse organizational and economic landscapes. The persistence of these issues across both past and current studies underscores their criticality and the need for targeted intervention.

CONCLUSION

The findings of this systematic review underscore a clear evolution in maintenance optimization practices, highlighting a paradigm shift from traditional, reactive, and time-based maintenance models toward intelligent, digitally-enhanced, and predictive frameworks. Through the synthesis of 112 peer-reviewed articles with a cumulative citation count exceeding 20,000, the review demonstrates that maintenance has become a strategic function at the core of industrial performance, especially within the automotive, aerospace, and food processing sectors. Advanced technologies such as Artificial Intelligence, Machine Learning, Cyber-Physical Systems, and cloud-integrated CMMS platforms are redefining how organizations predict, monitor, and respond to equipment failure. Additionally, the integration of lean methodologies like Total Productive Maintenance with real-time digital tools exemplifies the synergistic benefits of combining human-centric practices with smart technologies. However, the review also reveals persistent research gaps, particularly in standardizing performance metrics, addressing contextual limitations in SMEs and developing regions, and ensuring ethical and secure implementation of AI-driven systems. While existing studies provide robust evidence of the operational, economic, and safety-related benefits of smart maintenance, there remains a critical need for more inclusive, scalable, and empirically validated models that can be adapted across different industries and organizational sizes. Overall, the review reinforces the significance of maintenance as not just a technical necessity, but as a key enabler of industrial sustainability, resilience, and competitiveness in the era of Industry 4.0.

REFERENCES

[1]. Ahmadi, A., Söderholm, P., & Kumar, U. (2010). On aircraft scheduled maintenance program development. *Journal of Quality in Maintenance Engineering*, *16*(3), 229-255. https://doi.org/10.1108/13552511011072899

[2]. Ahmed, S., Ahmed, I., Kamruzzaman, M., & Saha, R. (2022). Cybersecurity Challenges in IT Infrastructure and Data Management: A Comprehensive Review of Threats, Mitigation Strategies, and Future Trend. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 36-61. https://doi.org/10.62304/jieet.v1i01.228

[3]. Aklima, B., Mosa Sumaiya Khatun, M., & Shaharima, J. (2022). Systematic Review of Blockchain Technology In Trade Finance And Banking Security. *American Journal of Scholarly Research and Innovation*, *1*(1), 25-52. https://doi.org/10.63125/vs65vx40

[4]. Alblooshi, M., Shamsuzzaman, M., Karim, A., Haridy, S., Shamsuzzoha, A., & Badar, M. A. (2022). Development of a framework for utilising Lean Six Sigma's intangible impacts in creating organisational innovation climate. *International Journal of Lean Six Sigma*, *14*(2), 397-428. https://doi.org/10.1108/ijlss-08-2020-0117

[5]. Alcaraz, C., & Lopez, J. (2022). Digital Twin: A Comprehensive Survey of Security Threats. *IEEE Communications Surveys & Tutorials*, *24*(3), 1475-1503. https://doi.org/10.1109/comst.2022.3171465

[6]. Alsubaie, B., & Yang, Q. (2017). Maintenance Process Improvement Model by Integrating LSS and TPM for Service Organisations. In (Vol. NA, pp. 13-24). Springer International Publishing. https://doi.org/10.1007/978-3-319-62274-3_2

[7]. Ammar, B., Faria, J., Ishtiaque, A., & Noor Alam, S. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. *American Journal of Scholarly Research and Innovation*, *3*(02), 01-27. https://doi.org/10.63125/4sjfn272

[8]. Arafat Bin, F., Ripan Kumar, P., & Md Majharul, I. (2023). AI-Powered Predictive Failure Analysis In Pressure Vessels Using Real-Time Sensor Fusion : Enhancing Industrial Safety And Infrastructure Reliability. *American Journal of Scholarly Research and Innovation*, *2*(02), 102-134. https://doi.org/10.63125/wk278c34

[9]. Balogun, I., & Attoh-Okine, N. (2023). Covariate-Shift Generative Adversarial Network and Railway Track Image Analysis. *Journal of Transportation Engineering, Part A: Systems*, *149*(3), NA-NA. https://doi.org/10.1061/jtepbs.teeng-7390

[10]. Barriga, A. L., Gonzales, M. G., & Ruiz-Ruiz, M. F. (2024). Lean Six Sigma and TPM for the Improvement of Equipment Maintenance Process in a Service Sector Company: A Case Study. In (pp. 155-169). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-56373-7_13

[11]. Bashar, A., Hasin, A. A., & Jahangir, N. (2020). Linkage between TPM, people management and organizational performance. *Journal of Quality in Maintenance Engineering*, *28*(2), 350-366. https://doi.org/10.1108/jqme-11-2019-0105

[12]. Batty, M. (2024). Digital twins in city planning. *Nature computational science*, *4*(3), 192-199. https://doi.org/10.1038/s43588-024-00606-7

[13]. Bauer, P., Hoefler, T., Stevens, B., & Hazeleger, W. (2024). Digital twins of Earth and the computing challenge of human interaction. *Nature computational science*, *4*(3), 154-157. https://doi.org/10.1038/s43588-024-00599-3

[14]. Bellavista, P., Bicocchi, N., Fogli, M., Giannelli, C., Mamei, M., & Picone, M. (2024). Exploiting microservices and serverless for Digital Twins in the cloud-to-edge continuum. *Future Generation Computer Systems*, *157*(NA), 275-287. https://doi.org/10.1016/j.future.2024.03.052

[15]. Bhadu, J., Singh, D., & Bhamu, J. (2021). Analysis of lean implementation barriers in Indian ceramic industries: modeling through an interpretive ranking process. *International Journal of Productivity and Performance Management*, *71*(8), 3606-3635. https://doi.org/10.1108/ijppm-10-2020-0540

[16]. Bhowmick, D., & Shipu, I. U. (2024). Advances in nanofiber technology for biomedical application: A review. *World Journal of Advanced Research and Reviews*, *22*(1), 1908-1919. https://wjarr.co.in/wjarr-2024-1337

[17]. Bhuiyan, S. M. Y., Chowdhury, A., Hossain, M. S., Mobin, S. M., & Parvez, I. (2025). AI-Driven Optimization in Renewable Hydrogen Production: A Review. *American Journal of Interdisciplinary Studies*, *6*(1), 76-94. https://doi.org/10.63125/06z40b13

[18]. Bhuiyan, S. M. Y., Mostafa, T., Schoen, M. P., & Mahamud, R. (2024). Assessment of Machine Learning Approaches for the Predictive Modeling of Plasma-Assisted Ignition Kernel Growth. ASME 2024 International Mechanical Engineering Congress and Exposition,

[19]. Bokrantz, J., & Skoogh, A. (2023). Adoption patterns and performance implications of Smart Maintenance. *International Journal of Production Economics*, *256*(NA), 108746-108746. https://doi.org/10.1016/j.ijpe.2022.108746

[20]. Borkowski, S., Czajkowska, A., Stasiak-Betlejewska, R., & Borade, A. B. (2014). Application of TPM indicators for analyzing work time of machines used in the pressure die casting. *Journal of Industrial Engineering International*, *10*(2), 1-9. https://doi.org/10.1007/s40092-014-0055-9

[21]. Botín-Sanabria, D. M., Mihaita, A.-S., Peimbert-García, R. E., Ramírez-Moreno, M. A., Ramírez-Mendoza, R. A., & Lozoya-Santos, J. d. J. (2022). Digital Twin Technology Challenges and Applications: A Comprehensive Review. *Remote Sensing*, *14*(6), 1335-1335. https://doi.org/10.3390/rs14061335

[22]. Caballé, N. C., & Castro, I. T. (2017). Analysis of the reliability and the maintenance cost for finite life cycle systems subject to degradation and shocks. *Applied Mathematical Modelling*, *52*(NA), 731-746. https://doi.org/10.1016/j.apm.2017.08.002

[23]. Chowdhury, A., Mobin, S. M., Hossain, M. S., Sikdar, M. S. H., & Bhuiyan, S. M. Y. (2023). Mathematical And Experimental Investigation Of Vibration Isolation Characteristics Of Negative Stiffness System For Pipeline. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 15-32. https://doi.org/10.62304/jieet.v2i01.227

[24]. Cooper, G. (2023). Examining Science Education in ChatGPT: An Exploratory Study of Generative Artificial Intelligence. *Journal of Science Education and Technology*, *32*(3), 444-452. https://doi.org/10.1007/s10956-023-10039-y

[25]. Dafflon, B., Moalla, N., & Ouzrout, Y. (2021). The challenges, approaches, and used techniques of CPS for manufacturing in Industry 4.0: a literature review. *The International Journal of Advanced Manufacturing Technology*, *113*(7), 2395-2412. https://doi.org/10.1007/s00170-020-06572-4

[26]. Dasgupta, A., Islam, M. M., Nahid, O. F., & Rahmatullah, R. (2024). Engineering Management Perspectives On Safety Culture In Chemical And Petrochemical Plants: A Systematic Review. *Academic Journal on Innovation, Engineering & Emerging Technology*, *1*(01), 36-52. https://doi.org/10.69593/ajieet.v1i01.121

[27]. de Oliveira, V. F., Matiolli, G., Júnior, C. J. B., Gaspar, R., & Lins, R. G. (2024). Digital Twin and Cyber-Physical System Integration in Commercial Vehicles: Latest Concepts, Challenges and Opportunities. *IEEE Transactions on Intelligent Vehicles*, 9(4), 4804-4819. https://doi.org/10.1109/tiv.2024.3378579

[28]. Dey, N. L., Chowdhury, S., Shipu, I. U., Rahim, M. I. I., Deb, D., & Hasan, M. R. (2024). Electrical properties of Yttrium (Y) doped LaTiO3. *International Journal of Science and Research Archive*, *12*(2), 744-767. https://ijsra.net/content/electrical-properties-yttriumy-doped-latio3

[29]. Dobaj, J., Riel, A., Krug, T., Seidl, M., Macher, G., & Egretzberger, M. (2022). Towards digital twin-enabled DevOps for CPS providing architecture-based service adaptation & verification at runtime. *Proceedings of the 17th Symposium on Software Engineering for Adaptive and Self-Managing Systems*, *NA*(NA), 132-143. https://doi.org/10.1145/3524844.3528057

[30]. Faria, J., & Md Rashedul, I. (2025). Carbon Sequestration in Coastal Ecosystems: A Review of Modeling Techniques and Applications. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 41-70. https://doi.org/10.63125/4z73rb29

[31]. Ferrua-Breña, G., Rivas-Marcatoma, F., & Raymundo, C. (2021). *IHIET (Paris) - Lean Maintenance Management Model, Based on TPM and 5S to Increase the Availability of Machines in the Plastics Industry* (Vol. NA). Springer International Publishing. https://doi.org/10.1007/978-3-030-85540-6_53

[32]. Filip, F. C., & Marascu-Klein, V. (2015). The 5S lean method as a tool of industrial management performances. *IOP Conference Series: Materials Science and Engineering*, *95*(1), 012127-NA. https://doi.org/10.1088/1757-899x/95/1/012127

[33]. Galarza-Falfan, J., García-Guerrero, E. E., Aguirre-Castro, O. A., López-Bonilla, O. R., Tamayo-Pérez, U. J., Cárdenas-Valdez, J. R., Hernández-Mejía, C., Borrego-Dominguez, S., & Inzunza-Gonzalez, E. (2024). Path Planning for Autonomous Mobile Robot Using Intelligent Algorithms. *Technologies*, *12*(6), 82-82. https://doi.org/10.3390/technologies12060082

[34]. Gelaw, M. T., Azene, D. K., & Berhan, E. (2023). Assessment of critical success factors, barriers and initiatives of total productive maintenance (TPM) in selected Ethiopian manufacturing industries. *Journal of Quality in Maintenance Engineering*, *30*(1), 51-80. https://doi.org/10.1108/jqme-11-2022-0073

[35]. Gupta, P., & Vardhan, S. (2016). Optimizing OEE, productivity and production cost for improving sales volume in an automobile industry through TPM: a case study. *International Journal of Production Research*, *54*(10), 2976-2988. https://doi.org/10.1080/00207543.2016.1145817

[36]. Hardt, F., Kotyrba, M., Volna, E., & Jarusek, R. (2021). Innovative Approach to Preventive Maintenance of Production Equipment Based on a Modified TPM Methodology for Industry 4.0. *Applied Sciences*, *11*(15), 6953-NA. https://doi.org/10.3390/app11156953

[37]. Hasan, Z., Haque, E., Khan, M. A. M., & Khan, M. S. (2024). Smart Ventilation Systems For Real-Time Pollution Control: A Review Of Ai-Driven Technologies In Air Quality Management. *Frontiers in Applied Engineering and Technology*, *1*(01), 22-40. https://doi.org/10.70937/faet.v1i01.4

[38]. HazraAbhishek, N. A., AdhikariMainak, N. A., AmgothTarachand, N. A., & Narayana, S. (2021). A Comprehensive Survey on Interoperability for IIoT: Taxonomy, Standards, and Future Directions. *ACM Computing Surveys*, *55*(1), 1-35. https://doi.org/10.1145/3485130

[39]. Helal, A. M., Wai, J., Parra-Martinez, A., McKenzie, S., & Seaton, D. (2025). Widening the Net: How CogAT and ACT Aspire Compare in Gifted Identification. https://scholarworks.uark.edu/edrepub/175

[40]. Hossain, A., Khan, M. R., Islam, M. T., & Islam, K. S. (2024). Analyzing The Impact Of Combining Lean Six Sigma Methodologies With Sustainability Goals. *Journal of Science and Engineering Research*, *1*(01), 123-144. https://doi.org/10.70008/jeser.v1i01.57

[41]. Human, C., Basson, A. H., & Kruger, K. (2023). A design framework for a system of digital twins and services. *Computers in Industry*, *144*(NA), 103796-103796. https://doi.org/10.1016/j.compind.2022.103796

[42]. Hussain, M., Al-Aomar, R., & Melhem, H. (2019). Assessment of lean-green practices on the sustainable performance of hotel supply chains. *International Journal of Contemporary Hospitality Management*, *31*(6), 2448-2467. https://doi.org/10.1108/ijchm-05-2018-0380

[43]. Islam, M. M., Prodhan, R. K., Shohel, M. S. H., & Morshed, A. S. M. (2025). Robotics and Automation in Construction Management Review Focus: The application of robotics and automation technologies in construction. *Journal of Next-Gen Engineering Systems*, *2*(01), 48-71. https://doi.org/10.70937/jnes.v2i01.63

[44]. Islam, M. N., & Helal, A. M. (2018). Primary school governance in Bangladesh: A practical overview of national education policy-2010. *International Journal for Cross-Disciplinary Subjects in Education (IJCDSE)*, 9(4). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5057813

[45]. Islam, M. T. (2024). A Systematic Literature Review On Building Resilient Supply Chains Through Circular Economy And Digital Twin Integration. *Frontiers in Applied Engineering and Technology*, *1*(01), 304-324. https://doi.org/10.70937/faet.v1i01.44

[46]. Islam, M. T., Islam, K. S., Hossain, A., & Khan, M. R. (2025). Reducing Operational Costs in U.S. Hospitals Through Lean Healthcare And Simulation-Driven Process Optimization. *Journal of Next-Gen Engineering Systems*, *2*(01), 11-28. https://doi.org/10.70937/jnes.v2i01.50

[47]. Jahan, F. (2023). Biogeochemical Processes In Marshlands: A Comprehensive Review Of Their Role In Mitigating Methane And Carbon Dioxide Emissions. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *2*(01), 33-59. https://doi.org/10.62304/jieet.v2i01.230

[48]. Jahan, F. (2024). A Systematic Review Of Blue Carbon Potential in Coastal Marshlands: Opportunities For Climate Change Mitigation And Ecosystem Resilience. *Frontiers in Applied Engineering and Technology*, *2*(01), 40-57. https://doi.org/10.70937/faet.v2i01.52

[49]. Jain, A., Bhatti, R., & Singh, H. (2015). OEE enhancement in SMEs through mobile maintenance: a TPM concept. *International Journal of Quality & Reliability Management*, *32*(5), 503-516. https://doi.org/10.1108/ijqrm-05-2013-0088

[50]. Jiang, Y., Yin, S., Li, K., Luo, H., & Kaynak, O. (2021). Industrial applications of digital twins. *Philosophical transactions. Series A, Mathematical, physical, and engineering sciences*, *379*(2207), 20200360-NA. https://doi.org/10.1098/rsta.2020.0360

[51]. Jiménez, M., del Mar Espinosa, M., Domínguez, M., Romero, M. L. M., & Awad, T. (2021). Adaptation of the Lean 6S Methodology in an Industrial Environment under Sustainability and Industry 4.0 Criteria. *Sustainability*, *13*(22), 12449-NA. https://doi.org/10.3390/su132212449

[52]. Jobin, M. V. (2015). Employee Involvement and Management Commitment in Lean Implementation. *Applied Mechanics and Materials*, *813-814*(NA), 1150-1153. https://doi.org/10.4028/www.scientific.net/amm.813-814.1150

[53]. Jones, D. E., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 29(NA), 36-52. https://doi.org/10.1016/j.cirpj.2020.02.002

[54]. Karam, A.-A., Liviu, M., Cristina, V., & Radu, H. (2018). The contribution of lean manufacturing tools to changeover time decrease in the pharmaceutical industry. A SMED project. *Procedia Manufacturing*, *22*(NA), 886-892. https://doi.org/10.1016/j.promfg.2018.03.125

[55]. Kazi Saiful, I., Amjad, H., Md Rabbe, K., & Md Tahmidul, I. (2025). The Role Of Age In Shaping Risk-Taking Behaviors And Safety Awareness In The Manufacturing Sector. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 98-121. https://doi.org/10.63125/sq8jta62

[56]. Keramida, E., Psomas, E., & Gotzamani, K. (2023). The impact of Lean adoption on organizational performance in a public service: the case of the Greek citizen's service centers. *International Journal of Lean Six Sigma*, *14*(7), 1544-1565. https://doi.org/10.1108/ijlss-01-2023-0004

[57]. Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553

[58]. Kim, M., & Hong, S. (2024). Integrating Artificial Intelligence to Biomedical Science: New Applications for Innovative Stem Cell Research and Drug Development. *Technologies*, *12*(7), 95-95. https://doi.org/10.3390/technologies12070095

[59]. Kinney, S. (2006). Example One: TPM Ownership. In (Vol. NA, pp. 301-315). Elsevier. https://doi.org/10.1016/b978-075067960-2/50026-9

[60]. Koç, Z., & Ecevit Alpar, Ş. (2023). Do lean practices increase nurses' organizational commitment and job satisfaction in Turkey? – A private hospital model. *Journal of Human Sciences*, *20*(2), 129-142. https://doi.org/10.14687/jhs.v20i2.6293

[61]. Koković, V., Pavlović, K., Mijanović, A., Kovačević, S., Mačužić, I., & Božović, V. (2024). Exploring statistical and machine learning methods for modeling probability distribution parameters in downtime length analysis: a paper manufacturing machine case study. *Journal of Big Data*, *11*(1), NA-NA. https://doi.org/10.1186/s40537-024-01030-4

[62]. Konecny, P. A., & Thun, J.-H. (2011). Do it separately or simultaneously—An empirical analysis of a conjoint implementation of TQM and TPM on plant performance. *International Journal of Production Economics*, *133*(2), 496-507. https://doi.org/10.1016/j.ijpe.2010.12.009

[63]. Kose, Y., Muftuoglu, S., Cevikcan, E., & Durmusoglu, M. B. (2022). Axiomatic design for lean autonomous maintenance system: an application from textile industry. *International Journal of Lean Six Sigma*, *14*(3), 555-587. https://doi.org/10.1108/ijlss-01-2022-0020

[64]. Kosse, S., Vogt, O., Wolf, M., König, M., & Gerhard, D. (2022). Digital Twin Framework for Enabling Serial Construction. *Frontiers in Built Environment*, *8*(NA), NA-NA. https://doi.org/10.3389/fbuil.2022.864722

[65]. Kumar, J., Soni, V. K., & Agnihotri, G. (2014). Impact of TPM implementation on Indian manufacturing industry. *International Journal of Productivity and Performance Management*, *63*(1), 44-56. https://doi.org/10.1108/ijppm-06-2012-0051

[66]. Kuruvatti, N. P., Habibi, M. A., Partani, S., Han, B., Fellan, A., & Schotten, H. D. (2022). Empowering 6G Communication Systems With Digital Twin Technology: A Comprehensive Survey. *IEEE Access*, *10*(NA), 112158-112186. https://doi.org/10.1109/access.2022.3215493

[67]. Lei, B., Janssen, P., Stoter, J., & Biljecki, F. (2023). Challenges of urban digital twins: A systematic review and a Delphi expert survey. *Automation in Construction*, *147*(NA), 104716-104716. https://doi.org/10.1016/j.autcon.2022.104716

[68]. Leng, J., Wang, D., Shen, W., Li, X., Liu, Q., & Chen, X. (2021). Digital twins-based smart manufacturing system design in Industry 4.0: A review. *Journal of Manufacturing Systems*, *60*(NA), 119-137. https://doi.org/10.1016/j.jmsy.2021.05.011

[69]. Liza Ludeña, B., Paulino Fierro, G., & Altamirano Flores, E. (2022). Design of a Lean Manufacturing model to reduce order delivery in a Textile Mype. *Proceedings of the 2nd LACCEI International Multiconference on Entrepreneurship, Innovation and Regional Development (LEIRD 2022): "Exponential Technologies and Global Challenges: Moving toward a new culture of entrepreneurship and innovation for sustainable development"*, *NA*(NA), NA-NA. https://doi.org/10.18687/leird2022.1.1.93

[70]. Lu, Q., Xie, X., Parlikad, A. K., & Schooling, J. (2020). Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance. *Automation in Construction*, *118*(NA), 103277-NA. https://doi.org/10.1016/j.autcon.2020.103277

[71]. Lv, Z. (2023). Digital Twins in Industry 5.0. *Research (Washington, D.C.)*, *6*(NA), 0071-NA. https://doi.org/10.34133/research.0071

[72]. Malakuti, S., Borrison, R., Kotriwala, A., Kloepper, B., Nordlund, E., & Ronnberg, K. (2021). An Integrated Platform for Multi-Model Digital Twins. *Proceedings of the 11th International Conference on the Internet of Things*, *NA*(NA), 9-16. https://doi.org/10.1145/3494322.3494324

[73]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, *2*(02), 52-74. https://doi.org/10.63125/8xbkma40

[74]. Masoud, E., Alahmed, A., Alsuwaidi, F., & Alahmed, S. (2025). Analyzing the influence of Lean Management strategies on organizational performance: A case study of Majan Printing & Packaging company in the UAE. *Quality Management Journal*, 1-17. https://doi.org/10.1080/10686967.2025.2483173

[75]. Md, A., Rokhshana, P., Mahiya Akter, S., & Anisur, R. (2025). AI-Powered Personalization In Digital Banking: A Review Of Customer Behavior Analytics And Engagement. *American Journal of Interdisciplinary Studies*, *6*(1), 40- 71. https://doi.org/10.63125/z9s39s47

[76]. Md Jakaria, T., Md, A., Zayadul, H., & Emdadul, H. (2025). Advances In High-Efficiency Solar Photovoltaic Materials: A Comprehensive Review Of Perovskite And Tandem Cell Technologies. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 201-225. https://doi.org/10.63125/5amnvb37

[77]. Md Mahfuj, H., Md Rabbi, K., Mohammad Samiul, I., Faria, J., & Md Jakaria, T. (2022). Hybrid Renewable Energy Systems: Integrating Solar, Wind, And Biomass for Enhanced Sustainability And Performance. *American Journal of Scholarly Research and Innovation*, *1*(1), 1-24. https://doi.org/10.63125/8052hp43

[78]. Md Majharul, I., Arafat Bin, F., & Ripan Kumar, P. (2022). AI-Based Smart Coating Degradation Detection For Offshore Structures. *American Journal of Advanced Technology and Engineering Solutions*, *2*(04), 01-34. https://doi.org/10.63125/1mn6bm51

[79]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327

[80]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08

[81]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391

[82]. Md. Rafiqul Islam, R., Iva, M. J., Md Merajur, R., & Md Tanvir Hasan, S. (2024, 2024/01/25). Investigating Modern Slavery in the Post-Pandemic Textile and Apparel Supply Chain: An Exploratory Study. International Textile and Apparel Association Annual Conference Proceedings,

[83]. Melesse, T. Y., Di Pasquale, V., & Riemma, S. (2021). Digital Twin models in industrial operations: State-of-the-art and future research directions. *IET Collaborative Intelligent Manufacturing*, *3*(1), 37-47. https://doi.org/10.1049/cim2.12010

[84]. Michael, J., Pfeiffer, J., Rumpe, B., & Wortmann, A. (2022). Integration challenges for digital twin systems-of-systems. *Proceedings of the 10th IEEE/ACM International Workshop on Software Engineering for Systems-of-Systems and Software Ecosystems*, *NA*(NA), 9-12. https://doi.org/10.1145/3528229.3529384

[85]. Minerva, R., & Crespi, N. (2021). Digital Twins: Properties, Software Frameworks, and Application Scenarios. *IT Professional*, *23*(1), 51-55. https://doi.org/10.1109/mitp.2020.2982896

[86]. Minerva, R., Lee, G. M., & Crespi, N. (2020). Digital Twin in the IoT Context: A Survey on Technical Features, Scenarios, and Architectural Models. *Proceedings of the IEEE*, *108*(10), 1785-1824. https://doi.org/10.1109/jproc.2020.2998530

[87]. Mohammad Shahadat Hossain, S., Md Shahadat, H., Saleh Mohammad, M., Adar, C., & Sharif Md Yousuf, B. (2024). Advancements In Smart and Energy-Efficient HVAC Systems: A Prisma-Based Systematic Review. *American Journal of Scholarly Research and Innovation*, *3*(01), 1-19. https://doi.org/10.63125/ts16bd22
[88]. Mollahassani-pour, M., Rashidinejad, M., & Abdollahi, A. (2017). Appraisal of eco-friendly Preventive Maintenance scheduling strategy impacts on GHG emissions mitigation in smart grids. *Journal of Cleaner Production*, *143*(NA), 212-223. https://doi.org/10.1016/j.jclepro.2016.12.127
[89]. Mourtzis, D., Angelopoulos, J., & Panopoulos, N. (2020). Intelligent Predictive Maintenance and Remote Monitoring Framework for Industrial Equipment Based on Mixed Reality. *Frontiers in Mechanical Engineering*, *6*(NA), NA-NA. https://doi.org/10.3389/fmech.2020.578379
[90]. Mourtzis, D., Angelopoulos, J., & Panopoulos, N. (2023). Blockchain Integration in the Era of Industrial Metaverse. *Applied Sciences*, *13*(3), 1353-1353. https://doi.org/10.3390/app13031353
[91]. Mourtzis, D., Tsoubou, S., & Angelopoulos, J. (2023). Robotic Cell Reliability Optimization Based on Digital Twin and Predictive Maintenance. *Electronics*, *12*(9), 1999-1999. https://doi.org/10.3390/electronics12091999
[92]. Naderi, H., & Shojaei, A. (2023). Digital twinning of civil infrastructures: Current state of model architectures, interoperability solutions, and future prospects. *Automation in Construction*, *149*(NA), 104785-104785. https://doi.org/10.1016/j.autcon.2023.104785
[93]. Naseri, F., Gil, S., Barbu, C., Cetkin, E., Yarimca, G., Jensen, A. C., Larsen, P. G., & Gomes, C. (2023). Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms. *Renewable and Sustainable Energy Reviews*, *179*(NA), 113280-113280. https://doi.org/10.1016/j.rser.2023.113280
[94]. Negri, E., Fumagalli, L., & Macchi, M. (2017). A Review of the Roles of Digital Twin in CPS-based Production Systems. *Procedia Manufacturing*, *11*(NA), 939-948. https://doi.org/10.1016/j.promfg.2017.07.198
[95]. Noor Alam, S., Golam Qibria, L., Md Shakawat, H., & Abdul Awal, M. (2023). A Systematic Review of ERP Implementation Strategies in The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02
[96]. Ospina Cifuentes, B. J., Suárez, Á., García Pineda, V., Alvarado Jaimes, R., Montoya Benitez, A. O., & Grajales Bustamante, J. D. (2024). Analysis of the Use of Artificial Intelligence in Software-Defined Intelligent Networks: A Survey. *Technologies*, *12*(7), 99-99. https://doi.org/10.3390/technologies12070099
[97]. Paniagua, C., & Delsing, J. (2021). Industrial Frameworks for Internet of Things: A Survey. *IEEE Systems Journal*, *15*(1), 1149-1159. https://doi.org/10.1109/jsyst.2020.2993323
[98]. Piroumian, V. (2021). Digital Twins: Universal Interoperability for the Digital Age. *Computer*, *54*(1), 61-69. https://doi.org/10.1109/mc.2020.3032148
[99]. Purwanto, C., & Jaqin, C. (2021). Improving Curing Process Productivity in The Tire Industry Using OEE, TPM and FMEA Methods. *Proceedings of the International Conference on Industrial Engineering and Operations Management*, *NA*(NA), NA-NA. https://doi.org/10.46254/an11.20211152
[100]. Rahman, C. M. L. (2015). Assessment of total productive maintenance implementation in a semiautomated manufacturing company through downtime and mean downtime analysis. *2015 International Conference on Industrial Engineering and Operations Management (IEOM)*, *NA*(NA), 1-9. https://doi.org/10.1109/ieom.2015.7093762
[101]. Ribeiro, I. M., Godina, R., Pimentel, C., Silva, F., & Matias, J. C. O. (2019). Implementing TPM supported by 5S to improve the availability of an automotive production line. *Procedia Manufacturing*, *38*(NA), 1574-1581. https://doi.org/10.1016/j.promfg.2020.01.128
[102]. Ripan Kumar, P., Md Majharul, I., & Arafat Bin, F. (2022). Integration Of Advanced NDT Techniques & Implementing QA/QC Programs In Enhancing Safety And Integrity In Oil & Gas Operations. *American Journal of Interdisciplinary Studies*, *3*(02), 01-35. https://doi.org/10.63125/9pzxgq74
[103]. Robertsone, G., Mezinska, I., & Lapina, I. (2021). Barriers for Lean implementation in the textile industry. *International Journal of Lean Six Sigma*, *13*(3), 648-670. https://doi.org/10.1108/ijlss-12-2020-0225
[104]. Rodrigues, M., & Hatakeyama, K. (2006). Analysis of the fall of TPM in companies. *Journal of Materials Processing Technology*, *179*(1-3), 276-279. https://doi.org/10.1016/j.jmatprotec.2006.03.102
[105]. Roksana, H. (2023). Automation In Manufacturing: A Systematic Review Of Advanced Time Management Techniques To Boost Productivity. *American Journal of Scholarly Research and Innovation*, *2*(01), 50-78. https://doi.org/10.63125/z1wmcm42
[106]. Roksana, H., Ammar, B., Noor Alam, S., & Ishtiaque, A. (2024). Predictive Maintenance in Industrial Automation: A Systematic Review Of IOT Sensor Technologies And AI Algorithms. *American Journal of Interdisciplinary Studies*, *5*(01), 01-30. https://doi.org/10.63125/hd2ac988
[107]. Roy, R. B., Mishra, D., Pal, S. K., Chakravarty, T., Panda, S., Chandra, M. G., Pal, A., Misra, P., Chakravarty, D., & Misra, S. (2020). Digital twin: current scenario and a case study on a manufacturing process. *The International Journal of Advanced Manufacturing Technology*, *107*(9), 3691-3714. https://doi.org/10.1007/s00170-020-05306-w
[108]. Saini, S., & Singh, D. (2020). Impact of implementing lean practices on firm performance: a study of Northern India SMEs. *International Journal of Lean Six Sigma*, *11*(6), 1005-1034. https://doi.org/10.1108/ijlss-06-2019-0069
[109]. Sarker, M. T. H. (2025). Case Study Analysis of AI-Powered Sensor Fabrics for Continuous Health Monitoring in Chronic Disease Management. *Strategic Data Management and Innovation*, *2*(01), 160-180. https://doi.org/10.71292/sdmi.v2i01.18
[110]. Sarker, M. T. H., Ahmed, I., & Rahaman, M. A. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08
[111]. Serror, M., Hack, S., Henze, M., Schuba, M., & Wehrle, K. (2021). Challenges and Opportunities in Securing the Industrial Internet of Things. *IEEE Transactions on Industrial Informatics*, *17*(5), 2985-2996. https://doi.org/10.1109/tii.2020.3023507
[112]. Shafique, K., Khawaja, B. A., Sabir, F., Qazi, S., & Mustaqim, M. (2020). Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends and Prospects for Emerging 5G-IoT Scenarios. *IEEE Access*, *8*(NA), 23022-23040. https://doi.org/10.1109/access.2020.2970118

[113]. Shahan, A., Anisur, R., & Md, A. (2023). A Systematic Review Of AI And Machine Learning-Driven IT Support Systems: Enhancing Efficiency And Automation In Technical Service Management. *American Journal of Scholarly Research and Innovation*, *2*(02), 75-101. https://doi.org/10.63125/fd34sr03

[114]. Shahin, M., Chen, F. F., Hosseinzadeh, A., & Zand, N. (2023). Using machine learning and deep learning algorithms for downtime minimization in manufacturing systems: an early failure detection diagnostic service. *The International Journal of Advanced Manufacturing Technology*, *128*(9-10), 3857-3883. https://doi.org/10.1007/s00170-023-12020-w

[115]. Sharif, K. S., Uddin, M. M., & Abubakkar, M. (2024). NeuroSignal Precision: A Hierarchical Approach for Enhanced Insights in Parkinson's Disease Classification. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),

[116]. Shlonsky, A., & Wagner, D. (2005). The next step: Integrating actuarial risk assessment and clinical judgment into an evidence-based practice framework in CPS case management. *Children and Youth Services Review*, *27*(4), 409-427. https://doi.org/10.1016/j.childyouth.2004.11.007

[117]. Shofiullah, S., Shamim, C. M. A. H., Islam, M. M., & Sumi, S. S. (2024). Comparative Analysis Of Cost And Benefits Between Renewable And Non-Renewable Energy Projects: Capitalizing Engineering Management For Strategic Optimization. *Academic Journal On Science, Technology, Engineering & Mathematics Education*, *4*(03), 103-112. https://doi.org/10.69593/ajsteme.v4i03.100

[118]. Siddiqui, N. A. (2025). Optimizing Business Decision-Making Through AI-Enhanced Business Intelligence Systems: A Systematic Review of Data-Driven Insights in Financial And Strategic Planning. *Strategic Data Management and Innovation*, *2*(1), 202-223. https://doi.org/10.71292/sdmi.v2i01.21

[119]. Siddiqui, N. A., Limon, G. Q., Hossain, M. S., & Mintoo, A. A. (2023). A Systematic Review Of ERP Implementation Strategies In The Retail Industry: Integration Challenges, Success Factors, And Digital Maturity Models. *American Journal of Scholarly Research and Innovation*, *2*(02), 135-165. https://doi.org/10.63125/pfdm9g02

[120]. Singh, K., & Ahuja, I. S. (2014). Effectiveness of TPM implementation with and without integration with TQM in Indian manufacturing industries. *Journal of Quality in Maintenance Engineering*, *20*(4), 415-435. https://doi.org/10.1108/jqme-01-2013-0003

[121]. Singh, M., Fuenmayor, E., Hinchy, E. P., Qiao, Y., Murray, N., & Devine, D. M. (2021). Digital Twin: Origin to Future. *Applied System Innovation*, *4*(2), 36-NA. https://doi.org/10.3390/asi4020036

[122]. Singh, R., & Gurtu, A. (2021). Prioritizing success factors for implementing total productive maintenance (TPM). *Journal of Quality in Maintenance Engineering*, *28*(4), 810-830. https://doi.org/10.1108/jqme-09-2020-0098

[123]. Sohel, A., Alam, M. A., Hossain, A., Mahmud, S., & Akter, S. (2022). Artificial Intelligence In Predictive Analytics For Next-Generation Cancer Treatment: A Systematic Literature Review Of Healthcare Innovations In The USA. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 62-87. https://doi.org/10.62304/jieet.v1i01.229

[124]. Sohel, R. (2025). AI-Driven Fault Detection and Predictive Maintenance In Electrical Power Systems: A Systematic Review Of Data-Driven Approaches, Digital Twins, And Self-Healing Grids. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 258-289. https://doi.org/10.63125/4p25x993

[125]. Somers, R. J., Douthwaite, J. A., Wagg, D. J., Walkinshaw, N., & Hierons, R. M. (2023). Digital-twin-based testing for cyber–physical systems: A systematic literature review. *Information and Software Technology*, *156*(NA), 107145-107145. https://doi.org/10.1016/j.infsof.2022.107145

[126]. Stavropoulos, P., Souflas, T., Papaioannou, C., Bikas, H., & Mourtzis, D. (2022). An adaptive, artificial intelligence-based chatter detection method for milling operations. *The International Journal of Advanced Manufacturing Technology*, *124*(7-8), 2037-2058. https://doi.org/10.1007/s00170-022-09920-8

[127]. Suhail, S., Iqbal, M., Hussain, R., & Jurdak, R. (2023). ENIGMA: An explainable digital twin security solution for cyber–physical systems. *Computers in Industry*, *151*(NA), 103961-103961. https://doi.org/10.1016/j.compind.2023.103961

[128]. Sun, H., Yam, R. C. M., & Wai-Keung, N. (2003). The implementation and evaluation of Total Productive Maintenance (TPM)—an action case study in a Hong Kong manufacturing company. *The International Journal of Advanced Manufacturing Technology*, *22*(3), 224-228. https://doi.org/10.1007/s00170-002-1463-3

[129]. Syaifoelida, F., Amin, I., & Hamdan, A. M. M. (2020). The designing analysis process of constituent attributes by using VSM and Six Sigma to enhance the productivity in industry of bearings. *IOP Conference Series: Materials Science and Engineering*, *788*(1), 012021-NA. https://doi.org/10.1088/1757-899x/788/1/012021

[130]. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital Twin in Industry: State-of-the-Art. *IEEE Transactions on Industrial Informatics*, *15*(4), 2405-2415. https://doi.org/10.1109/tii.2018.2873186

[131]. Thomas, A., Jones, G. R., & Vidales, P. (2006). An Integrated Approach to TPM and Six Sigma Development in the Castings Industry. In (Vol. NA, pp. 620-625). Elsevier. https://doi.org/10.1016/b978-008045157-2/50108-5

[132]. Uddin Shipu, I., Bhowmick, D., & Lal Dey, N. (2024). Development and applications of flexible piezoelectric nanogenerators using BaTiO3, PDMS, and MWCNTs for energy harvesting and sensory integration in smart systems. *International Journal of Scientific and Research Publications*, *14*(6), 221. https://scholarworks.utrgv.edu/chem_fac/280/

[133]. Ullah, N., Ahmad, Z., Siddique, M. F., Im, K., Shon, D.-K., Yoon, T.-H., Yoo, D.-S., & Kim, J.-M. (2023). An Intelligent Framework for Fault Diagnosis of Centrifugal Pump Leveraging Wavelet Coherence Analysis and Deep Learning. *Sensors (Basel, Switzerland)*, *23*(21), 8850-8850. https://doi.org/10.3390/s23218850

[134]. Vachálek, J., Sismisova, D., Vasek, P., Fiťka, I., Slovak, J., & Simovec, M. (2021). Design and Implementation of Universal Cyber-Physical Model for Testing Logistic Control Algorithms of Production Line's Digital Twin by Using Color Sensor. *Sensors (Basel, Switzerland)*, *21*(5), 1842-NA. https://doi.org/10.3390/s21051842

[135]. Villalonga, A., Negri, E., Biscardo, G., Castaño, F., Haber, R. E., Fumagalli, L., & Macchi, M. (2021). A decision-making framework for dynamic scheduling of cyber-physical production systems based on digital twins. *Annual Reviews in Control*, *51*(NA), 357-373. https://doi.org/10.1016/j.arcontrol.2021.04.008

[136]. Wahab, A. N. A., Mukhtar, M., & Sulaiman, R. (2013). A Conceptual Model of Lean Manufacturing Dimensions. *Procedia Technology*, *11*(11), 1292-1298. https://doi.org/10.1016/j.protcy.2013.12.327

[137]. Wang, J., Xu, C., Zhang, J., & Zhong, R. Y. (2022). Big data analytics for intelligent manufacturing systems: A review. *Journal of Manufacturing Systems*, *62*(NA), 738-752. https://doi.org/10.1016/j.jmsy.2021.03.005

[138]. Willmott, P., & McCarthy, D. (2001). Managing the TPM journey. In (Vol. NA, pp. 165-180). Elsevier. https://doi.org/10.1016/b978-075064447-1/50011-4

[139]. Wu, S., & Castro, I. T. (2020). Maintenance policy for a system with a weighted linear combination of degradation processes. *European Journal of Operational Research*, *280*(1), 124-133. https://doi.org/10.1016/j.ejor.2019.06.048

[140]. Xu, M., Gao, X., & Zhang, F. (2019). An Approach of Implementing SW-TPM in Real-Time Operating System. In (Vol. NA, pp. 99-112). Springer Singapore. https://doi.org/10.1007/978-981-13-5913-2_7

[141]. Yazdi, M. R. H., Saner, T., & Darvishmotevali, M. (2019). Application of an Artificial Intelligence Decision-Making Method for the Selection of Maintenance Strategy. In (Vol. NA, pp. 246-253). Springer International Publishing. https://doi.org/10.1007/978-3-030-35249-3_31

[142]. Zeb, S., Mahmood, A., Hassan, S. A., Piran, M. D. J., Gidlund, M., & Guizani, M. (2022). Industrial digital twins at the nexus of NextG wireless networks and computational intelligence: A survey. *Journal of Network and Computer Applications*, *200*(NA), 103309-NA. https://doi.org/10.1016/j.jnca.2021.103309

[143]. Zhai, S., Gehring, B., & Reinhart, G. (2021). Enabling predictive maintenance integrated production scheduling by operation-specific health prognostics with generative deep learning. *Journal of Manufacturing Systems*, *61*(NA), 830-855. https://doi.org/10.1016/j.jmsy.2021.02.006

[144]. Zhong, R. Y., Xu, C., Chen, C., & Huang, G. Q. (2015). Big Data Analytics for Physical Internet-based intelligent manufacturing shop floors. *International Journal of Production Research*, *55*(9), 2610-2621. https://doi.org/10.1080/00207543.2015.1086037