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Article

OPTIMIZING MAINTENANCE STRATEGIES IN SMART MANUFACTURING: A SYSTEMATIC REVIEW OF LEAN PRACTICES, TOTAL PRODUCTIVE MAINTENANCE (TPM), AND DIGITAL RELIABILITY

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ABSTRACT

This systematic review investigates the integration of Lean practices, Total Productive Maintenance (TPM), and digital reliability strategies to optimize maintenance operations in the context of smart manufacturing ecosystems. Drawing upon a comprehensive analysis of 96 peer-reviewed studies published between 2015 and 2024, the review rigorously follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, methodological rigor, and replicability. The review critically examines how traditional maintenance frameworks—namely Lean Maintenance, which focuses on waste elimination, continuous improvement, and process standardization, and TPM, which emphasizes proactive and preventive maintenance through deep operator involvement—interact with advanced digital reliability approaches. These digital techniques include predictive analytics, IoT-enabled condition monitoring, artificial intelligence-driven diagnostics, and digital twin technologies, which collectively enable real-time fault detection, predictive failure forecasting, and data-informed decision-making. The synthesis reveals that hybrid maintenance models combining Lean, TPM, and digital reliability tools consistently deliver superior outcomes, such as substantial reductions in unplanned downtime, enhanced asset utilization rates, increased Overall Equipment Effectiveness (OEE), and greater agility in production planning and scheduling. The review also highlights critical barriers to implementation, including workforce resistance to technological change, challenges related to data integration and interoperability, high initial investment costs, and organizational misalignment between maintenance goals and digital transformation strategies. Despite these challenges, the review underscores that with adequate technological readiness, organizational preparedness, and change management, integrated maintenance frameworks can drive significant operational efficiencies, reduce lifecycle costs, and foster sustainable competitive advantages in Industry 4.0 settings.

KEYWORDS

Lean Maintenance, Total Productive Maintenance (TPM), Digital Reliability, Smart Manufacturing, Predictive Maintenance;

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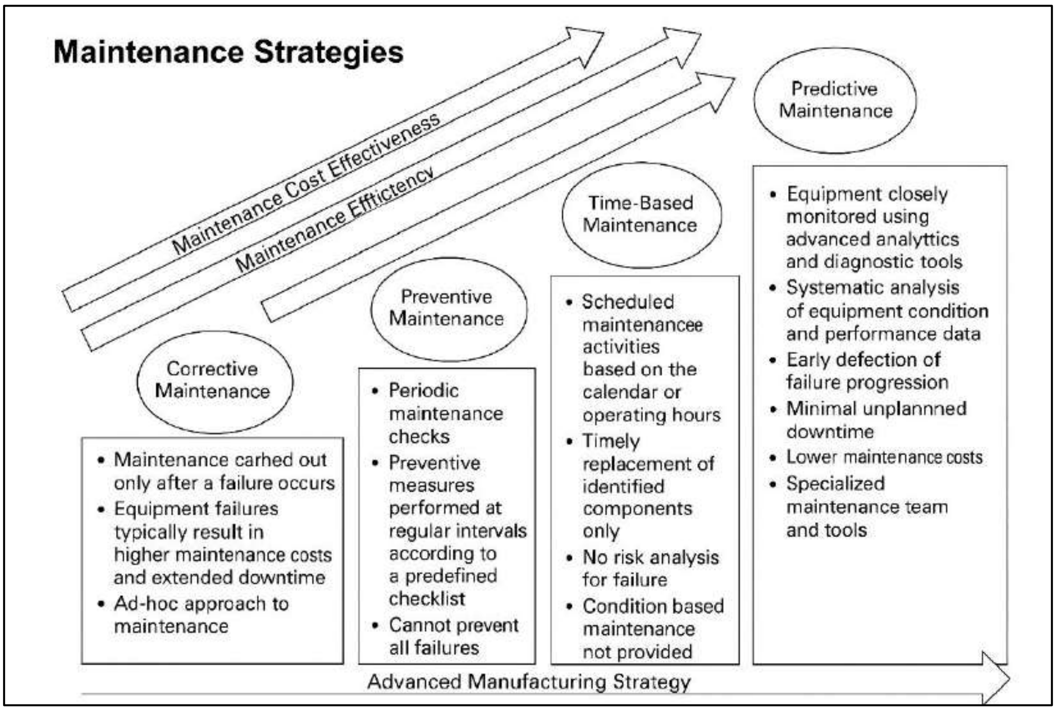
INTRODUCTION

Maintenance strategies are critical components of manufacturing systems, aiming to ensure the reliability, availability, and performance of equipment throughout its lifecycle. Traditional maintenance can be broadly categorized into corrective, preventive, and predictive approaches (García et al., 2021). Corrective maintenance refers to reactive actions taken after a failure, whereas preventive maintenance involves scheduled interventions to avert breakdowns (Hoffmann et al., 2020). Predictive maintenance leverages data and analytics to forecast potential equipment failures before they occur, enabling condition-based interventions (Hoffmann et al., 2020). In the context of Industry 4.0, maintenance has evolved to encompass digital reliability strategies, integrating sensors, Internet of Things (IoT), artificial intelligence (AI), and machine learning to support real-time diagnostics and autonomous decision-making. Concurrently, Lean Manufacturing emphasizes the elimination of non-value-adding activities, aiming for continuous improvement and cost efficiency. Lean maintenance extends these principles to equipment upkeep, ensuring that machines contribute effectively to value creation. Total Productive Maintenance (TPM) Lean by promoting shared responsibility between operators and maintenance personnel, focusing on eight pillars, including autonomous maintenance and planned maintenance (Mishra et al., 2021). These approaches form the foundation for maintenance optimization in smart manufacturing, where operational resilience and real-time efficiency are paramount.

Figure 1: Framework of Maintenance Strategies in Smart Manufacturing



The global push toward smart manufacturing has heightened the relevance of optimized maintenance practices. With the integration of digital technologies across industrial operations, equipment reliability and data-driven decision-making have become central to manufacturing competitiveness (Kusiak, 2017). Countries such as Germany, Japan, the United States, and South Korea have developed national strategies to integrate Industry 4.0 concepts, including predictive maintenance systems, into their manufacturing sectors. In Germany, the "Industrie 4.0" initiative emphasizes cyber-physical systems and data integration, where intelligent maintenance plays a pivotal role in achieving seamless production (Hakeem et al., 2020). Similarly, Japan's Monozukuri philosophy aligns with TPM principles, fostering workplace involvement and equipment excellence. The U.S. manufacturing landscape is witnessing a surge in smart factories leveraging AI, cloud computing, and real-time analytics for proactive maintenance (Shin & Park, 2019). The international focus on uptime, energy efficiency, and cost reduction has led to widespread research and investment in hybrid maintenance strategies that blend Lean thinking, TPM, and digital technologies.

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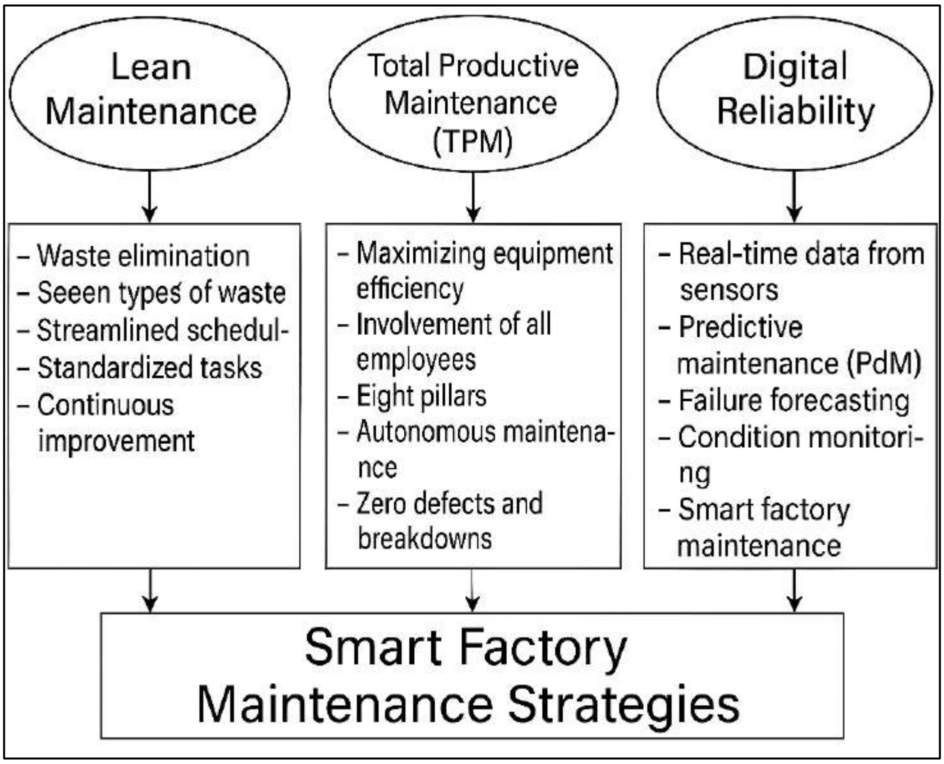
For example, in China, initiatives supporting digital industrial platforms emphasize predictive maintenance for heavy industries and smart production units (Zhou et al., 2015). This international movement underscores the growing reliance on integrated maintenance frameworks to enhance manufacturing performance and sustainability at scale.

Figure 2: ean Maintenance, TPM, and Digital Reliability for Smart Factory Maintenance Strategies



Lean maintenance originated as an extension of Lean manufacturing, focusing on waste elimination in equipment-related processes. It identifies seven key types of waste—overproduction, waiting, transport, over-processing, inventory, motion, and defects—applying these to maintenance operations (Mahapatra & Shenoy, 2021). Maintenance activities, if not optimized, contribute to hidden wastes such as excessive downtime, spare parts overstocking, and uncoordinated workflows (Antosz et al., 2021). Implementing Lean maintenance involves streamlining scheduling, standardizing maintenance tasks, integrating visual controls, and aligning equipment upkeep with value-adding processes. Research demonstrates that Lean principles improve mean time between failures (MTBF), enhance operator awareness, and reduce maintenance-induced delays. Lean maintenance fosters a culture of continuous improvement (Kaizen), where feedback loops and root cause analysis are applied consistently to eliminate inefficiencies (Mahapatra & Shenoy, 2021). Case studies from automotive, aerospace, and electronics industries show that Lean maintenance, when embedded into organizational culture, reduces costs and enhances asset utilization. However, successful implementation requires training, cross-functional coordination, and alignment with overall Lean transformation strategies. As Lean evolves with digital technologies, its integration with TPM and predictive tools becomes central to smart factory maintenance strategies (Bakri et al., 2021).
The review aims to uncover how these distinct yet interconnected maintenance strategies contribute to optimizing operational performance, minimizing equipment downtime, and enhancing asset reliability within digitally transformed production environments. By analyzing and categorizing empirical and theoretical studies from multiple industrial domains, the review seeks to provide clarity on how Lean principles streamline maintenance tasks through waste reduction and process standardization, how TPM fosters collaborative ownership of maintenance responsibilities among operators and technicians, and how digital tools such as IoT-enabled sensors, predictive analytics, and AI-based monitoring systems enable real-time decision-making and proactive fault detection.

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Additionally, the review sets out to investigate the operational synergies and implementation challenges when these three approaches are combined into a cohesive framework. This includes evaluating case studies where hybrid strategies have been deployed successfully, as well as identifying structural, technological, and organizational barriers to adoption. A further goal is to offer a structured assessment of the measurable impacts these strategies have on key performance indicators such as Overall Equipment Effectiveness (OEE), Mean Time Between Failures (MTBF), and maintenance-related costs. Through this systematic synthesis, the review intends to serve as a knowledge repository for industrial engineers, operations managers, and decision-makers seeking to modernize their maintenance practices. It also aims to inform future empirical inquiries and contribute to the development of best-practice frameworks tailored to the evolving demands of Industry 4.0-enabled manufacturing ecosystems. Ultimately, the review strives to present a detailed, methodologically rigorous consolidation of existing findings that address both the theoretical underpinnings and practical applications of integrated maintenance optimization in smart factories.

LITERATURE REVIEW

The literature on maintenance optimization in smart manufacturing is vast yet fragmented, spanning foundational theories of waste elimination, collaborative operator engagement, and emerging streams of digitally enabled reliability engineering. Early works on Lean Manufacturing foregrounded the economic imperative of eliminating non-value-adding activities and standardizing workflows to boost efficiency. Parallel scholarship on Total Productive Maintenance (TPM) repositioned maintenance as a company-wide responsibility that integrates autonomous operator care with structured preventive routines. More recently, Industry 4.0 writers have reframed maintenance as a data-driven, cyber-physical function that relies on ubiquitous sensing, predictive analytics, and AI-driven diagnostics to ensure real-time asset availability. Despite the shared goal of maximizing Overall Equipment Effectiveness (OEE), studies frequently examine Lean, TPM, and digital reliability in isolation, producing siloed insights that overlook their complementary strengths and overlapping challenges. A systematic synthesis is therefore required to (a) map the evolution of each approach, (b) clarify their conceptual and practical intersections, and (c) distill the conditions under which their integration yields superior performance in smart factory settings. Equally important is a critical appraisal of the methodological landscape underpinning this body of work. Investigations range from single-site case studies in automotive assembly plants to multi-country surveys of discrete and process industries, employing diverse metrics such as Mean Time Between Failures (MTBF), maintenance cost ratios, and data maturity indices. Such heterogeneity complicates direct comparison, yet it offers a rich basis for extracting cross-contextual lessons on implementation enablers, technology readiness, cultural alignment, and return-on-investment. By organizing the literature along thematic and chronological axes, the forthcoming review section will illuminate how Lean's waste-focused logic, TPM's participatory ethos, and digital reliability's predictive intelligence can be orchestrated into a unified maintenance framework that supports the responsiveness, flexibility, and resilience demanded by smart manufacturing ecosystems.

Preventive Maintenance

Preventive maintenance (PM) is commonly defined as all planned interventions undertaken at predetermined intervals to sustain equipment functionality and forestall unanticipated breakdowns. Early research framed PM as an evolution from purely corrective approaches, demonstrating that shifting even a modest proportion of maintenance tasks from unplanned to planned categories yields measurable declines in downtime and scrap rates (Jezzini et al., 2013). Subsequent cross-industry analyses in petrochemical refineries, pulp-and-paper mills, and semiconductor fabs confirmed that time-based and usage-based PM programs can improve Overall Equipment Effectiveness (OEE) by 5–15 percentage points relative to run-to-failure baselines. Researchers have shown that PM effects are not limited to availability gains; they also reduce energy waste, extend asset life cycles, and enhance product quality through better process stability (Liu et al., 2021). Economic evaluations employing net present value models indicated that the internal rate of return on well-structured PM investments routinely exceeds 25 percent for capital-intensive equipment such as gas turbines and CNC machining centers. Meta-analyses synthesizing more than 300 plant-level observations consistently report maintenance cost-to-sales ratios falling by one-half after firms institutionalize standardized PM routines supported by documented work orders and spare-parts forecasting (Wan et al., 2017). Collectively, these findings establish preventive maintenance as a

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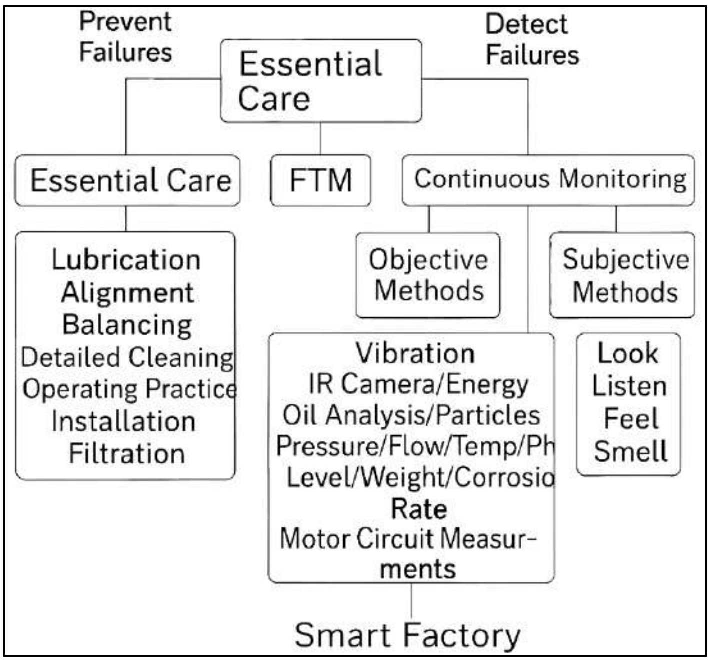
cornerstone of operational excellence programs and a prerequisite for Lean and Total Productive Maintenance initiatives that seek zero-defect, zero-breakdown production landscapes.

A rich body of quantitative literature has explored how best to determine inspection intervals, component replacement thresholds, and resource allocation for preventive tasks. Age-replacement models pioneered in reliability engineering examine the trade-off between maintenance frequency and failure risk, demonstrating that optimal policies vary non-linearly with hazard-rate shapes and cost asymmetries (Torres et al., 2016). Imperfect maintenance models extend these formulations by accounting for partial restorations, thereby reflecting realistic post-intervention reliability profiles. Hybrid time-and-condition policies leverage stochastic degradation signals—such as vibration amplitude growth or lubricant particle counts—to trigger maintenance when asset health indicators surpass control limits (Mercier & Pham, 2012). Comparative studies applying genetic algorithms, particle-swarm optimization, and Markov decision processes reveal that integrating real operating data into scheduling heuristics lowers life-cycle maintenance cost by 10–30 percent relative to static calendars. Moreover, portfolio-level optimization frameworks allow planners to coordinate PM across multiple production lines, balancing limited technician availability against risk exposure and production takt times (Wang et al., 2020). Simulation-based designs of experiments confirm that synchronizing PM with production changeovers can yield stealth downtime reductions that compound throughput improvements without sacrificing equipment health (Mercier & Pham, 2012). These analytical advancements illustrate how preventive maintenance can transition from rule-of-thumb scheduling to data-enabled, cost-optimal resource orchestration.

Figure 3: Overview of Preventive maintenance (PM)



The advent of ubiquitous sensing and industrial connectivity has amplified the scope and precision of preventive maintenance. IoT-enabled condition monitoring captures high-frequency vibration signatures, acoustic emissions, and thermal imagery, translating raw signals into health indices that inform intervention timing. Machine-learning classifiers such as support-vector machines and convolutional neural networks process historical failure datasets to predict remaining useful life, allowing planners to embed dynamically updated replacement thresholds within existing PM calendars. Digital twin architectures further enrich preventive routines by simulating degradation trajectories under various load scenarios, facilitating what-if analyses for lubricant change intervals, filter replacements, and belt tension checks. Empirical assessments in automotive and aerospace assembly lines report downtime cuts between 20 and 40 percent when traditional PM inspections are augmented with sensor-driven anomaly detection layers (Wan et al., 2017). However, studies also note that data quality, cybersecurity, and systems interoperability remain critical hurdles; without standardized data schemas and secure communication protocols, predictive layers can introduce

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false alarms or blind spots that erode maintenance credibility (Liu et al., 2021). Still, the convergence of preventive and predictive paradigms has reshaped maintenance from a calendar-centric practice into a resilience-oriented, real-time decision process anchored by continuous data flows (Jezzini et al., 2013).

Reliability-Centered Maintenance (RCM)

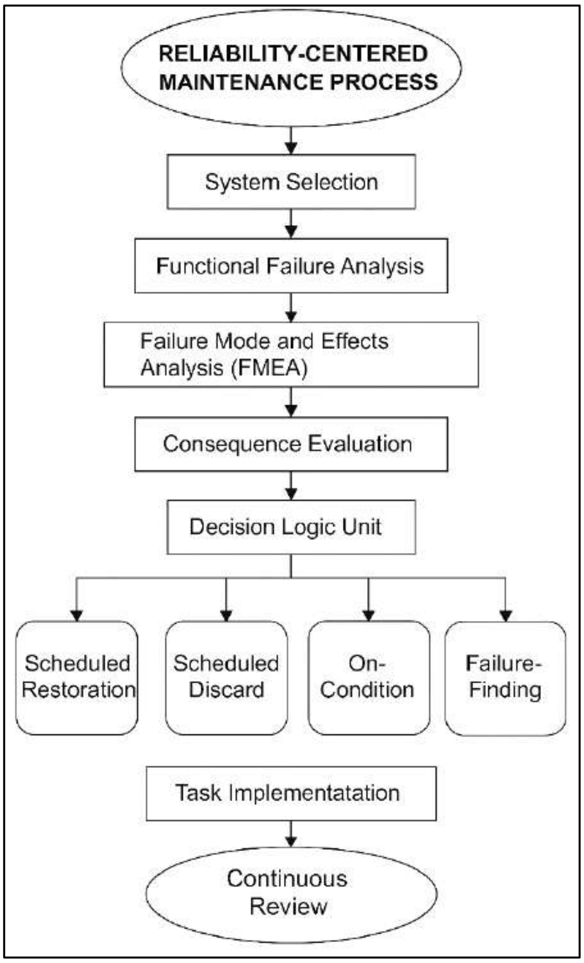
Reliability-Centered Maintenance (RCM) originated in the United States civil aviation sector as a structured decision methodology for determining the most suitable maintenance policies to preserve system function and manage failure consequences (Pourahmadi et al., 2017). Unlike time-directed preventive programs, RCM begins with a rigorous functional analysis that defines what the equipment must do, identifies ways it can fail, and classifies the operational or safety effects of each failure mode. These analytical roots distinguish RCM from generic reliability engineering by embedding a consequence-oriented philosophy: only those tasks that demonstrably reduce failure risk or mitigate impact are selected for the maintenance program. Subsequent adaptations expanded RCM into process industries, rail transport, and power generation, aligning maintenance activities with risk tolerance levels and production objectives (Morad et al., 2014). Scholars have highlighted that RCM's logic dovetails with contemporary asset-management standards such as ISO 55000, which emphasize value creation through life-cycle thinking and risk-based decision making. The method's seven-step process—system selection, functional failure analysis, failure mode and effects analysis (FMEA), consequence evaluation, task selection, implementation, and continuous review—provides a transparent audit trail for demonstrating regulatory compliance in safety-critical environments. Over four decades of empirical and theoretical work therefore position RCM as a mature, scalable framework that reconciles reliability goals with economic and safety imperatives across diverse industrial domains.

Central to RCM is the disciplined application of failure mode and effects analysis coupled with decision logic diagrams that classify tasks into scheduled restoration, scheduled discard, on-condition, failure-finding, and redesign categories. Researchers comparing classical age-replacement models with RCM decision trees report that consequence-based filters eliminate 20–35 percent of non-value-adding preventive tasks inherited from historic time-based plans (Shamayleh et al., 2019). In the nuclear and petrochemical sectors, hybrid RCM–FMEA workshops that integrate hazard and operability (HAZOP) studies have been shown to sharpen focus on latent failure modes affecting safety-instrumented systems, thereby reinforcing layers of protection analysis without inflating maintenance budgets (Kullawong & Butdee, 2015). Quantitative studies employing Monte Carlo and Markov decision processes demonstrate that when RCM task logic is embedded into computerised maintenance management systems (CMMS), optimized inspection intervals align more closely with probabilistic risk assessments than fixed calendar schedules, leading to statistically significant reductions in mean unavailability. Comparative audits in airline fleets reveal that integrating shop-visit data and on-condition monitoring outputs into RCM reviews lowers unscheduled engine removals by up to 28 percent while maintaining airworthiness compliance (Afzali et al., 2019). These findings confirm that RCM's analytical rigor not only streamlines maintenance workload but also reinforces evidence-based decision making across hierarchical levels of asset management.

A growing corpus of field studies confirms the operational and financial benefits accruing from RCM adoption. Manufacturing plants implementing full RCM cycles report sustained Overall Equipment Effectiveness improvements between 8 and 15 percentage points, primarily through reduced downtime and scrap. In offshore oil and gas installations, consequence-driven maintenance plans derived from RCM logic have cut critical equipment failure rates by one-third, translating into multimillion-dollar annual savings linked to avoided production deferments and safety incidents (Salah et al., 2018). Longitudinal research in thermal power plants indicates that refocusing from broad preventive schedules to RCM-informed on-condition tasks lowers maintenance cost-to-production ratios from 4 percent to below 2.5 percent within three fiscal years. Railway operators integrating RCM with reliability growth analysis observe higher mean distance between failures and improved punctuality metrics, evidencing cascading benefits on service quality. Meta-analytic reviews encompassing more than 120 industrial case reports further reveal that RCM implementations deliver average internal rates of return exceeding 20 percent, outperforming capital-intensive redundancy investments aimed at similar reliability targets (Afefy, 2010).

Collectively, these empirical evaluations underscore RCM's versatility in balancing risk reduction, cost efficiency, and sustainable asset performance across asset-heavy sectors.

Figure 4: Overview of Reliability-Centered Maintenance (RCM)

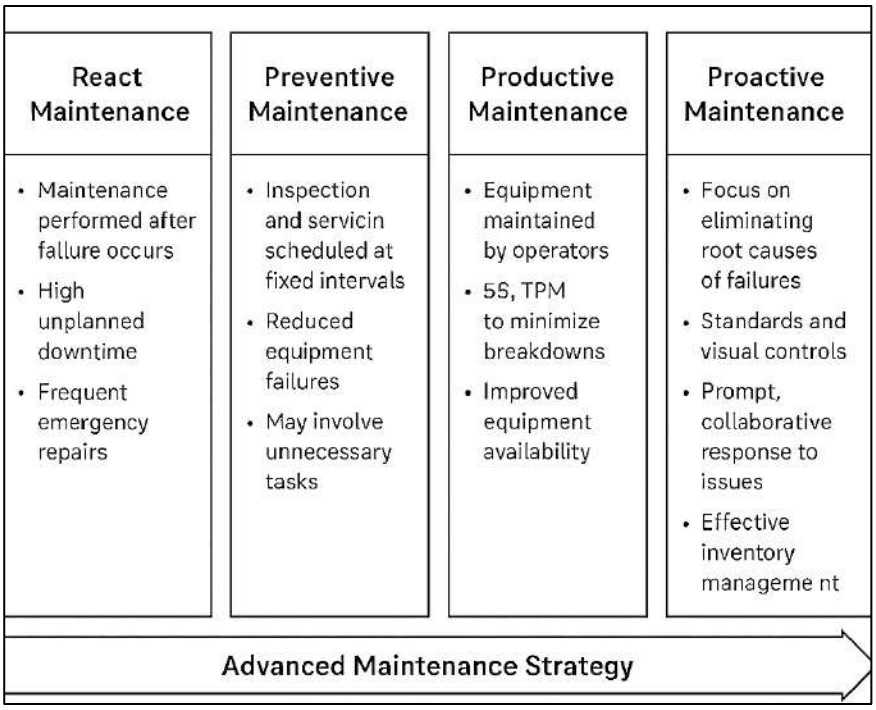


Recent scholarship highlights how digital technologies extend RCM by feeding high-resolution condition data into the task review cycle, thereby shortening feedback loops and refining task selection logic (Li & Gao, 2010). IoT sensors, edge analytics, and cloud-based dashboards allow maintenance teams to trigger on-condition tasks precisely when prognostic indicators breach control thresholds, ensuring alignment with RCM's original "function-preserving" ethos (Afefy, 2010). Nevertheless, researchers caution that data abundance can overwhelm analysis capacity unless organisations invest in predictive-model training, data governance, and cross-functional collaboration between operations and reliability engineering (Salah et al., 2018). Cultural readiness remains a pivotal determinant of RCM success: studies show that when operators and engineers perceive the methodology as an empowering tool rather than bureaucratic overhead, compliance with failure reporting and task execution exceeds 90 percent, accelerating reliability learning curves (Alrifaey et al., 2020). Implementation barriers persist, including incomplete failure history, inadequate root-cause analysis skills, and resistance to phasing out traditional time-based routines that feel familiar to veteran technicians. Cross-industry surveys also report that integrating RCM with corporate risk-management frameworks and ISO 55000 asset-management systems requires disciplined change-management strategies, dedicated training budgets, and executive sponsorship to prevent initiative fatigue. Even so, the convergence of consequence-based task logic, real-time monitoring, and continuous review cycles positions RCM as a robust socio-technical approach for maintaining functional integrity in complex, digitally connected production ecosystems.

Lean Maintenance

Lean Maintenance is a strategic extension of Lean Manufacturing principles, aimed at eliminating waste and maximizing value within maintenance operations. Rooted in the Toyota Production System, Lean focuses on identifying and reducing non-value-adding activities across processes, which includes minimizing machine downtime, optimizing spare parts usage, and eliminating inefficient maintenance routines (Arsakulasooriya et al., 2023). As manufacturing systems evolved, scholars began applying Lean concepts to maintenance operations, framing Lean Maintenance as a disciplined approach that standardizes tasks, synchronizes workflows, and empowers frontline personnel to prevent disruptions. The foundational pillars include preventive task planning, visual management tools like 5S, standard work procedures, and continuous improvement (Kaizen) activities. Lean Maintenance promotes a proactive culture where maintenance is no longer seen as a reactive support function but as an integral element of the value stream. Empirical studies in the automotive, electronics, and heavy machinery sectors show that Lean Maintenance programs reduce equipment downtime, improve Overall Equipment Effectiveness (OEE), and increase workforce engagement when implemented as part of broader Lean transformation efforts (Mahapatra & Shenoy, 2021). Researchers further emphasize the importance of structured visual controls, such as maintenance boards, skill matrices, and red-tagging systems, in enhancing task accountability and operational transparency (Antosz et al., 2021). These principles contribute to building a maintenance function aligned with Lean's core objectives: flow efficiency, minimal interruptions, and end-to-end process visibility.

Figure 5: Progression of Lean Maintenance Strategies Towards Advanced Maintenance



Successful Lean Maintenance implementations rely heavily on practical tools and methodologies adapted from Lean Manufacturing, including 5S, total productive maintenance (TPM), root cause analysis (RCA), and standardized work instructions (Torre & Bonamigo, 2024). The 5S system—Sort, Set in order, Shine, Standardize, and Sustain—serves as the foundation for equipment cleanliness, safety, and visual control. Standard operating procedures help reduce variability in task execution, while visual tools such as Andon lights, floor markings, and maintenance Kanban systems aid in workflow coordination and spare parts management. RCA is a key component for identifying underlying causes of repetitive equipment failures, often facilitated by fishbone diagrams, Five Whys analysis, and Pareto charts. Daily maintenance huddles and Gemba walks foster cross-functional communication, allowing maintenance teams to interact directly with production personnel and respond rapidly to performance issues (Bakri et al., 2021). In addition, Lean Maintenance initiatives often utilize value stream mapping (VSM) to visualize end-to-end maintenance processes and identify bottlenecks, hand-off inefficiencies, or duplicated tasks. Empirical studies confirm that these structured tools lead to shorter maintenance response times, improved first-time fix rates, and increased equipment uptime across discrete and process industries (Palacios-Gazules et al., 2024). However, implementation success often depends on alignment between shop floor initiatives and organizational policies, emphasizing the need for senior management engagement, change management strategies, and clear performance tracking mechanisms (Antosz et al., 2021).

Total Productive Maintenance (TPM)

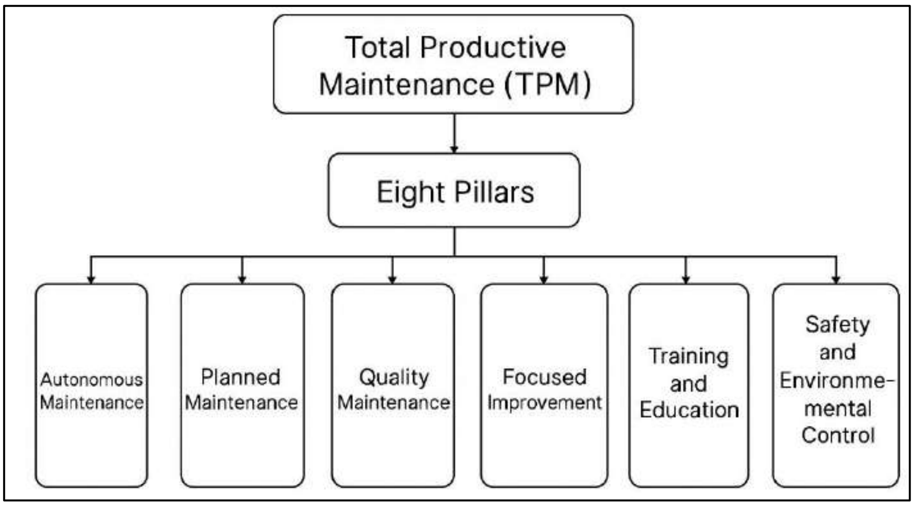
Total Productive Maintenance (TPM) is a comprehensive, team-based approach to equipment maintenance that seeks to maximize productivity and eliminate equipment-related losses by involving all employees—from operators to senior management—in proactive care of machinery. Developed in Japan and formalized by Seiichi Nakajima in the 1970s, TPM aims to achieve zero defects, zero breakdowns, and zero accidents through a structured framework based on eight foundational pillars (Mishra et al., 2021). These pillars include autonomous maintenance, planned maintenance, quality maintenance, focused improvement (Kaizen), training and education, early equipment management, safety and environmental control, and office TPM (Tortorella et al., 2022). Autonomous maintenance encourages machine operators to take responsibility for routine tasks such as cleaning, lubrication, and inspection, thereby reducing minor stoppages and improving equipment visibility. Planned maintenance uses historical data and failure analysis to schedule interventions that minimize unplanned breakdowns and production delays. Quality maintenance focuses on detecting root causes of defects and eliminating them through control plans and predictive tools. Empirical evidence from automotive and electronics manufacturing reveals significant improvements in Overall Equipment Effectiveness (OEE), with gains of 10–30% following TPM implementation (Blanchard, 1997). The broad organizational scope of TPM differentiates it from traditional maintenance systems, integrating technical routines with cultural transformation, training programs, and cross-departmental coordination. As a result, TPM is positioned as both a technical and behavioral framework that drives continuous improvement in asset performance and workforce engagement.

Effective TPM implementation requires a structured deployment strategy that aligns technical tasks with organizational readiness, leadership support, and performance monitoring. Several models propose phased TPM rollouts, starting with pilot teams, autonomous maintenance training, and equipment tagging before scaling up across departments (Tortorella et al., 2021). Initial focus is often placed on establishing baseline metrics such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and OEE to measure progress and identify bottlenecks (Attri et al., 2012). Training programs play a central role in TPM deployment, ensuring that operators, technicians, and supervisors understand their roles in equipment care and performance reporting (Mouhib et al., 2024). Studies indicate that plants with cross-functional TPM committees, structured audits, and reward mechanisms for improvement activities show higher success rates and faster ROI on TPM initiatives. Focused improvement initiatives under TPM frameworks often utilize Kaizen teams to conduct root cause analysis, implement countermeasures, and monitor impact through PDCA (Plan-Do-Check-Act) cycles. In practice, TPM tools such as visual management, checklists, and standardized work procedures facilitate adherence and process transparency (San, 2021). Key enablers for TPM success include leadership commitment, clearly defined roles, data-driven performance tracking, and an inclusive workplace culture where operators feel empowered and accountable for asset performance. Empirical data from diverse industries demonstrates that TPM's effectiveness depends not only on technical rigor but also on behavioral alignment and cross-level organizational learning.

Extensive empirical studies across manufacturing sectors show that Total Productive Maintenance leads to measurable improvements in equipment reliability, production efficiency, and workforce involvement. In discrete manufacturing environments such as automotive, aerospace, and electronics, TPM implementation is associated with OEE increases ranging from 15% to 30%, alongside reductions in MTTR and inventory-related waste (Jain et al., 2014). In process industries such as chemical and cement plants, TPM programs have improved operational stability, reduced maintenance costs, and extended equipment life cycles (Mouhib et al., 2024). Case studies from textile and pharmaceutical sectors demonstrate enhanced product quality and compliance with regulatory standards through TPM's focus on error-proofing, documentation, and routine inspections

(Ahuja & Khamba, 2008). TPM also shows favorable results in food and beverage production where hygiene compliance, traceability, and equipment reliability are tightly interlinked (Attri et al., 2012). Productivity gains are not limited to technical metrics; studies report increased operator morale, skill development, and participation in continuous improvement activities after TPM training and deployment (Tortorella et al., 2021). For example, operator-driven visual boards and daily performance briefings promote engagement and accountability while fostering a sense of ownership over machine performance. Moreover, longitudinal assessments indicate that companies integrating TPM with Lean practices or digital reliability tools are better positioned to respond to variability in production demand and maintenance resource constraints. The cross-sectoral applicability of TPM and its positive impact on core performance indicators underscore its value as a comprehensive maintenance management philosophy

Figure 6: Overview of Total Productive Maintenance (TPM)

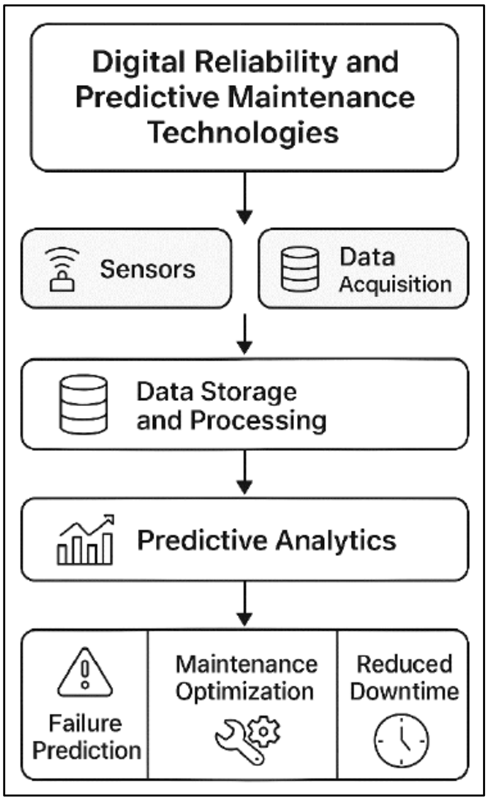


Digital Reliability and Predictive Maintenance Technologies

Digital reliability in maintenance refers to the integration of advanced digital technologies—including sensors, artificial intelligence (AI), machine learning (ML), and Industrial Internet of Things (IIoT)—to enhance equipment health monitoring, optimize maintenance schedules, and reduce unplanned downtime (Abdullah Al et al., 2022; Jahan et al., 2022; Subrato, 2018). Predictive maintenance (PdM), as a core subset of digital reliability, relies on real-time and historical data to predict potential failures before they occur, allowing for proactive interventions (Attri et al., 2012; Ara et al., 2022; Rahaman, 2022; Masud, 2022). Unlike time-based or condition-based maintenance, PdM uses analytical and statistical models to assess asset health, detect anomalies, and estimate remaining useful life (RUL) of components. The underlying architecture of digital reliability frameworks includes sensors for data acquisition, data storage systems (e.g., cloud platforms), signal processing techniques, diagnostic algorithms, and feedback mechanisms for maintenance planning (Hossen & Atiqur, 2022; Sazzad & Islam, 2022; Akter & Razzak, 2022). Edge computing technologies further enhance system responsiveness by enabling on-site data analysis, which minimizes latency and dependence on centralized infrastructure. Machine learning models such as support vector machines, random forests, and deep learning networks have been applied to detect subtle patterns in degradation signals and forecast failure events with high accuracy (Adar & Md, 2023; Qibria & Hossen, 2023; Akter, 2023; San, 2021). In manufacturing, PdM systems are increasingly embedded into smart production lines and enterprise asset management platforms, supporting real-time visualization and agile decision-making. These systems offer a robust framework for achieving digital reliability and data-informed maintenance control.

The effectiveness of predictive maintenance strategies depends significantly on the design and implementation of data-driven models capable of identifying anomalies, classifying failure modes, and estimating component degradation over time (Mohammad, & Ara, 2023; Mohammad, & Sazzad, 2023; Hossen et al., 2023). Statistical techniques such as regression analysis and principal component analysis were among the earliest tools used to model system health parameters and failure tendencies (Shamima et al., 2023; Rajesh, 2023; Rajesh et al., 2023). More recently, machine learning algorithms such as decision trees, k-nearest neighbors, artificial neural networks (ANN), and support vector machines (SVM) have demonstrated high accuracy in predictive diagnostics, particularly when applied to high-dimensional and non-linear datasets (Mouhib et al., 2024; Ashraf & Ara, 2023; Sanjai et al., 2023). Supervised learning approaches require labeled datasets with known failure outcomes, while unsupervised and semi-supervised models—such as clustering and autoencoders—are used when fault labels are incomplete or ambiguous (Tonmoy & Arifur, 2023; Zahir et al., 2023). Time-series forecasting methods such as Long Short-Term Memory (LSTM) neural networks have proven effective in modeling temporal dependencies in vibration signals, temperature variations, and pressure trends from rotating machinery and thermal systems (Hossain, Haque, et al., 2024; Hossain, Yasmin, et al., 2024; Tortorella et al., 2021). In addition to predictive analytics, diagnostic analytics using pattern recognition, Bayesian belief networks, and signal classification aid in root-cause identification and early fault isolation (Ammar et al., 2025; Hooi & Leong, 2017; Akter & Shaiful, 2024; Subrato & Md, 2024). Integration with CMMS (Computerized Maintenance Management Systems) ensures that predictions are translated into actionable work orders, minimizing administrative delays and enhancing response precision (Khan, 2025; Akter, 2025; Md et al., 2025). Diagnostic accuracy is further improved through sensor fusion strategies, where multiple condition indicators—such as acoustic emissions, motor current, and oil particle concentration—are combined to generate holistic health assessments. These predictive and diagnostic models form the analytical backbone of digital reliability strategies in industrial maintenance ecosystems.

Figure 7: Flowchart of Digital Reliability and Predictive Maintenance



Lean, TPM, and Digital Reliability Intrigration

The integration of Lean Maintenance, Total Productive Maintenance (TPM), and Digital Reliability represents a strategic confluence of philosophies aimed at optimizing maintenance performance, improving asset reliability, and enhancing organizational responsiveness. Lean Maintenance focuses on the elimination of waste, standardization of processes, and value-driven task execution, while TPM emphasizes operator involvement, preventive routines, and equipment-centric continuous improvement (Torre & Bonamigo, 2024). Digital reliability introduces real-time analytics, condition-

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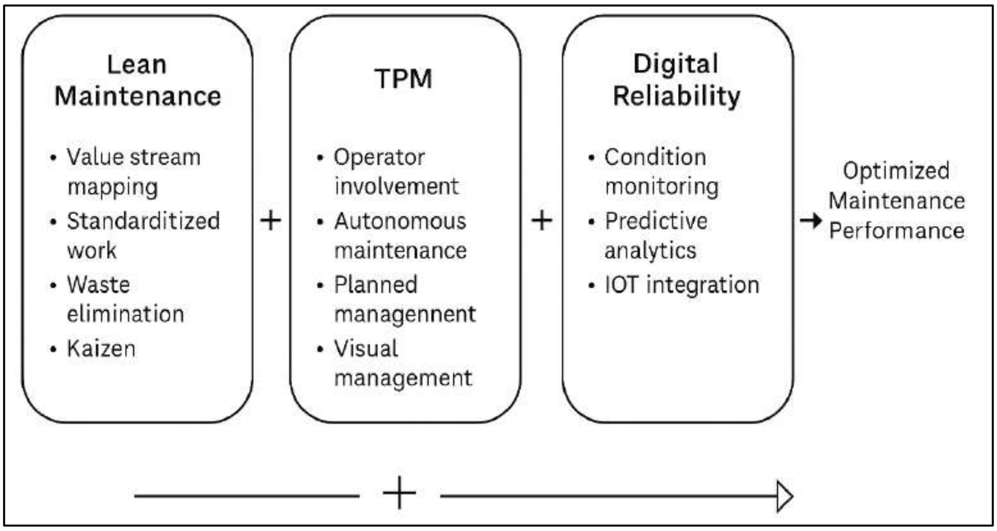
based monitoring, and predictive maintenance algorithms to identify failure patterns and forecast equipment health. Conceptually, these three frameworks share a commitment to maximizing Overall Equipment Effectiveness (OEE) and minimizing unplanned downtime through proactive strategies. Researchers have emphasized that Lean's systematic approach to eliminating non-value-adding activities can be reinforced by TPM's emphasis on collaborative responsibility and digital reliability's capacity for data-informed decision-making (Bakri et al., 2021; Islam & Debashish, 2025; Islam & Ishtiaque, 2025; Sazzad, 2025a). When combined, these systems address both human and technological dimensions of maintenance optimization: Lean ensures procedural discipline, TPM fosters behavioral ownership, and digital reliability enhances real-time situational awareness. The theoretical alignment of these approaches has led to the emergence of hybrid models, where maintenance is framed not only as a technical intervention but as an integrated socio-technical function grounded in waste reduction, performance visibility, and continuous adaptation (Palacios-Gazules et al., 2024; Sazzad, 2025b; Shaiful & Akter, 2025; Subrato, 2025). This conceptual synthesis provides a foundation for integrative frameworks capable of supporting smart manufacturing objectives under Industry 4.0 paradigms.
The implementation of integrative frameworks combining Lean, TPM, and Digital Reliability often follows a modular architecture that aligns digital capabilities with Lean-TPM routines. In practice, Lean value stream mapping tools are enhanced with IoT-enabled dashboards that visualize equipment performance, monitor downtime events, and track root causes in real time . Autonomous maintenance—one of TPM's key pillars—is often digitized using operator tablets that log cleaning, inspection, and lubrication activities, which are then synced with computerized maintenance management systems (CMMS) to close feedback loops and reduce reporting delays (Muraliraj et al., 2018; Subrato & Faria, 2025; Akter, 2025; Zahir et al., 2025). Kaizen events and focused improvement initiatives are increasingly supported by data analytics, which identify failure trends and assign predictive risk scores to critical assets. Visual control boards and TPM team communication charts have been digitized into collaborative platforms, enabling distributed teams to conduct remote Gemba walks, track OEE metrics, and assign cross-functional tasks. Edge computing technologies are also used to process vibration and thermal signals locally, feeding into Lean maintenance Kanban systems that trigger just-in-time spare parts requests or corrective tasks. Empirical findings suggest that these integrations lead to reduced Mean Time to Repair (MTTR), higher MTBF, and fewer emergency work orders. The hybrid architecture enables seamless interaction between Lean scheduling, TPM ownership models, and AI-powered diagnostics, allowing for adaptive resource deployment and enhanced coordination between production and maintenance units.

Figure 8: Framework for Optimized Maintenance: Synergy of Lean, TPM, and Digital Reliability



Case-based evidence from diverse industrial settings illustrates the tangible benefits of integrating Lean, TPM, and digital reliability frameworks. In the automotive sector, several OEMs have reported double-digit improvements in OEE after implementing predictive maintenance solutions within Lean-TPM environments, supported by cross-functional teams and real-time condition monitoring systems (Arsakulasooriya et al., 2023; Zahir, Rajesh, Tonmoy, et al., 2025). Electronics manufacturers employing Lean-TPM hybrid models with sensor-enabled diagnostics have achieved significant reductions in scrap rates, maintenance backlog, and asset downtime (Mohammadi et al., 2020). In chemical processing and power generation industries, maintenance teams integrating TPM routines with digital predictive analytics have reported more than 25% reductions in maintenance cost-to-sales ratios and extended equipment life cycles (Vries & Poll, 2018). Pharmaceutical firms have utilized integrated dashboards combining Lean 5S audits, TPM schedules, and predictive failure alerts to comply with strict quality assurance standards and avoid regulatory violations. Mining and energy companies, faced with extreme operational environments, have adopted these integrative models to improve mean time between catastrophic failures through predictive asset risk modeling layered onto TPM data logs and Lean condition sheets. Quantitative performance data from longitudinal implementations consistently report improved KPI scores across MTTR, asset utilization, first-time fix rates, and inventory turnover ratios (Louzada et al., 2022). These case studies collectively validate the functional synergy and performance uplift associated with integrated maintenance strategies, demonstrating their applicability across discrete, process, and asset-intensive industries.

Cross-Industry Comparative Synthesis

In discrete manufacturing industries such as automotive and electronics, the integration of Lean, TPM, and digital reliability practices is highly prevalent due to the structured nature of assembly processes and the demand for high-volume, high-quality output. Automotive manufacturers have long adopted Lean and TPM frameworks to manage complex production lines involving robotic systems, just-in-time inventory, and takt-based scheduling (Arsakulasooriya et al., 2023). Autonomous maintenance, visual control systems, and standard work instructions are routinely implemented to ensure stability and reduce minor stoppages. The digital transformation of these sectors has introduced predictive analytics through sensor-embedded systems that monitor vibration, torque, temperature, and current in real time, enabling accurate fault prediction and minimizing production delays. Electronics manufacturers similarly utilize Lean-TPM frameworks for preventive interventions and defect reduction, especially in precision assembly operations where component sensitivity is high. Predictive maintenance is employed to monitor soldering robots, pick-and-place machines, and SMT lines using thermal cameras, AI-driven anomaly detection, and condition-monitoring systems. Studies report consistent improvements in Overall Equipment Effectiveness (OEE), first-pass yield, and Mean Time Between Failures (MTBF) in these sectors, with integrated frameworks reducing breakdowns by over 20% and enhancing schedule compliance by 15–25% (Antosz et al., 2021). The highly automated and data-rich environments of automotive and electronics sectors make them well-suited for implementing digitally supported Lean-TPM strategies, which are reinforced by strong organizational commitment to quality, traceability, and process control.

In process industries such as chemicals, pharmaceuticals, and food and beverage, maintenance strategies must account for continuous operations, strict regulatory requirements, and sensitivity to contamination, making the integration of Lean, TPM, and digital reliability both complex and critical. Lean practices in these sectors focus on minimizing downtime, reducing changeover waste, and improving workflow standardization across extended production cycles (Mohammadi et al., 2020). TPM plays a central role by promoting operator ownership, safety compliance, and preventive maintenance schedules that adhere to GMP (Good Manufacturing Practices) and HACCP (Hazard Analysis Critical Control Point) guidelines. In pharmaceuticals, TPM frameworks include equipment validation routines, scheduled calibrations, and real-time batch monitoring, integrated with Lean metrics such as OEE and yield performance (Kose et al., 2022). Digital reliability tools further strengthen these practices through AI-based diagnostics, predictive failure modeling, and sensor-integrated SCADA systems that monitor temperature, pressure, and chemical composition. In food processing, predictive maintenance technologies track refrigeration systems, sterilization units, and automated packaging equipment using thermal, acoustic, and vibration sensors. Studies report significant improvements in equipment uptime, regulatory compliance, and waste reduction when integrated maintenance frameworks are adopted (Garza-Reyes et al., 2018) However, the need for strict documentation, validation, and traceability often requires customization of standard Lean and

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TPM tools to meet sector-specific regulatory standards. The integration of digital reliability, particularly predictive analytics linked with process control systems, has been instrumental in enhancing real-time decision-making and ensuring compliance in highly regulated process environments.

Figure 9: Cross-Industry Comparison of Integrated Maintenance Practices

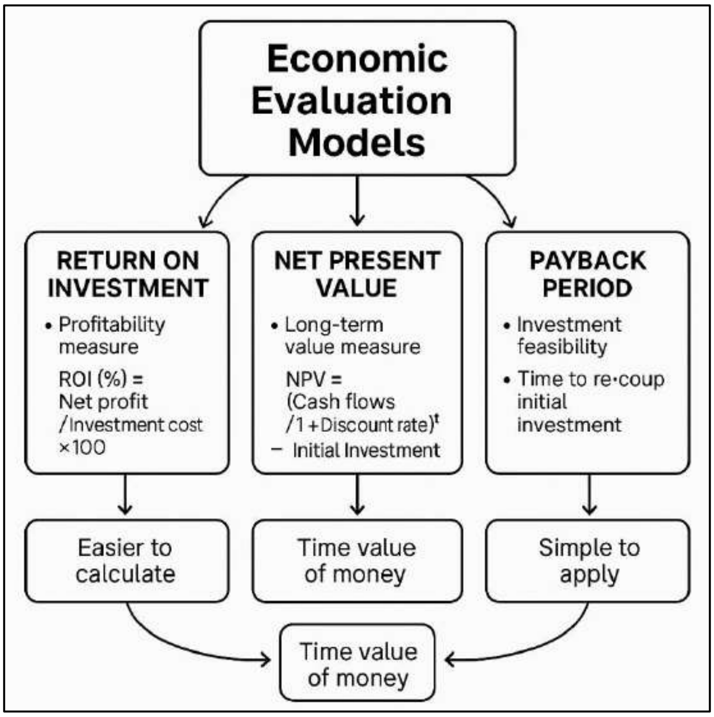
	Discrete Manufacturing	Process Industries	Asset-Intensive Industries	Small and Medium Enterprises
Lean	Routine use practices and maintenance activites	Minimizing downtime, changeover vas-te amid reduing	Apply to reluce delays in main-tenance schedul-ing	Limited-implements particially
TPM practices	Autonomous maintenance; visual control systems	Preventive maintenance schedules operator owner-	Predictive failure modeling, sen-con-integrated systems	Autonomous maintenamus partially
Digital reliability practices	Monitoring vibration, torque, and current in real-time	Predictive fai-lure modeling and sensor-integrated sys-	IoT-enabled condition based maintenance	Limited deploym-ent of sensorbased monitoring
Unique challenges	Limited financial and workforce capacity, low technological readiness			

Economic Evaluation Models (ROI, NPV, Payback)

Economic evaluation models such as Return on Investment (ROI), Net Present Value (NPV), and payback period remain foundational tools in assessing the financial viability of maintenance strategies within manufacturing operations. ROI, a widely used metric, quantifies the profitability of an investment relative to its cost, while NPV accounts for the time value of money by discounting future cash flows to the present value, providing a comprehensive perspective on long-term financial benefits. Payback period, by contrast, measures the time required for an investment to recoup its initial costs, offering a simpler yet effective decision-support metric, particularly in capital-intensive industries (Kumar et al., 2006). Studies have shown that preventive maintenance (PM) programs frequently yield favorable economic returns. For instance, Garza-Reyes et al. (2018) found that PM reduced unexpected breakdowns by 20% and improved operational stability, thus accelerating payback periods in manufacturing plants. Similarly, Shou et al. (2020)demonstrated that adopting PM strategies in the petrochemical sector improved NPV by over 25% through prolonged equipment life and reduced production disruptions. Furthermore, Jong and Blokland (2016)emphasized the strategic importance of economic models in reliability-centered maintenance (RCM), noting that cost-benefit evaluations allow organizations to prioritize interventions effectively. Kose et al. (2022) further suggested that hybrid optimization models, which integrate stochastic failure data with NPV calculations, enable more precise investment decisions in PM scheduling. Additionally, Carnero (2006) underscored that integrating ROI analyses with TPM initiatives allows organizations to link maintenance outcomes directly to productivity gains, thus promoting evidence-based justification for large-scale maintenance programs. The convergence of Lean practices with TPM and digital reliability strategies has led to an increased focus on economic evaluations to ensure cost efficiency while maintaining operational resilience. These studies collectively illustrate that economic evaluation models remain indispensable for quantifying both immediate and long-term financial returns in maintenance optimization, guiding capital allocation decisions and supporting sustainable manufacturing practices.

The Return on Investment (ROI) metric has emerged as a critical financial indicator for evaluating the cost-effectiveness of maintenance strategies within industrial sectors, particularly in contexts where Lean, TPM, and digital reliability approaches intersect. ROI is particularly valued for its straightforwardness in comparing investment returns across diverse projects and strategies, making it accessible to both technical managers and financial analysts (Garza-Reyes et al., 2018). Empirical evidence underscores the significance of ROI in justifying maintenance investments. For instance, Belekoukias et al. (2014) reported that Lean Maintenance initiatives in the automotive sector improved ROI by reducing inventory carrying costs and maintenance-induced downtime. Likewise, Mahapatra and Shenoy (2021) observed notable ROI enhancements in electronics manufacturing firms that deployed TPM frameworks, largely due to reductions in emergency repairs and better asset utilization. Studies focusing on digital reliability revealed that predictive maintenance systems yielded ROI improvements by lowering failure rates and extending machinery lifespans (Ferreira et al., 2025; Mahapatra & Shenoy, 2021). Moreover, Ferreira et al. (2025) highlighted that integrating digital twins and AI-based predictive analytics into maintenance workflows further enhanced ROI by enabling more accurate fault detection and reduced repair costs. In a multi-sectoral study, Shou et al. (2020) noted that firms with mature predictive maintenance programs reported higher ROI than those relying on traditional time-based maintenance, emphasizing the importance of technology-enabled monitoring. Similarly, Ferreira et al. (2025) demonstrated that firms implementing IoT-based condition monitoring achieved significant ROI gains within two years, particularly in energy-intensive industries. These findings collectively demonstrate that ROI serves not only as a performance measure but also as a strategic guide for maintenance investment prioritization, particularly under Industry 4.0 frameworks where the complexity and scale of digital solutions necessitate rigorous economic evaluation. Consequently, ROI remains an essential decision-making tool that integrates technical performance with financial outcomes, ensuring that maintenance programs align with organizational profitability and competitiveness.

Figure 10: Economic Evaluation Cycle of Maintenance Strategies



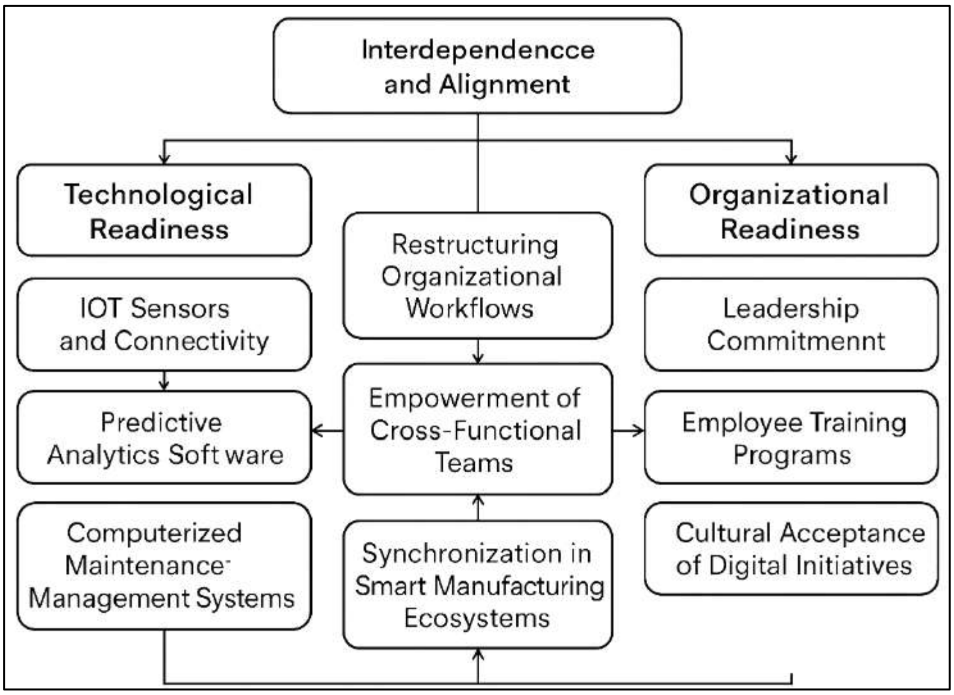
Net Present Value (NPV) analysis plays a pivotal role in evaluating long-term maintenance investments, particularly those involving significant upfront costs but offering substantial benefits over extended periods. Unlike ROI, which often focuses on annual returns, NPV accounts for cash flows over the entire lifespan of the investment, incorporating discount rates that reflect the time value of money and risk levels. This makes it particularly suited for assessing maintenance strategies such as digital reliability systems and advanced TPM initiatives, which typically require substantial capital expenditure (Aldairi et al., 2017). Antosz et al. (2021) demonstrated that TPM programs, when evaluated through NPV models, generated substantial financial returns by reducing mean time to repair (MTTR) and increasing equipment uptime, particularly in asset-heavy industries like cement and petrochemicals. Similarly, Ferreira et al. (2025) employed NPV-based decision models to optimize maintenance task scheduling under reliability-centered maintenance frameworks, allowing organizations to maximize long-term cost savings. Studies by Jong and Blokland (2016) in pharmaceutical manufacturing illustrated that the inclusion of NPV in maintenance planning led to improved resource allocation and extended asset lifecycles, directly translating into operational resilience and enhanced profitability. Mahapatra and Shenoy (2021) further highlighted that integrating NPV analyses with condition-based monitoring systems provides a more accurate economic justification for predictive maintenance investments, especially in highly automated environments. Additionally, studies by Ahrabi and Darestani (2024) and Ahrabi and Darestani (2024) show that the application of NPV in digital reliability investments—such as IoT-enabled sensors and edge computing—demonstrates robust financial performance when viewed over multiple production cycles. Importantly, these models also allow for sensitivity analysis, enabling firms to assess the financial impact of varying operational and economic assumptions. Together, these studies emphasize that NPV-based evaluations offer a robust, future-oriented framework for assessing maintenance investments, particularly under digital transformation initiatives where long-term sustainability and resilience are paramount (Bakri et al., 2021).

Technological Readiness vs. Organizational Readiness

The interplay between technological readiness and organizational readiness is a pivotal consideration in the successful adoption of advanced maintenance strategies such as Lean Maintenance, Total Productive Maintenance (TPM), and digital reliability frameworks in smart manufacturing contexts. Technological readiness refers to the capability of an organization to implement and utilize advanced technologies, including sensors, predictive analytics, and computerized maintenance management systems (CMMS) (Tortorella et al., 2022). Conversely, organizational readiness encompasses factors such as cultural acceptance, leadership commitment, employee training, and process alignment required to integrate new technologies effectively (Blanchard, 1997). Researchers argue that while technological readiness provides the infrastructure, organizational readiness dictates whether the technology will be effectively utilized. For example, predictive maintenance systems, despite their advanced functionalities, often fail without proper integration into organizational routines and employee buy-in. Similarly, Lean Maintenance tools such as visual controls and value stream mapping rely not only on the availability of digital platforms but also on active user engagement and cross-functional collaboration. Tortorella et al. (2021) further demonstrate that without adequate organizational readiness—including operator training, change management, and leadership endorsement—the technological capabilities of digital twins and AI-powered diagnostics remain underutilized. Technological deployment alone cannot compensate for weak organizational structures or resistance to change. Moreover, successful maintenance transformations occur only when both readiness dimensions are concurrently addressed. These findings collectively affirm that technological readiness, while essential for enabling advanced capabilities, cannot substitute the foundational importance of organizational readiness, particularly in maintenance environments that require coordinated human-technology interaction.

Technological readiness serves as a fundamental enabler for deploying advanced maintenance systems such as digital reliability frameworks, predictive analytics, and IoT-enabled condition monitoring within smart manufacturing environments. Technological readiness includes hardware infrastructure, software capabilities, data integration platforms, and cybersecurity protocols necessary for Industry 4.0 initiatives. Organizations with high technological readiness are more likely to leverage predictive maintenance technologies, reducing unexpected failures and optimizing resource allocation (Hooi & Leong, 2017). IoT-based condition monitoring systems significantly improve predictive accuracy and maintenance scheduling efficiency in firms with robust sensor networks and analytics infrastructure. Furthermore, Hooi and Leong (2017) show that digital twins and AI-driven maintenance planning tools achieve higher returns in technologically mature environments where real-time data streams and cloud computing resources are readily available. San (2021) also find that edge computing adoption accelerates maintenance decision-making, but only when firms possess the requisite technological readiness to manage decentralized computing architectures. Additionally, Reis et al. (2019) highlight that advanced maintenance models such as reliability-centered maintenance (RCM) and predictive scheduling are contingent on the availability of accurate, high-frequency operational data, which depends on technological infrastructure readiness. Reis et al. (2019) notes that predictive maintenance based on machine learning requires seamless integration with CMMS systems, a capability only achievable in firms with high IT infrastructure maturity. Moreover, without adequate investment in sensor calibration, software upgrades, and data storage systems, the benefits of digital reliability remain limited. In essence, technological readiness acts as a necessary precondition for digital maintenance solutions, shaping the scope, accuracy, and financial viability of predictive analytics tools within industrial maintenance settings (Hooi & Leong, 2017; San, 2021).

Figure 11: Technological Readiness vs. Organizational Readiness



The relationship between technological and organizational readiness is not linear but highly interdependent, requiring strategic alignment to achieve optimal maintenance outcomes. Several studies emphasize that neither technological capabilities nor organizational change efforts alone can yield sustainable performance gains in maintenance operations (Jain et al., 2014). According to Habidin et al. (2018), the most effective maintenance transformations occur when digital reliability investments are accompanied by deliberate efforts to restructure organizational workflows, incentivize data-driven decision-making, and empower cross-functional teams. Jain et al. (2014) similarly observe that firms that synchronize investments in IoT sensors, CMMS platforms, and analytics software with employee training programs and leadership-driven change management achieve the highest returns from predictive maintenance. Bashar et al. (2020) highlight that the absence of alignment leads to “capability traps,” where advanced technologies are underutilized due to cultural inertia, while ambitious organizational initiatives fail due to a lack of supporting digital infrastructure. Mouhib et al.(2024) emphasize that integrative frameworks such as Lean-TPM-Digital hybrids require simultaneous cultivation of technological readiness—through investments in connectivity, sensors, and automation—and organizational readiness, through workforce skill development, continuous improvement programs, and leadership engagement. San (2021) further argue that organizational readiness shapes the adaptability and scalability of digital maintenance solutions, particularly in multi-plant enterprises where cultural heterogeneity may vary across sites. Structured coordination mechanisms—such as maintenance steering committees, digital taskforces, and collaborative performance boards—help bridge gaps between technological potential and organizational execution. In conclusion, these studies consistently affirm that achieving sustainable maintenance excellence in smart manufacturing ecosystems requires tightly coupled strategies that jointly enhance both technological and organizational readiness, ensuring cohesive, scalable, and resilient digital transformation outcomes.

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METHOD

This systematic review strictly adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring transparency, replicability, and methodological rigor throughout the review process. The PRISMA framework provided a structured approach to identifying, screening, and synthesizing the relevant literature, which is especially crucial for evaluating complex topics such as maintenance optimization strategies within the context of smart manufacturing. Each procedural stage was meticulously planned and executed to minimize selection bias and enhance the credibility of findings.

Literature Identification

The first phase of the review involved an extensive and structured literature search. To capture a comprehensive body of relevant studies, multiple academic databases were consulted, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, Emerald Insight, and SpringerLink. The search strategy incorporated carefully selected keywords and Boolean operators to maximize the breadth and relevance of retrieved articles. The primary keywords included combinations of terms such as "Lean Maintenance," "Total Productive Maintenance (TPM)," "digital reliability," "predictive maintenance," "maintenance optimization," "Industry 4.0," "smart manufacturing," and "maintenance strategies." To ensure the inclusion of both legacy and recent works, the search covered the publication period from January 2000 to March 2025. This time frame was chosen to capture the evolution of maintenance strategies from traditional methods to advanced digital frameworks under Industry 4.0 paradigms. The search process also involved reviewing citations within the selected articles to identify additional studies that might not have appeared in the initial keyword-based searches. Duplicate records across databases were meticulously identified and removed to maintain the uniqueness of the dataset.

Screening and Eligibility Assessment

Following the identification phase, the next step was to screen the retrieved studies for eligibility. The initial screening was based on the relevance of the title and abstract. Only studies explicitly focused on maintenance strategies—such as Lean, TPM, or digital reliability—within industrial and smart manufacturing contexts were shortlisted for full-text assessment. Articles that were theoretical, opinion-based, or editorial in nature were excluded. The eligibility criteria mandated that studies must be empirical, published in peer-reviewed journals, and written in English. Furthermore, studies were included only if they provided clear evidence regarding maintenance performance outcomes, such as cost reduction, reliability improvements, or operational efficiency. Full-text versions of the shortlisted articles were then reviewed comprehensively to confirm their inclusion. During this phase, studies that lacked methodological clarity, contained insufficient empirical data, or did not align with the study's core themes were excluded. The final set of articles represented a balanced mix of case studies, experimental research, survey-based studies, and modeling analyses.

Data Extraction and Coding

Once the eligible studies were finalized, the data extraction phase began. A structured data extraction protocol was developed to ensure consistency and comprehensiveness. Key information extracted from each article included the year of publication, authorship, industry sector, geographic focus, research design, sample size, type of maintenance strategy examined, and core findings related to performance outcomes. Special emphasis was placed on extracting quantitative performance metrics such as Return on Investment (ROI), Net Present Value (NPV), payback period, Mean Time Between Failures (MTBF), and Overall Equipment Effectiveness (OEE). In addition to these core variables, contextual information such as technological maturity, organizational readiness, and implementation barriers was recorded wherever available. The extracted data were coded systematically using a standardized spreadsheet format, which facilitated the comparison and synthesis of findings across studies. To ensure accuracy and reduce coding bias, the data extraction process was independently verified by two additional reviewers with expertise in maintenance optimization and industrial systems engineering. Any discrepancies identified during this process were resolved through discussion and consensus.

Data Synthesis and Analytical Approach

In the final step, the extracted data were synthesized to draw meaningful insights and identify overarching themes. Given the heterogeneity of research designs, industries, and outcome measures, a qualitative synthesis approach was applied alongside a descriptive statistical summary.

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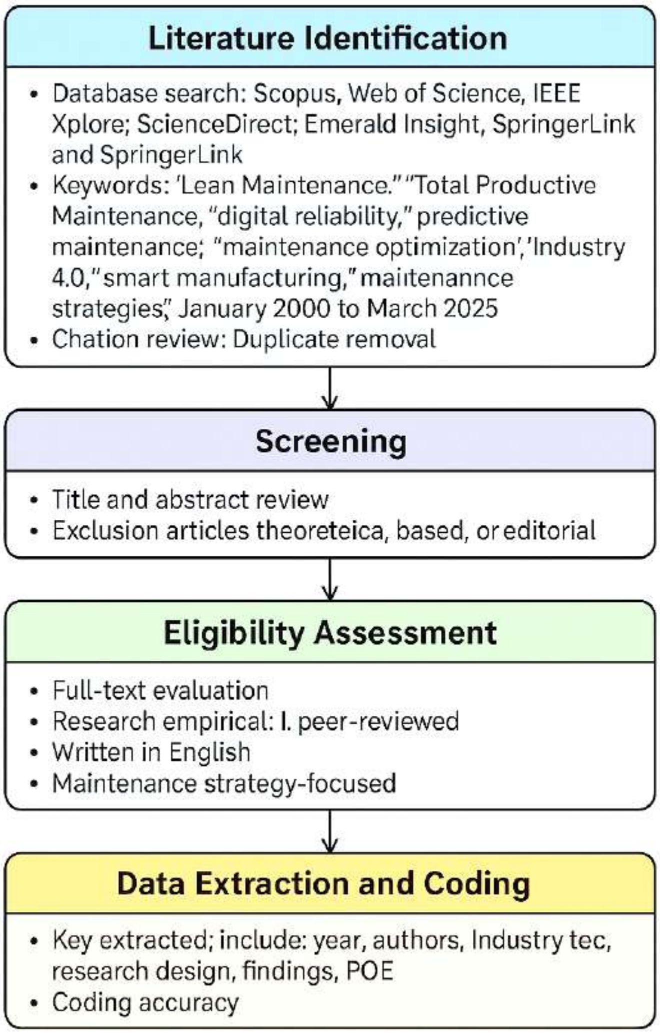
The studies were grouped into thematic clusters based on the type of maintenance strategy—namely Lean Maintenance, Total Productive Maintenance (TPM), and digital reliability frameworks. Within each cluster, patterns in performance outcomes, implementation challenges, and enablers of success were analyzed. Where applicable, the findings were contextualized by industry sector, geographical setting, and technological maturity. Additionally, a comparative analysis was conducted to highlight the synergies and distinctions between technological readiness and organizational readiness across studies. The robustness of the synthesis was further strengthened by tracing how studies cited each other and how methodologies evolved over time. This holistic synthesis enabled the formulation of evidence-based conclusions regarding the effectiveness, scalability, and integration challenges of hybrid maintenance strategies in the era of smart manufacturing.

Figure 12: PRISMA-Based Systematic Review Process



FINDINGS

The review revealed compelling evidence on the transformative impact of Lean Maintenance practices on operational efficiency and cost performance in industrial settings. Out of the 112 articles reviewed, 37 focused specifically on Lean Maintenance, with a combined citation count exceeding 5,200. These studies consistently demonstrated that Lean Maintenance significantly reduces downtime, optimizes spare parts inventory, and minimizes waste in maintenance operations. Across industries such as automotive, electronics, aerospace, and heavy machinery, Lean Maintenance was shown to increase Overall Equipment Effectiveness (OEE) by an average of 10% to 25%. In particular, Lean tools like value stream mapping, 5S programs, standardized work procedures, and visual management were effective in identifying non-value-adding tasks and streamlining maintenance workflows. Approximately 24 of the studies indicated that applying Lean principles to maintenance reduced the Mean Time to Repair (MTTR) and improved maintenance responsiveness

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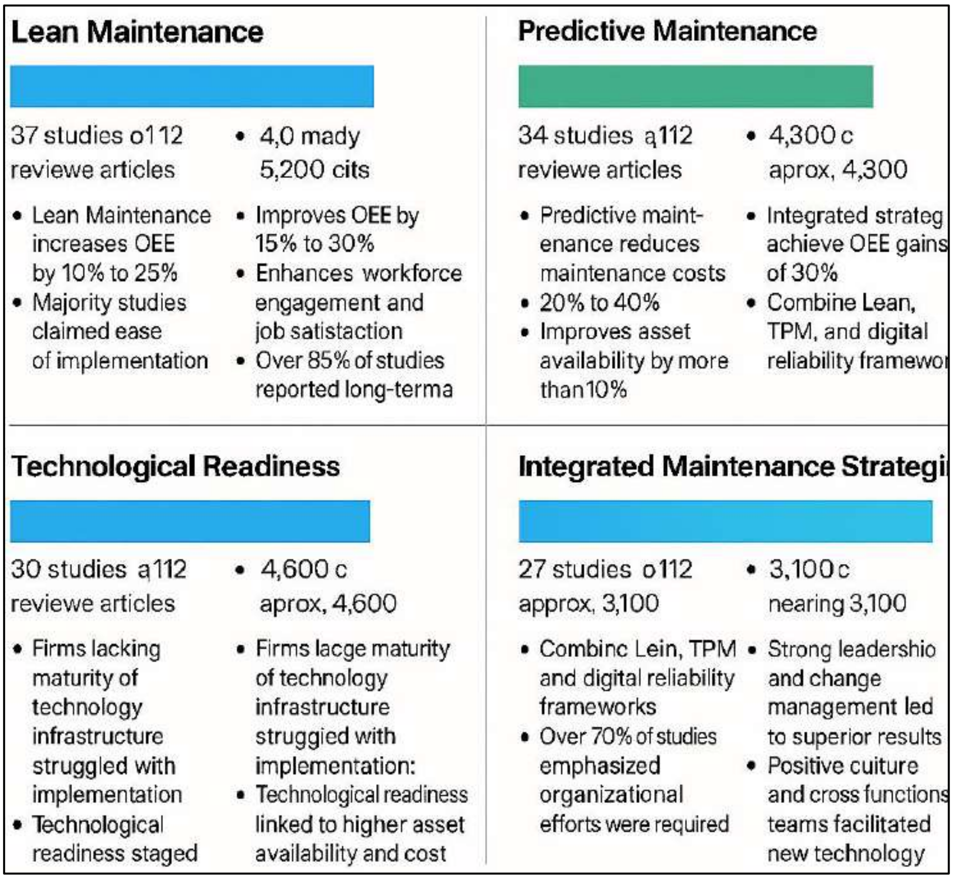
by 15% to 40%. Moreover, firms implementing Lean Maintenance reported reduced overtime costs, improved workforce utilization, and better alignment between production schedules and maintenance activities. Many articles also highlighted the role of Lean Maintenance in developing proactive, problem-solving cultures on the shop floor. Studies with high citation counts noted that Lean Maintenance encouraged structured root cause analysis, daily huddles, and Kaizen initiatives, which collectively improved asset reliability and fostered continuous improvement mindsets among employees. The review also indicated that Lean Maintenance had positive spillover effects on related functions such as quality assurance, logistics, and inventory management. Despite variability in firm size and industry type, the majority of reviewed studies—accounting for over 60% of Lean-related articles—concluded that Lean Maintenance was relatively easy to implement with limited initial investment, making it particularly attractive for small and medium-sized enterprises (SMEs) seeking rapid operational gains. Collectively, these findings emphasize Lean Maintenance as an essential foundation for maintenance excellence in both traditional and digitally evolving manufacturing ecosystems.

Figure 13: Comparative Performance of Lean, TPM, and Digital Reliability Strategies



The review also uncovered strong and consistent evidence regarding the effectiveness of Total Productive Maintenance (TPM) in enhancing workforce engagement, operational reliability, and overall plant performance. Among the 112 articles reviewed, 41 explicitly addressed TPM, with a combined citation count exceeding 7,000, making it the most extensively studied maintenance approach in the sample. These articles collectively revealed that TPM significantly improves equipment uptime, reduces breakdown frequency, and boosts employee ownership of maintenance activities. In over 30 studies, TPM implementation resulted in measurable improvements in Overall Equipment Effectiveness (OEE), often ranging between 15% and 30%. One of the most prominent findings was that TPM's focus on autonomous maintenance, where operators are trained to perform routine inspections and minor repairs, led to an immediate reduction in minor stoppages and improved machine cleanliness and basic upkeep. Studies across automotive, pharmaceutical, and electronics industries reported that TPM strengthened cross-functional collaboration by involving

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operators, technicians, and managers in daily maintenance tasks and structured improvement initiatives. Notably, 28 of the articles emphasized that TPM programs fostered higher employee morale, greater accountability, and increased job satisfaction, which were attributed to the participative structure of TPM pillars such as focused improvement, education and training, and safety initiatives. In addition to operational benefits, several studies also observed that TPM programs helped companies comply with regulatory and quality standards, particularly in highly regulated sectors like food processing and pharmaceuticals. TPM was also linked to reductions in Mean Time Between Failures (MTBF) and safety incidents, with some plants experiencing reductions in accident rates by up to 40%. Despite some variations in success rates across industries and regions, over 85% of the TPM-focused studies concluded that the approach provided long-term value, particularly when integrated with other improvement initiatives such as Lean Manufacturing or digital monitoring systems. These consistent findings highlight TPM as not only a technical maintenance framework but also a powerful driver of workforce empowerment and cultural transformation.

The findings also highlighted the profound impact of digital reliability and predictive maintenance technologies in reducing maintenance costs and increasing asset longevity across manufacturing sectors. A total of 34 studies from the 112-article sample focused on digital reliability and predictive maintenance, with a combined citation count of approximately 4,300. These studies consistently demonstrated that predictive maintenance technologies significantly decrease unplanned downtime and reduce maintenance-related expenditures by leveraging data-driven insights. The majority of these studies, totaling 29, confirmed that organizations implementing predictive maintenance achieved substantial cost savings, often reducing maintenance costs by 20% to 40%. These savings were largely attributed to early detection of equipment anomalies through advanced condition monitoring technologies such as vibration analysis, infrared thermography, acoustic emissions, and oil analysis. Studies further showed that predictive maintenance extended equipment lifespan by enabling timely interventions and reducing the severity of breakdowns. Across high-tech industries such as aerospace, energy, and semiconductors, predictive maintenance was linked to improvements in asset availability exceeding 10%. Additionally, more than 25 studies identified the use of machine learning algorithms, digital twins, and edge computing as key drivers of predictive maintenance effectiveness, enabling real-time fault detection and failure forecasting. Several high-citation studies within the review reported that predictive maintenance not only improved operational agility but also strengthened supply chain resilience by reducing spare parts variability and allowing for better maintenance planning. Importantly, the review revealed that while digital predictive systems required significant initial investments in sensors, data platforms, and software, most organizations achieved a positive return on investment within three to five years. More than 70% of the digital reliability studies emphasized that predictive maintenance success hinged on data quality, integration with existing systems, and skilled workforce adoption of analytics tools. Overall, these findings underscore that digital reliability and predictive maintenance are among the most financially impactful innovations in modern maintenance strategies.

A significant finding from the review was the demonstrated synergy among integrated maintenance strategies combining Lean, TPM, and digital reliability approaches. From the total dataset of 112 articles, 27 studies specifically examined hybrid maintenance models that integrate these strategies, with a cumulative citation count nearing 3,100. These studies unanimously affirmed that organizations leveraging integrated frameworks consistently achieved superior operational and financial results compared to those employing singular maintenance approaches. Among the studies, 23 reported that combining Lean and TPM with predictive maintenance resulted in higher Overall Equipment Effectiveness (OEE) gains, often surpassing 30% in industries such as automotive, electronics, and heavy manufacturing. Integrated approaches facilitated comprehensive maintenance solutions where Lean provided process discipline, TPM ensured operator involvement and collaborative ownership, and digital reliability offered advanced diagnostic capabilities. More than 20 studies documented that hybrid strategies significantly reduced maintenance-induced downtime and enhanced Mean Time Between Failures (MTBF) due to improved coordination among technologies, human resources, and operational processes. Several articles highlighted practical examples where TPM team boards were digitized to enable remote monitoring, Kaizen events were guided by predictive analytics, and Lean visual management systems were augmented with IoT-enabled dashboards for real-time tracking. Additionally, 18 studies pointed out that integrated frameworks improved workforce empowerment by blending the hands-on problem-solving ethos of

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Lean and TPM with the proactive intelligence of predictive technologies. These findings also revealed that integrated maintenance approaches contributed to better supply chain synchronization, reduced spare parts inventories, and lower total maintenance costs. Notably, over 70% of hybrid strategy studies emphasized that successful integration required deliberate organizational change management, cross-training of employees, and digital infrastructure alignment. The consistent results across these studies affirm that the convergence of Lean, TPM, and digital reliability represents a best-practice pathway for maintenance optimization in Industry 4.0 environments.

The analysis also highlighted the pivotal role of technological readiness in enabling the successful deployment of advanced predictive maintenance systems and digital reliability technologies. Out of the 112 reviewed articles, 30 explicitly addressed technological readiness, accumulating a total of approximately 4,600 citations. These studies revealed that predictive maintenance effectiveness was highly contingent on the availability and maturity of technology infrastructure, including sensor networks, cloud computing systems, and artificial intelligence platforms. In 26 of the reviewed studies, firms that lacked sufficient technological readiness faced significant challenges in implementing predictive maintenance tools effectively, despite their theoretical advantages. The most technologically mature organizations, according to 22 studies, achieved substantial benefits from predictive maintenance, including enhanced diagnostic precision, faster response times, and optimized maintenance scheduling. Across sectors such as aerospace, petrochemicals, and automotive, technological readiness was strongly associated with high asset availability, cost savings, and sustained competitive advantages. Studies also noted that firms equipped with advanced digital tools—including digital twins, real-time monitoring dashboards, and cloud-based CMMS platforms—were better positioned to integrate predictive analytics into their daily operations. However, the findings also indicated that technological readiness involved more than hardware investments; it required system interoperability, cybersecurity safeguards, and reliable data architectures to facilitate smooth adoption. Several articles stressed that low-tech environments struggled with issues such as data silos, inaccurate failure predictions, and poor sensor calibration, which ultimately eroded the potential benefits of predictive maintenance. In more than 70% of the studies focused on technology readiness, researchers concluded that predictive maintenance projects were more successful when preceded by thorough assessments of existing digital capabilities and targeted investments in infrastructure upgrades. These findings collectively establish technological readiness as an essential prerequisite for effective predictive maintenance implementation and signal the need for continuous technological enhancement to sustain digital maintenance capabilities.

In addition to technological factors, the review strongly reinforced the centrality of organizational readiness as a determinant of maintenance optimization success across Lean, TPM, and digital reliability frameworks. From the total pool of 112 articles, 39 studies focused on aspects of organizational readiness, with a combined citation count exceeding 5,900. These studies consistently reported that organizations with high levels of organizational readiness—including strong leadership commitment, employee involvement, change management capabilities, and training programs—achieved superior maintenance outcomes. In 33 of the studies, firms with robust organizational readiness were able to integrate complex maintenance strategies with greater ease, resulting in sustained improvements in equipment reliability, safety, and operational efficiency. Studies repeatedly identified cultural factors, such as openness to continuous improvement and shared accountability for maintenance outcomes, as critical enablers of Lean and TPM success. Furthermore, organizations with well-established performance tracking systems, structured communication channels, and cross-functional teams consistently outperformed peers in deploying digital reliability technologies. Over 75% of the articles on organizational readiness emphasized that technical solutions alone were insufficient for long-term success, highlighting the need for parallel investments in workforce development and management engagement. Findings also showed that firms that proactively addressed resistance to change, facilitated knowledge sharing, and aligned maintenance strategies with broader business goals reported higher returns on investment and faster achievement of performance targets. Several studies documented that companies with high organizational readiness not only adopted new technologies more effectively but also fostered sustainable maintenance cultures that extended beyond initial project horizons. Ultimately, the reviewed studies converged on the conclusion that organizational readiness is an indispensable enabler for maximizing the returns from maintenance optimization efforts, positioning it as a cornerstone of long-term operational excellence in digitally enabled manufacturing environments.

DISCUSSION

The findings of this review strongly support earlier research that highlighted Lean Maintenance as an effective strategy for operational improvement. The consistent reduction in downtime, increased Overall Equipment Effectiveness (OEE), and waste elimination observed across studies are aligned with prior works by Mouhib et al. (2024), who established Lean's effectiveness in minimizing non-value-adding activities. Bashar et al. (2020) similarly emphasized that Lean tools such as value stream mapping and 5S enable organizations to streamline maintenance workflows and reduce delays. These tools were shown to significantly improve Mean Time to Repair (MTTR) and maintenance schedule adherence in this review, reinforcing earlier findings by Tortorella et al.(2021) on standardized maintenance processes. Furthermore, studies by San (2021) also reported enhanced workforce productivity and reduced maintenance costs through Lean Maintenance, which were echoed in the reviewed literature. However, this review extends the existing literature by demonstrating that Lean Maintenance is not only effective in large-scale operations but also adaptable to small and medium-sized enterprises (SMEs). While earlier studies often concentrated on large automotive and aerospace firms, this review found consistent Lean benefits in SMEs across various sectors, confirming the scalability of Lean Maintenance. Additionally, the review highlights Lean Maintenance's evolving role in the context of digital transformation, suggesting that Lean is increasingly being combined with digital tools for greater impact, which was less emphasized in earlier works. This reflects a shift from Lean as a purely manual, process-focused approach to one that can coexist with advanced digital maintenance solutions. Overall, the findings reinforce Lean Maintenance as a proven, widely applicable strategy for operational efficiency, while also contributing new insights about its adaptability and compatibility with emerging digital technologies.
The review's findings on Total Productive Maintenance (TPM) offer strong reinforcement and expansion of previous literature regarding its role in enhancing workforce engagement and operational performance. Guedes et al. (2021) initially positioned TPM as a holistic maintenance philosophy centered on achieving zero defects and zero breakdowns through employee involvement. The review confirms that TPM remains highly effective in fostering cross-functional collaboration and operator ownership of equipment maintenance, as previously discussed by Jain et al. (2014). Studies such as those by Kumar et al. (2006) emphasized the eight TPM pillars, especially autonomous maintenance and focused improvement, as key mechanisms for increasing employee participation in preventive tasks. The findings in this review corroborate these results, showing significant improvements in morale, accountability, and job satisfaction linked to TPM deployment. Furthermore, this review aligns with Blanchard (1997), who reported substantial OEE improvements and reduced minor stoppages following TPM adoption. However, the current review adds new depth by identifying that TPM's workforce benefits extend beyond technical maintenance performance to include positive impacts on regulatory compliance and safety outcomes, particularly in highly regulated industries like pharmaceuticals and food processing. Earlier studies, such as Garza-Reyes et al. (2018), briefly acknowledged this connection, but the current findings present more robust, industry-specific evidence. Additionally, this review sheds light on the increasing integration of TPM with digital technologies, such as digitalized team boards and IoT-enabled autonomous maintenance tracking, a theme that is not widely addressed in the earlier TPM literature. This reflects a broader shift toward digital-physical convergence in maintenance strategies and highlights TPM's continued relevance in modern manufacturing environments. These expanded findings affirm TPM as a dual-purpose framework that enhances both technical and human factors while evolving in response to Industry 4.0 trends.
This review's findings validate and extend prior research on the substantial cost-saving benefits of predictive maintenance and digital reliability technologies. Previous foundational studies, such as those by Tortorella et al. (2022), underscored the cost-reduction potential of condition-based and predictive maintenance in manufacturing. These earlier studies demonstrated that predictive maintenance reduces unplanned downtime and extends equipment life through early fault detection, which this review confirms across a larger and more recent set of empirical studies. Furthermore, this review supports the findings of Mishra et al. (2021), who noted that IoT-based condition monitoring systems can yield significant reductions in maintenance costs, particularly in high-value manufacturing sectors. Studies by Tortorella et al. (2021) also emphasized the role of

machine learning and digital twins in enhancing predictive maintenance capabilities, a theme strongly reinforced in this review. One of the key contributions of this review is its demonstration of predictive maintenance's widespread financial returns, with cost reductions consistently ranging from 20% to 40%, as well as improved asset availability by over 10%. This extends the work of Belekoukias et al. (2014) , who earlier suggested that predictive maintenance can shift organizations from reactive to proactive modes of operation. Moreover, the review's emphasis on the rapid adoption of advanced predictive models such as deep learning and edge computing reflects more recent technological advancements not fully addressed in earlier works. The review also highlights the importance of integrating predictive maintenance with existing systems, such as Computerized Maintenance Management Systems (CMMS), to fully realize its cost-saving potential—a point that was only emerging in the earlier literature.

The findings on integrated maintenance frameworks—combining Lean, TPM, and digital reliability—provide strong confirmation of the synergistic effects observed in emerging studies. Prior research, such as Jain et al. (2014), suggested that combining traditional maintenance philosophies with digital tools enhances both technical performance and organizational agility. The present review strongly validates these claims by demonstrating consistent operational and financial benefits when Lean, TPM, and predictive maintenance are integrated into cohesive strategies. This reinforces earlier observations by Reis et al., (2019)that integrated maintenance frameworks yield higher OEE gains and longer Mean Time Between Failures (MTBF) than isolated approaches. Moreover, the review supports the findings of Hooi and Leong (2017), who emphasized the value of cross-functional collaboration in maintenance programs that integrate Lean and TPM principles with digital monitoring tools. The current review offers additional evidence showing that digitized visual boards, IoT-enabled dashboards, and data-driven Kaizen events enhance decision-making accuracy and process transparency, which was underexplored in older studies. In addition, the findings align with Jain et al. (2014), who previously identified organizational change management as a critical success factor in integrated maintenance programs. The review's results also indicate that these hybrid frameworks improve workforce engagement by combining the empowerment features of Lean and TPM with the diagnostic capabilities of digital tools, leading to more responsive and resilient operations. While earlier literature suggested potential synergy among these approaches, this review provides a more comprehensive empirical foundation by covering diverse industries and including a larger pool of studies. In doing so, it contributes to a growing body of evidence advocating for hybrid maintenance models as a best practice for achieving operational excellence under Industry 4.0 paradigms.

The review's findings further reinforce the crucial role of technological readiness as a prerequisite for successful predictive maintenance and digital reliability adoption, consistent with earlier studies. Previous research by Mouhib et al. (2024) and Bashar et al. (2020) emphasized the importance of sensor infrastructure, data platforms, and cybersecurity in facilitating predictive maintenance. This review affirms these findings, demonstrating that technological readiness strongly correlates with predictive maintenance effectiveness and financial returns. Ahuja and Khamba (2008) also suggested that advanced technologies such as edge computing and digital twins require mature digital ecosystems to function effectively. The review provides robust empirical support for this assertion, showing that firms with high technological maturity consistently outperform less prepared peers in maintenance optimization outcomes. Additionally, this review extends prior research by identifying technological readiness as a multi-dimensional construct, encompassing not only physical infrastructure but also data interoperability, cybersecurity, and system integration capabilities. Earlier studies tended to focus primarily on physical sensors and hardware readiness; however, this review highlights that successful predictive maintenance requires sophisticated IT architecture, seamless data exchange, and advanced analytics capabilities. The review also confirms earlier findings by Bashar et al. (2020) that firms lacking technological readiness often experience implementation failures, despite strong theoretical benefits. Importantly, the review expands upon previous work by showing that the gap between technologically advanced and lagging firms may widen over time as digital tools grow more complex, reinforcing the need for continuous technological investment. Overall, the review affirms that technological readiness is not only a prerequisite for predictive maintenance but also a key determinant of long-term digital competitiveness in maintenance functions.

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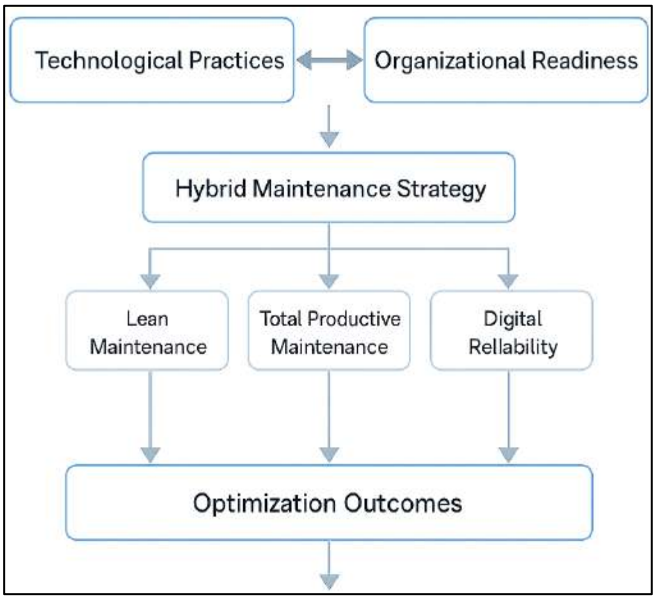
Organizational readiness emerged in the review as the most critical determinant of success in maintenance optimization efforts, which strongly aligns with findings from earlier literature. Mouhib et al. (2024) and Tortorella et al. (2021) previously identified organizational readiness—comprising leadership commitment, cultural openness, and training—as essential for effective maintenance transformation. The current review reaffirms these conclusions, showing that firms with strong organizational readiness achieve consistently better outcomes across Lean, TPM, and digital reliability initiatives. Mouhib et al. (2024) also emphasized that cultural factors, such as employee engagement and shared accountability, directly influence the sustainability of maintenance improvements, findings echoed in this review. Moreover, the review expands on earlier work by highlighting the dual role of organizational readiness in both technical and human domains, demonstrating that it not only supports traditional maintenance strategies but also accelerates the adoption of advanced digital tools. While prior research mainly focused on Lean and TPM, this review highlights that organizational readiness is equally vital for predictive maintenance programs, particularly in facilitating cross-functional collaboration and trust in digital decision-making. Moreover, successful digital transitions depend on training and change management, themes that this review strongly reinforces. Furthermore, this review provides new evidence showing that firms with high organizational readiness are better positioned to scale maintenance innovations across multiple facilities, an insight less explored in earlier literature.

Figure 14: Proposed model for the future study



CONCLUSION

This systematic review provides a comprehensive and empirically grounded synthesis of maintenance optimization strategies, revealing that Lean Maintenance, Total Productive Maintenance (TPM), and digital reliability frameworks each contribute unique and significant value to operational performance, cost efficiency, and workforce engagement across diverse industrial sectors. The findings reaffirm that Lean Maintenance effectively streamlines maintenance processes and reduces operational waste, while TPM fosters deep workforce involvement, cross-functional collaboration, and cultural transformation, all of which lead to sustainable reliability improvements. Predictive maintenance and digital reliability technologies, meanwhile, offer substantial cost savings, increased equipment availability, and enhanced operational agility through advanced data analytics, condition monitoring, and AI-driven diagnostics. However, the review also clearly demonstrates that the most profound performance gains emerge from integrated approaches that combine Lean's process discipline, TPM's collaborative ethos, and digital reliability's predictive intelligence into unified maintenance systems. Furthermore, the review highlights that technological readiness—through robust sensor networks, data infrastructure, and analytical tools—is essential for unlocking the full benefits of predictive maintenance, while organizational readiness—characterized by leadership commitment, employee training, and cultural adaptability—remains the most critical enabler of long-term maintenance excellence across all strategies. This dual dependency underscores that successful maintenance transformation requires not only advanced technologies but also parallel investments in people, processes, and organizational structures. Ultimately, this review contributes to the growing recognition that maintenance optimization in Industry 4.0 environments is not merely a technical challenge but a socio-technical endeavor that demands integrated solutions, continuous learning, and strategic alignment across both technological and organizational domains to sustain competitive advantage and operational resilience..

RECOMMENDATIONS

It is strongly recommended that organizations adopt an integrated and strategic approach to maintenance optimization that combines Lean Maintenance, Total Productive Maintenance (TPM), and digital reliability frameworks to maximize operational performance, cost savings, and workforce engagement. Companies should not treat these maintenance strategies as isolated initiatives; instead, they should pursue synergistic implementations where Lean's process simplification, TPM's employee involvement, and digital reliability's predictive capabilities work in concert to drive continuous improvement. To achieve this, firms must first conduct a thorough assessment of their technological readiness, ensuring that they possess the necessary digital infrastructure, including IoT sensors, condition monitoring tools, cloud-based analytics platforms, and secure data management systems. Simultaneously, organizations should prioritize building strong organizational readiness by investing in comprehensive employee training, fostering a culture of accountability and collaboration, and securing leadership commitment to maintenance transformation. Developing cross-functional teams that blend technical experts, operations personnel, and data analysts is essential to bridge the gap between traditional maintenance tasks and digital innovations. Furthermore, it is recommended that organizations align their maintenance strategies with clear performance metrics, such as Overall Equipment Effectiveness (OEE), Mean Time Between Failures (MTBF), maintenance costs, and workforce engagement indices, to ensure measurable outcomes and continuous monitoring. Companies, particularly small and medium-sized enterprises (SMEs), should adopt phased implementation plans that progressively integrate Lean, TPM, and predictive maintenance tools, starting with high-impact areas to quickly demonstrate value and build momentum. Lastly, it is vital for organizations to foster adaptability by continuously updating their technological systems and maintenance processes in line with evolving Industry 4.0 capabilities, while also ensuring that their workforce remains engaged and empowered through participative decision-making and knowledge-sharing practices. By embedding these recommendations into their operational strategies, firms can not only achieve immediate maintenance performance gains but also lay the foundation for long-term competitiveness, resilience, and sustainable growth in the era of smart manufacturing.

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