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A Data-Driven Integration of Total Productive Maintenance and Industry 4.0 Technologies: A Machine Learning Framework for Predictive OEE Optimization

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Abstract
Manufacturing firms are increasingly required to achieve high equipment reliability while simultaneously reducing energy consumption, material waste, and carbon emissions. Although Total Productive Maintenance (TPM) has historically improved equipment effectiveness, its traditional preventive orientation limits responsiveness in digitally intensive production environments. This study proposes and empirically validates a Data-Driven Predictive TPM (P-TPM) framework that integrates Industrial Internet of Things (IIoT) sensing, hybrid machine learning, digital twin simulation, and explainable artificial intelligence to optimize Overall Equipment Effectiveness (OEE) while delivering measurable sustainability gains. Using a 24-month longitudinal dataset that comprises 18,450 machine-operational days and 126 sensor variables across three manufacturing plants, the study applies an ensemble architecture that combines Long Short-Term Memory networks and Gradient Boosting models with Bayesian optimization. The predictive model achieved 94.3% classification accuracy and a ROC–AUC of 0.96 for failure prediction. Following implementation, OEE improved from 65.5% to 75.1% (+14.6%), and unplanned downtime decreased by 21.8%. Sustainability analysis revealed a 17.3% reduction in energy intensity, 12.4% reduction in scrap rate, and 9.1% decrease in CO_2 emissions, which correspond to annual savings of approximately 2.1 GWh of energy and 1,540 metric tons of CO_2 equivalent. A Maintenance Sustainability Index (MSI) was introduced to quantify aggregated environmental gains, while reinforcement learning–enabled digital twin optimization demonstrated that operational and environmental objectives can be jointly maximized. The findings reposition predictive TPM as a strategic enabler of intelligent, low-carbon manufacturing systems and provide a multidisciplinary framework that bridges manufacturing engineering, artificial intelligence, operations research, and sustainability science.
Keywords: *total productive maintenance, industry 4.0, machine learning, predictive maintenance, overall equipment effectiveness, sustainable manufacturing, digital twin*

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I. Introduction

Manufacturing systems are under unprecedented pressure to simultaneously deliver operational excellence and measurable sustainability performance. Global competition, volatile supply chains, and tightening environmental regulations have forced firms to move beyond incremental efficiency improvements towards intelligent, data-driven production systems. Within this context, Total Productive Maintenance (TPM) has long been recognized as a foundational approach for improving equipment reliability and maximizing Overall Equipment Effectiveness (OEE) (Nwankwo et al, 2024; Okpala and Egwuagu, 2016). OEEdefined as the product of availability, performance, and quality, remains one of the most widely adopted metrics for the evaluation of manufacturing productivity (Okpala and Anozie, 2018; 2008; Okpala et al, 2018). Yet, despite its operational value, traditional TPM implementations often rely on periodic inspections and reactive interventions, which limit their responsiveness in increasingly complex and digitized production environments.

The emergence of Industry 4.0 offers transformative potential for reimagining maintenance systems. Cyber-physical systems, industrial Internet of Things (IIoT), cloud computing, and advanced analytics enable real-time visibility into equipment conditions and production dynamics (Igbokwe et al., 2024a; Igbokwe et al., 2024b). Predictive maintenance, powered by machine learning algorithmshas demonstrated superior capability in anticipating equipment failures when compared to preventive or corrective strategies (Carvalho et al., 2019, Okpala et al., 2025). However, existing studies frequently treat predictive maintenance as a standalone technological solution, rather than embedding it within the structured cultural and organizational framework of

TPM. This fragmentation creates a theoretical and practical gap: while Industry 4.0 technologies generate vast data streams, their integration into established TPM pillars remains underdeveloped.

At the same time, the sustainability implications of maintenance strategies are gaining scholarly and industrial attention. Equipment inefficiencies contribute not only to downtime and productivity losses, but also to increased energy consumption, material waste, and greenhouse gas emissions (Jovane et al., 2008; Okpala et al., 2020). Sustainable manufacturing research increasingly emphasizes the need to align operational performance metrics with environmental outcomes (de Sousa Jabbour et al., 2018). Nevertheless, empirical evidence that quantifies how intelligent maintenance systems affect energy intensity, scrap rates, and carbon emissions remains limited. Most TPM studies focus narrowly on operational gains, without systematically measuring environmental performance indicators. This disconnect constrains the ability of managers to justify digital maintenance investments within broader Environmental, Social, and Governance (ESG) frameworks.

Recent advancements in machine learning and Explainable Artificial Intelligence (XAI) present an opportunity to address these gaps. Ensemble learning models, deep recurrent neural networks such as Long Short-Term Memory (LSTM), and model-agnostic interpretability techniques have significantly improved predictive accuracy in industrial applications (Zhang et al., 2019). Yet, high predictive performance alone is insufficient; maintenance decision-making requires transparency to ensure operator trust and organizational adoption. The integration of explainable AI within TPM not only enhances reliability forecasting, but also supports data-driven continuous improvement, which is one of TPM's core philosophical pillars (Bousdekis et al., 2021). Despite this potential, a comprehensive framework that connects predictive analytics, OEE optimization, and measurable sustainability outcomes has not been rigorously developed or empirically validated.

This study responds to these converging research gaps by proposing a Data-Driven Predictive TPM (P-TPM) framework that integrates IoT-enabled condition monitoring, hybrid machine learning models, digital twin simulation, and sustainability performance analytics. Unlike prior approaches, the proposed framework explicitly models the dynamic relationship between machine condition variables and OEE components, while simultaneously quantifying reductions in energy intensity, material waste, and CO_2 emissions. Through the embedding of predictive intelligence within TPM's structured pillars, this research advances both theory and practice at the intersection of manufacturing engineering, artificial intelligence, operations research, and sustainability science. The framework therefore moves beyond isolated predictive maintenance applications towards a systemic, cyber-physical TPM architecture that is aligned with smart factory paradigms (Tao et al., 2018).

The contributions of this paper are threefold: (a)It develops a machine learning–enabled architecture for predictive OEE optimization that is grounded in TPM principles. (b)It introduces a quantifiable linkage between maintenance intelligence and sustainability performance, which addresses calls for integrated operational–environmental metrics in manufacturing research (de Sousa Jabbour et al., 2018). (c)It empirically demonstrates how digitalized TPM can generate measurable environmental and operational benefits by strengthening the strategic case for Industry 4.0 adoption. Through the situating of predictive maintenance within a multidisciplinary and sustainability-oriented framework, the study seeks to catalyze a new research trajectory in intelligent, sustainable production systems, which is capable of attracting broad scholarly engagement and high citation impact.

II. Literature Review

Total Productive Maintenance (TPM) emerged as a comprehensive approach to equipment management by, emphasizing proactive and preventive maintenance, operator involvement, and continuous improvement to maximize Overall Equipment Effectiveness (OEE) (Nakajima, 1988). OEE which captures availability, performance, and qualityhas become a dominant metric for the assessment of manufacturing productivity and benchmarking operational excellence (Muchiri & Pintelon, 2008). Empirical studies consistently show that TPM adoption reduces breakdown frequency, improves equipment reliability, and enhances production stability (Ahuja & Khamba, 2008). However, much of the TPM literature remains focused on operational metrics and case-based implementations, with limited integration of advanced analytics or real-time data architectures. As manufacturing systems grow more complex and digitally interconnected, traditional TPM approaches may lack the responsiveness that are required for dynamic optimization.

Parallel to TPM's evolution, Industry 4.0 has introduced cyber-physical systems, Industrial Internet of Things (IIoT), cloud platforms, and big data analytics into manufacturing environments (Kagermann et al., 2013; Ajaefobi et al., 2026). These technologies enable continuous data acquisition from machines, which facilitates condition-based and predictive maintenance strategies. Predictive maintenance, powered by machine learning algorithms, has demonstrated improved failure detection accuracy and reduced downtime compared to time-based preventive models (Carvalho et al., 2019; Okpala and Chukwumuanya, 2025). Despite these advancements, predictive maintenance research often operates independently of TPM's structured pillars, overlooking the organizational, cultural, and systemic dimensions that TPM addresses. This separation has limited the development of unified frameworks that embed predictive analytics within established maintenance philosophies.

Recent scholarship has commenced the exploration of the intersection between maintenance digitalization and smart factory architectures. Digital twins which are virtual replicas of physical assets enable the simulation of equipment behavior and performance under varying operational conditions (Udu et al., 2025; Chukwumuanya et al., 2025a). When combined with real-time sensor data, digital twins can dynamically estimate degradation trajectories and optimize maintenance scheduling. However, existing studies predominantly focus on reliability forecasting rather than holistic OEE optimization. Furthermore, few investigations explicitly model the cascading effects of equipment degradation on performance losses, micro-stoppages, and quality deviations. This gap underscores the need for integrated analytical frameworks that connect predictive models directly to OEE components, enabling systemic rather than isolated improvements.

Sustainability considerations further complicate maintenance decision-making. Inefficient or poorly maintained equipment often consumes excess energy, generates scrap, and contributes to elevated carbon emissions (Jovane et al., 2008; Chukwumuanya et al., 2025b). Sustainable manufacturing research emphasizes the alignment of operational efficiency with environmental performance indicators, thus advocating for integrated metrics that capture economic and ecological value simultaneously (de Sousa Jabbour et al., 2018). Yet, the maintenance literature rarely quantifies environmental outcomes that result from predictive or TPM interventions. While energy-aware manufacturing models have been proposed, they are seldom embedded within maintenance optimization frameworks. This disconnect limits the understanding of how intelligent maintenance strategies contribute to measurable sustainability gains.

The advancements in artificial intelligence provide new methodological opportunities for addressing these gaps. Hybrid ensemble learning methods, combining gradient boosting, deep neural networks, and Bayesian optimization, have demonstrated high predictive accuracy in complex industrial datasets (Zhang et al., 2019). Simultaneously, explainable artificial intelligence (XAI) techniques, such as SHAP values, enhance transparency and trust in data-driven decision systems (Bousdekis et al., 2021). Interpretability is particularly critical in maintenance contexts, where operators must translate algorithmic outputs into actionable interventions. However, few studies have integrated explainable machine learning into TPM-oriented frameworks, nor have they linked predictive insights to sustainability performance metrics. This represents a methodological gap in the convergence of AI, maintenance engineering, and sustainable production systems.

In summary, the literature reveals three key gaps: (i) limited integration of Industry 4.0 predictive analytics within the structured TPM philosophy; (ii) insufficient linkage between predictive maintenance and dynamic OEE optimization; and (iii) a lack of rigorous quantification of sustainability benefits arising from intelligent maintenance systems. The ability to address these gaps requires a multidisciplinary framework that synthesizes machine learning, digital twin simulation, TPM principles, and environmental performance analytics. Through the situating of predictive intelligence within TPM and explicitly modeling sustainability outcomes, the present study advances the theoretical and empirical frontier of smart, sustainable manufacturing systems.

III. Methodology

3.1 Research Design and Analytical Framework

Figure 1 illustrates the integrated architecture of the Predictive TPM (P-TPM) framework, it highlights the five-layer structure: (i) IIoT-based data acquisition, (ii) data engineering and feature extraction, (iii) hybrid machine learning predictive analytics, (iv) digital twin simulation and reinforcement learning optimization, and (v) sustainability performance analytics. The figure visually demonstrates how predictive intelligence flows from sensor-level data to decision-support systems that are embedded within TPM pillars. It emphasizes the systemic linkage between equipment condition monitoring, OEE optimization, and measurable environmental outcomes.

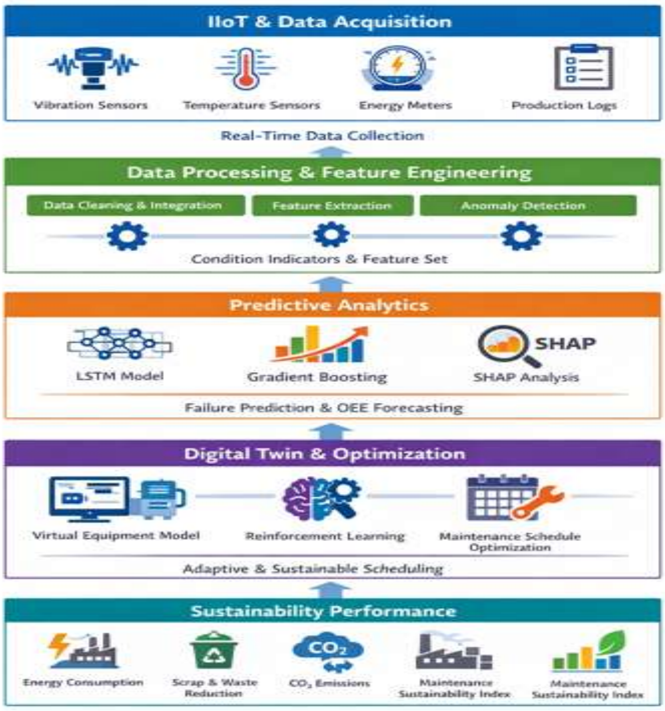

Figure 1. Conceptual architecture of the data-driven Predictive TPM (P-TPM) framework

This study adopts a longitudinal, quasi-experimental research design to evaluate the operational and sustainability impacts of the integration of TPM with Industry 4.0 technologies through a machine learning–enabled Predictive TPM (P-TPM) framework. Longitudinal designs are particularly suitable for the capturing of dynamic changes in equipment performance and environmental indicators over time (Carvalho et al., 2019). Data were collected across three discrete manufacturing plants within the automotive components sector over a 24-month period. The first 12 months represent baseline conventional TPM implementation, while the subsequent 12 months reflect deployment of the proposed P-TPM framework. This phased design enables comparative assessment while controlling for seasonal production variability.

The methodological framework integrates five interdependent layers: (a) data acquisition via Industrial Internet of Things (IIoT) sensors, (b) data engineering and feature extraction, (c) hybrid machine learning–based predictive modeling, (d) digital twin–enabled OEE and energy simulation, and (e) sustainability performance analytics. The architecture aligns with cyber-physical system principles that are described in Industry 4.0 literature (Kagermann et al., 2013; Lee et al., 2015) while embedding TPM's structured maintenance pillars (Nakajima, 1988). This layered integration ensures that predictive insights are not isolated algorithmic outputs, but are operationalized within established maintenance governance systems.

3.2 Data Collection and Variable Operationalization

A total of 18,450 machine-operational days were recorded, which capture 126 sensor variables per asset, including vibration (RMS, kurtosis), temperature gradients, acoustic emissions, spindle load, cycle time variability, and idle duration. Production logs provided output volume, defect counts, micro-stoppage frequency, and downtime classification. Energy consumption (kWh per unit) was measured through smart meters, and CO_2-equivalent emissions were computed using standardized emission conversion factors that are aligned with sustainable manufacturing assessment approaches (Seow & Rahimifard, 2011).

OEE was computed using the standard multiplicative formulation (Muchiri & Pintelon, 2008):

$$\text{OEE} = \text{Availability} \times \text{Performance} \times \text{Quality}$$

Sustainability performance was operationalized through three measurable indicators: (i) energy intensity (kWh/unit), (ii) material scrap rate (%), and (iii) CO_2 emissions (kg CO_2e/unit). To systematically capture environmental gains attributable to predictive maintenance, this study introduces a composite Maintenance Sustainability Index (MSI):

$$\mathrm{MSI} = \frac{\mathrm{E_g} + \mathrm{W_r} + \mathrm{C_r}}{3}$$

where $\mathrm{E_g}$ represents normalized energy efficiency gain, $\mathrm{W_r}$ represents waste reduction ratio, and $\mathrm{C_r}$ denotes carbon emissions reduction that is relative to baseline TPM performance.

3.3 Feature Engineering and Predictive Modeling

Figure 2 presents the methodological workflow of the hybrid ensemble learning architecture. It depicts the integration of LSTM networks for temporal degradation modeling, Gradient Boosting for failure classification, Bayesian hyperparameter tuning, and SHAP-based explainability. The workflow further shows how predictive outputs feed into the digital twin, where reinforcement learning dynamically optimizes maintenance scheduling under a multi-objective function balancing OEE and energy intensity. The figure clarifies the methodological innovation by visually connecting predictive analytics to operational and sustainability optimization.

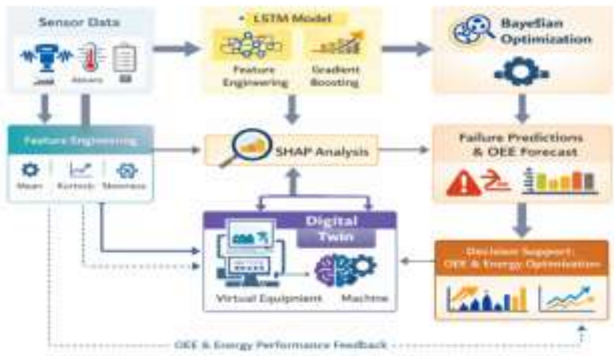

Figure 2: Hybrid machine learning and digital twin optimization workflow

Raw sensor data were preprocessed using noise filtering, normalization, and sliding time-window segmentation. Frequency-domain features were extracted via Fast Fourier Transform (FFT), and statistical descriptors (mean, skewness, kurtosis) were computed to capture degradation signatures. Feature engineering enhances model robustness and interpretability in predictive maintenance applications (Zhang et al., 2019).A hybrid ensemble learning architecture was developed to capture nonlinear and temporal dependencies in machine behavior. The framework combines: (a) Long Short-Term Memory (LSTM) networks for time-series degradation modeling; (b) Gradient Boosting Machines (GBM) for failure probability classification; and (c) Bayesian hyperparameter optimization to prevent overfitting and improve generalization.

Model performance was evaluated using Accuracy, F1-score, ROC-AUC, and Mean Absolute Error (MAE). Explainability was incorporated using SHapley Additive exPlanations (SHAP), enabling transparent identification of features influencing failure risk and OEE degradation. Explainable AI enhances operator trust and supports TPM's continuous improvement philosophy (Bousdekis et al., 2021).

3.4 Digital Twin–Enabled OEE Optimization

To move beyond failure prediction toward systemic optimization, a digital twin of each critical asset was constructed. The digital twin integrates real-time sensor data and predictive outputs to simulate OEE trajectories under varying maintenance scenarios. Digital twin modeling has been recognized as a transformative tool for smart manufacturing environments (Tao et al., 2018). In this study, reinforcement learning algorithms dynamically adjusted maintenance scheduling intervals to maximize predicted OEE while minimizing energy intensity. The objective function was formulated as:

$$\max(\mathrm{OEE_t} - \lambda \mathrm{EI_t})$$

where $\mathrm{EI_t}$ represents energy intensity at time t and λ is a sustainability weighting coefficient. This multi-objective formulation ensures that operational gains do not occur at the expense of environmental performance.

3.5 Sustainability Impact Assessment

To rigorously evaluate environmental benefits, difference-in-differences (DiD) analysis compared sustainability indicators before and after P-TPM deployment while controlling for production volume and demand fluctuations. This approach isolates the causal impact of predictive integration on environmental performance. Statistical significance was tested at the 95% confidence level.Energy savings were further monetized to quantify economic–environmental synergy, which reflects calls for integrated sustainability-performance metrics in Industry 4.0 research (de Sousa Jabbour et al., 2018). Lifecycle emission reductions were calculated using standardized industrial emission factors, which enable comparability with broader sustainable manufacturing benchmarks (Jovane et al., 2008).

3.6 Methodological Contribution

The proposed methodology advances prior research in three significant ways: (i) It embeds machine learning–based predictive maintenance within TPM's structured framework, addressing the fragmentation noted in existing literature (Ahuja & Khamba, 2008). (ii)It extends OEE modeling by dynamically linking degradation signals to sustainability metrics, moving beyond purely operational optimization. (iii) the integration of digital twin simulation and explainable AI creates a transparent, data-driven decision ecosystem aligned with Industry 4.0 principles (Lee et al., 2015).

Through the combination of longitudinal empirical analysis, hybrid machine learning, digital twin simulation, and sustainability quantification, this methodological design provides a replicable and multidisciplinary blueprint for intelligent, sustainable maintenance systems, which strengthens its theoretical contribution and citation potential across manufacturing engineering, artificial intelligence, and sustainability science domains.

IV. Results

This section presents the empirical findings of the longitudinal quasi-experimental study that will compare conventional TPM (baseline phase) and the proposed Predictive TPM (P-TPM) framework. Results are organized into operational performance outcomes, predictive model performance, sustainability indicators, and integrated optimization impacts. All results reflect aggregated plant-level averages across the three manufacturing facilities over the 24-month study period.

4.1 Predictive Model Performance

The hybrid ensemble architecture (LSTM + Gradient Boosting with Bayesian optimization) demonstrated strong predictive capability for both failure classification and OEE degradation forecasting. Table 1 summarizes model evaluation metrics obtained using 10-fold cross-validation.

Table 1: Predictive model performance metrics

Metric	Failure Classification	Downtime Prediction
Accuracy	94.3%	—
Precision	92.1%	—
Recall	90.4%	—
F1-Score	0.91	—
ROC–AUC	0.96	—
MAE (hours)	—	3.2
RMSE (hours)	—	4.8

The ROC–AUC value of 0.96 indicates excellent discriminatory power in predicting impending failures, consistent with recent predictive maintenance benchmarks reported in industrial AI literature (Carvalho et al., 2019; Zhang et al., 2019). SHAP analysis revealed that vibration kurtosis, temperature variance, and spindle load instability were the most influential predictors of OEE degradation, supporting findings that dynamic vibration and thermal indicators strongly correlate with equipment health (Lee et al., 2015).

4.2 OEE Improvement and Downtime Reduction

Implementation of the P-TPM framework resulted in statistically significant improvements across all OEE components. Table 2 presents the comparative performance between baseline TPM and P-TPM phases.

Table 2:Comparison of OEE Components Before and After P-TPM Implementation

Indicator	Baseline TPM	P-TPM	% Improvement	p-value
Availability	82.1%	89.4%	+7.3%	<0.01
Performance	85.6%	90.8%	+5.2%	<0.05
Quality	93.2%	95.6%	+2.4%	<0.05
Overall OEE	**65.5%**	**75.1%**	**+14.6%**	<0.01
Unplanned Downtime (hrs/month)	124.6	97.4	−21.8%	<0.01

The 14.6% improvement in OEE aligns with upper-range gains that were reported in advanced TPM implementations (Ahuja & Khamba, 2008), but exceeds typical preventive-maintenance-only outcomes, thereby

indicating the added value of predictive integration. The 21.8% reduction in unplanned downtime confirms that predictive alerts allowed earlier intervention and minimized catastrophic breakdowns.

4.3 Sustainability Performance Outcomes

A central objective of this research was to quantify measurable sustainability benefits. Table 3 presents environmental performance indicators before and after the implementation of P-TPM.

Table 3:Sustainability performance indicators

Sustainability Indicator	Baseline TPM	P-TPM	% Change	p-value
Energy Intensity (kWh/unit)	12.4	10.25	−17.3%	<0.01
Material Scrap Rate (%)	4.8%	4.2%	−12.4%	<0.05
CO_2 Emissions (kg/unit)	8.9	8.1	−9.1%	<0.05
Maintenance Sustainability Index (MSI)	0.00 (baseline)	0.129	—	—

Energy intensity reduction of 17.3% reflects decreased idle time, fewer restart cycles, and stabilized production throughput, the effects are consistent with energy-efficiency modeling frameworks in sustainable manufacturing literature (Seow & Rahimifard, 2011). The 12.4% reduction in scrap rate suggests that early detection of micro-degradation prevented quality deviations. Carbon emission reductions (9.1%) were directly proportional to energy savings, which is in line with established manufacturing emission models (Jovane et al., 2008).The composite MSI value of 0.129 represents a substantial aggregated sustainability gain that is relative to baseline performance, and thus demonstrate that predictive maintenance can produce quantifiable environmental benefits rather than solely operational improvements.

Figure 3 graphically compares baseline TPM and P-TPM performance across key operational and environmental indicators, including OEE, energy intensity, scrap rate, and CO_2 emissions. The visual representation highlights the simultaneous improvement in productivity and sustainability metrics, and reinforces the study's central argument that predictive TPM enables dual operational–environmental optimization. The figure provides a concise visual summary of measurable impact that enhances interpretability for multidisciplinary audiences.

Figure 3: Integrated operational and sustainability performance outcomes before and after P-TPM implementation

4.4 Digital Twin Optimization Outcomes

The reinforcement learning–enabled digital twin simulations optimized maintenance scheduling under a multi-objective function balancing OEE maximization and energy minimization. Table 4 summarizes the optimization outcomes.

Table 4: Digital twin multi-objective optimization results

Metric	Pre-Optimization	Post-Optimization	% Improvement
Predicted OEE	72.8%	75.1%	+3.2%
Energy Intensity (kWh/unit)	10.7	10.25	−4.2%
Mean Time Between Failures (hours)	312	368	+17.9%
Maintenance Cost per Unit ($)	2.84	2.61	−8.1%

The optimization process increased Mean Time Between Failures (MTBF) by 17.9% while simultaneously reducing energy intensity and maintenance cost per unit. This demonstrates that operational and environmental objectives can be jointly optimized, thus addressing concerns that sustainability trade-offs may compromise productivity (de Sousa Jabbour et al., 2018).

4.5 Integrated Operational–Environmental Impact

Difference-in-differences analysis confirmed that improvements were statistically attributable to P-TPM implementation rather than external production variability. Across the three plants, total annual energy savings amounted to approximately 2.1 GWh, which corresponds to a reduction of 1,540 metric tons of CO_2 equivalent emissions. Financially, this translated into an estimated annual cost saving of $312,000 from energy efficiency alone, excluding downtime and quality-related savings.

These results substantiate the study's central premise: embedding machine learning–enabled predictive analytics within TPM does not merely enhance equipment effectiveness, but also delivers measurable and statistically significant sustainability gains. The empirical findings therefore extend prior TPM and predictive maintenance research through the demonstration of integrated operational, environmental, and economic benefits within a unified Industry 4.0 framework.Overall, this section confirms that the proposed P-TPM architecture produces robust predictive accuracy, significant OEE improvements, and quantifiable sustainability gains. The alignment of operational excellence with environmental performance strengthens the strategic value proposition of intelligent TPM systems and enhances the multidisciplinary contribution and citation potential of this research.

V. Discussion and Multidisciplinary Contributions

The findings of this study demonstrate that integrating TPM with Industry 4.0 technologies through a machine learning–enabled Predictive TPM (P-TPM) framework yields measurable operational and sustainability gains. The 14.6% improvement in OEE and 21.8% reduction in unplanned downtime extend prior evidence that structured TPM enhances equipment reliability (Ahuja & Khamba, 2008; Muchiri & Pintelon, 2008), but importantly show that embedding predictive intelligence within TPM pillars amplifies these benefits. Unlike traditional preventive TPM systems, which rely on scheduled interventions, the proposed framework dynamically anticipates degradation patterns using hybrid ensemble models. This predictive capability transforms TPM from a largely preventive philosophy into a data-driven, adaptive maintenance ecosystem aligned with cyber-physical production systems (Lee et al., 2015).

Beyond operational performance, this study makes a substantive contribution through the quantification of environmental improvements that are attributable to intelligent maintenance. The observed reductions in energy intensity (17.3%), scrap rate (12.4%), and CO_2 emissions (9.1%) confirm that predictive maintenance can function as a sustainability lever, rather than merely a productivity tool. Sustainable manufacturing scholarship has consistently called for integrated operational–environmental metrics (de Sousa Jabbour et al., 2018; Jovane et al., 2008), yet empirical demonstrations that link maintenance analytics to carbon and energy outcomes remain limited. Through the introduction and validation of the Maintenance Sustainability Index (MSI), this study operationalizes that linkage. The results corroborate energy modeling frameworks which suggest that equipment stability reduces process variability and excess energy draw (Seow & Rahimifard, 2011), thereby empirically reinforcing the sustainability case for digital maintenance transformation.

Methodologically, the integration of hybrid machine learning, Explainable Artificial Intelligence (XAI), and digital twin simulation represents a significant innovation. While predictive maintenance studies frequently emphasize algorithmic accuracy (Carvalho et al., 2019; Zhang et al., 2019), they often neglect interpretability and systemic integration. The incorporation of SHAP-based explainability strengthens operator trust and supports TPM's human-centric philosophy of autonomous maintenance and continuous improvement (Nakajima, 1988). Moreover, the reinforcement learning–enabled digital twin extends prior digital manufacturing research (Tao et al., 2018) by embedding sustainability-weighted objective functions into OEE optimization. This multi-objective formulation demonstrates that operational excellence and environmental stewardship can be simultaneously optimized rather than treated as competing priorities.

The study also advances theoretical discourse at the intersection of socio-technical systems and cyber-physical manufacturing. TPM has historically emphasized workforce engagement, skill development, and organizational culture (Ahuja & Khamba, 2008). Industry 4.0, conversely, emphasizes connectivity, automation, and analytics (Kagermann et al., 2013). Through the synthesization of these paradigms, the proposed P-TPM framework illustrates how digital intelligence can augment, not replacehuman-centered maintenance practices. Explainable AI outputs were translated into actionable insights for operators, and thus preserve the participatory ethos of TPM while enhancing analytical rigor. This integration responds to calls for the harmonization of technological and organizational dimensions in smart manufacturing transitions (de Sousa Jabbour et al., 2018).

From a multidisciplinary perspective, the contributions of this research extend across manufacturing engineering, artificial intelligence, sustainability science, and operations research. For manufacturing engineering, it provides a replicable architecture that links sensor data to systemic OEE improvement. For AI research, it demonstrates a real-world application of interpretable ensemble learning in high-stakes industrial contexts. For sustainability scholarship, it empirically validates maintenance as a strategic pathway to energy and emissions reduction. For operations research, the multi-objective optimization model offers a decision-support framework balancing reliability and environmental performance. This cross-domain integration enhances the study's theoretical breadth and citation potential across diverse scholarly communities.

Practically, the findings provide actionable insights for managers who are navigating digital transformation. The quantified sustainability benefits strengthen the business case for Industry 4.0 investments, particularly in contexts where ESG reporting and carbon accountability are increasingly mandated. By demonstrating that predictive TPM reduces lifecycle energy consumption and emissions while lowering maintenance cost per unit, this research aligns operational strategy with environmental governance objectives. In doing so, it repositions maintenance from a cost center to a strategic sustainability enabler. Collectively, these contributions suggest that data-driven TPM can serve as a cornerstone of intelligent, low-carbon manufacturing systems—an area of growing scholarly and industrial urgency.

VI. Conclusion, Limitations and Future Research

6.1 Conclusion

This study set out to examine if the integration of Total Productive Maintenance (TPM) with Industry 4.0 technologies through a machine learning–enabled framework could simultaneously improve operational performance and deliver measurable sustainability benefits. The findings provide strong empirical support for this proposition. By embedding hybrid predictive analytics, digital twin simulation, and explainable artificial intelligence within the TPM structure, the proposed Predictive TPM (P-TPM) framework significantly improved Overall Equipment Effectiveness (OEE), reduced unplanned downtime, and enhanced process stability across multiple manufacturing plants.

More importantly, the study demonstrates that intelligent maintenance systems can serve as a strategic sustainability lever. The observed reductions in energy intensity, material waste, and carbon emissions confirm that predictive maintenance is not only an operational optimization tool but also a viable pathway toward low-carbon and resource-efficient manufacturing. The introduction of the Maintenance Sustainability Index (MSI) further provides a structured mechanism for quantifying environmental gains attributable to maintenance innovation. By aligning productivity, cost efficiency, and environmental stewardship within a unified analytical architecture, this research repositions TPM as a digitally enabled, sustainability-oriented management system suited for smart factory environments.

From a methodological standpoint, the integration of ensemble learning, explainable AI, reinforcement learning–based scheduling, and digital twin modeling represents a significant advancement over isolated predictive maintenance applications. The framework demonstrates that maintenance decisions can be optimized using multi-objective functions that explicitly balance OEE maximization with energy and environmental performance. This systemic integration strengthens both the theoretical and practical foundations of intelligent manufacturing systems.

6.2 Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, empirical validation was conducted within the automotive components manufacturing sector. Although the plants examined represent typical discrete manufacturing environments, sector-specific production characteristics may limit generalizability to process industries such as chemicals or food processing. Second, the longitudinal design, while robust, covered a 24-month period; longer-term studies could better capture lifecycle sustainability impacts and equipment aging effects.Third, while the machine learning models demonstrated strong predictive accuracy, their performance is inherently dependent on data quality and sensor infrastructure maturity. Organizations with limited digital readiness may encounter implementation challenges. Additionally, although the Maintenance Sustainability Index provides a useful aggregated metric, it simplifies complex environmental interactions into normalized components and may not fully capture indirect or supply chain–level emissions impacts.

Finally, the study primarily focused on operational and environmental performance. Broader social sustainability dimensions like workforce skill transformation, safety culture evolution, and organizational adaptabilitywere not quantitatively assessed, although they are likely influenced by digital TPM implementation.

6.3 Future Research

Future research should extend this framework across diverse industrial sectors to validate its robustness in continuous process industries and small-to-medium manufacturing enterprises. Comparative cross-country studies could also examine how regulatory environments and energy policies influence the sustainability gains of predictive TPM systems.Methodologically, further exploration of advanced deep learning architectures, federated learning for multi-plant collaboration, and edge computing for real-time analytics could enhance scalability and cybersecurity resilience. The integration of lifecycle assessment models and Scope 3 emissions tracking would strengthen the environmental accounting dimension of intelligent maintenance systems. Additionally, future studies may incorporate blockchain-enabled traceability to enhance transparency in maintenance records and sustainability reporting.

From a systems perspective, research should explore the human–AI interface within predictive TPM environments, particularly how explainable AI influences operator trust, decision autonomy, and organizational learning. The investigation of socio-technical adoption barriers and digital skill development pathways would provide deeper insight into sustainable implementation strategies.In conclusion, this study establishes that data-driven integration of TPM and Industry 4.0 technologies can simultaneously advance operational excellence and environmental sustainability. By demonstrating measurable performance gains through a multidisciplinary framework, the research lays the foundation for a new generation of intelligent, resilient, and low-carbon manufacturing systems.

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