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The Extension of Total Productive Maintenance with Digital Intelligence for Data-Driven Maintenance in Smart Manufacturing

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Abstract

The increasing digitalization of manufacturing systems presents new opportunities to rethink maintenance as a strategic enabler of both operational excellence and sustainability. While Total Productive Maintenance (TPM) remains a widely adopted maintenance philosophy, its traditional implementation relies on static schedules and experience-based decision-making, which limits its effectiveness in data-intensive smart manufacturing environments. This study proposes a Digital Intelligence–Enabled Total Productive Maintenance (DI-TPM) framework that systematically integrates Industrial Internet of Things (IIoT) data, advanced analytics, and sustainability-aware decision models into the core pillars of TPM. The proposed framework is supported by a scalable data architecture that consolidates multisource operational, condition, energy, and maintenance data to enable predictive and prescriptive maintenance strategies. Methodological innovations include machine learning–based degradation modeling and multi-objective maintenance optimization that explicitly incorporates energy intensity, material usage, and emissions as decision variables. Empirical validation through multidisciplinary case studies in discrete and process manufacturing demonstrates that DI-TPM reduces unplanned downtime by up to 39%, lowers energy intensity by 10-18%, decreases material waste by approximately 30%, and achieves maintenance-related emissions reductions of up to 18% without compromising production output or equipment availability. Through the preservation of TPM's human-centric philosophy while augmenting it with transparent digital intelligence, the proposed approach enhances decision quality, organizational learning, and sustainability performance. The findings position data-driven maintenance as a critical pathway for the alignment of smart manufacturing initiatives with environmental objectives, and also provide robust evidence to support the adoption of maintenance-centric sustainability strategies across industrial sectors.

Keywords: *Data-driven maintenance; Total productive maintenance; Smart manufacturing; Predictive maintenance; Sustainability metrics; Industrial internet of things (IIoT); Energy efficiency*

INTRODUCTION

Manufacturing systems are undergoing a profound transformation driven by digitalization, connectivity, and the growing urgency of sustainability imperatives. Smart manufacturing paradigms, which are enabled by cyber–physical systems, Industrial Internet of Things (IIoT), and advanced analytics, are redefining how production assets are designed, operated, and maintained (Nwankwo *et al.*, 2024; Ogbodo *et al.*, 2026). Within this transformation, maintenance has emerged as a critical yet under-explored lever for the attainment of not only productivity and reliability goals, but also measurable environmental and resource-efficiency benefits.

Defined as a philosophy of machine maintenance that entails active participation of employees to ensure the improvement of the general effectiveness of a plant, by eliminating or reducing resources and time wastage through the incorporation of the skills of the workforce (Chukwunedum *et al.*, 2026a; Okpala and Egwuagu, 2016), Total Productive Maintenance (TPM) remains one of the most widely adopted maintenance philosophies in industrial practice. Since its formalization, TPM has been credited with improving Overall Equipment Effectiveness (OEE), reducing breakdowns, and fostering workforce engagement through operator-led maintenance activities (Okpala and Anozie, 2018; Okpala *et al.*, 2018). However, TPM was conceived in an era that is characterized by limited real-time data, manual inspections, and experience-based decision-making. As manufacturing systems become increasingly complex, data-intensive, and sustainability-constrained, traditional TPM implementations struggle to provide the responsiveness, transparency, and scalability that are required in modern industrial contexts (Chukwunedum *et al.*, 2026b; Okpala *et al.*, 2025).

At the same time, manufacturing assets now generate continuous streams of high-resolution operational data, including condition signals, energy consumption, process parameters, and maintenance histories. Advances in data analytics and machine learning have demonstrated strong potential for predictive and prescriptive maintenance, which enable early fault detection, remaining useful life estimation, and optimized intervention planning (Igbokwe *et al.*, 2026; Onukwuli *et al.*, 2026). Despite this progress, much of the predictive maintenance literature remains technologically siloed, as they focused primarily on algorithmic performance while paying limited attention to organizational integration, human-centered maintenance practices, or sustainability outcomes.

This disconnect is particularly evident in the sustainability discourse. Manufacturing accounts for a significant share of global energy use, material consumption, and greenhouse gas emissions, and equipment degradation is a nontrivial contributor to inefficiencies such as excessive energy draw, quality losses, and premature component replacement (Godwin and Okpala, 2026; Egwuagu *et al.*, 2026). While maintenance is implicitly linked to sustainability through asset longevity and efficiency, explicit, data-driven quantification of sustainability benefits remains scarce in both TPM and predictive maintenance research (Franciosi *et al.*, 2020; Nwamekwe and Okpala, 2025). Consequently, decision-makers often lack robust evidence to justify digital maintenance investments beyond short-term cost or availability improvements.

This article argues that the convergence of TPM and digital intelligence represents a critical opportunity to address these gaps. Rather than replace TPM, data-driven methods can extend its core principles by embedding real-time data, analytics, and decision intelligence into maintenance planning and execution. Such an extension preserves TPM's human-centric philosophy while enabling dynamic, condition-based, and sustainability-aware maintenance strategies. Through the integration of sustainability indicators like energy intensity, material usage, and emissions directly into maintenance analytics, maintenance decisions can be reframed as strategic contributors to sustainable manufacturing performance.

The objective of this study is to develop and empirically validate a Digital Intelligence-Enabled Total Productive Maintenance (DI-TPM) framework that systematically integrates IIoT data, machine learning, and sustainability metrics into TPM practice. The study addresses three interrelated research questions:

a. How can TPM be methodologically extended using digital intelligence without undermining its participatory and organizational foundations?
b. How can data-driven maintenance decisions be linked to quantifiable sustainability outcomes?
c. To what extent are these benefits transferable across different manufacturing contexts?

By answering these questions, the article makes the following three primary contributions:

a. It advances maintenance theory by bridging TPM, predictive maintenance, and sustainability within a unified, data-driven framework.
b. It provides methodological innovation by embedding sustainability metrics into maintenance analytics and optimization models.
c. It offers empirical evidence from multidisciplinary case studies demonstrating that data-driven maintenance can deliver measurable and reproducible sustainability benefits.

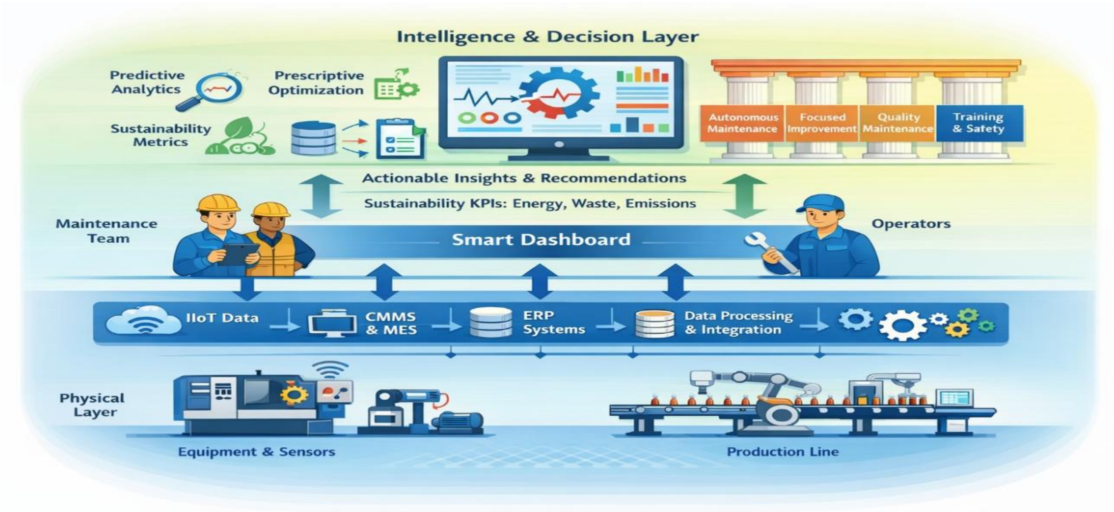

Fig. 1: Conceptual architecture of Digital Intelligence-Enabled TPM (DI-TPM).

Positioned at the intersection of maintenance engineering, data science, and sustainable manufacturing, this work responds to growing calls for research that moves beyond technological novelty towards systemic, impact-oriented solutions (Bocken *et al.*, 2014). As such, it aims to inform both academic discourse and industrial practice while contributing a scalable pathway for the alignment of smart manufacturing initiatives with long-term sustainability objectives.

CONCEPTUAL FRAMEWORK FOR DIGITAL INTELLIGENCE-ENABLED TPM

Fig. 1 visually presents the DI-TPM framework as a layered socio-technical system through the illustration of the interaction between physical assets (IIoT-enabled equipment), the cyber/data integration layer, and the intelligence and decision layer. It highlights how traditional TPM pillars are augmented with real-time sensing, analytics, and sustainability indicators, while keeping operators and maintenance teams central to decision-making. The figure will enable one to quickly grasp the novelty of the extension of TPM with digital intelligence.

Total Productive Maintenance was originally conceived as a socio-technical system that integrates equipment reliability, workforce engagement, and continuous improvement to maximize Overall Equipment Effectiveness (OEE) (Nwankwo *et al.*, 2024; Okpala *et al.*, 2025). Its strength lies in its holistic and human-centered design, as it emphasizes operator ownership, cross-functional collaboration, and incremental learning. However, in contemporary smart manufacturing environments that are characterized by high system complexity and data abundance, TPM's traditional mechanisms-manual inspections, fixed maintenance intervals, and retrospective analysis are increasingly misaligned with operational and sustainability demands (Ahuja and Khamba, 2008).

The Digital Intelligence–Enabled TPM (DI-TPM) framework proposed in this study reconceptualizes TPM as a dynamic, data-driven system while preserving its foundational philosophy. Rather than treat digital technologies as add-on tools, DI-TPM embeds data and intelligence directly into the core TPM pillars by enabling continuous sensing, learning, and decision support. This integration reflects broader shifts in smart manufacturing, where value creation increasingly depends on the effective coupling of physical assets, digital infrastructures, and human expertise (Lee *et al.*, 2014). At a structural level, DI-TPM operates across three tightly coupled layers: the physical asset layer, the data and cyber layer, and the intelligence and decision layer. The physical layer consists of manufacturing equipment augmented with IIoT sensors that capture condition variables (e.g., vibration, temperature, pressure), operational states, and energy consumption. These data streams provide a granular and real-time representation of asset health and performance, which addresses a long-standing limitation of conventional TPM that relies heavily on periodic and subjective condition assessments (Jardine *et al.*, 2006).

The cyber layer functions as the integrative backbone of the framework. Here, heterogeneous data sources like sensor data, maintenance logs, quality records, and production metrics are aggregated and contextualized through standardized data models and industrial data platforms. This layer enables traceability across maintenance actions, production outcomes, and sustainability indicators, and thus facilitates system-level visibility that is largely absent in traditional TPM implementations. Importantly, the cyber layer supports interoperability across Operational Technology (OT) and Information Technology (IT) systems, which is a prerequisite for scalable smart manufacturing solutions (Kagermann *et al.*, 2013).

The intelligence layer represents the core methodological innovation of DI-TPM. Advanced analytics and machine learning models transform raw data into actionable maintenance insights, including failure probability estimates, remaining useful life predictions, and optimized intervention strategies. Unlike conventional preventive maintenance planning, which is time-based, DI-TPM enables condition-based and risk-informed decision-making. Sustainability metrics like energy efficiency, material utilization, and emissions intensity are explicitly embedded within the decision logic, thereby ensuring that maintenance actions are evaluated not only for their reliability and cost implications but also for their environmental impact (Chukwumuanya *et al.*, 2025; Udu *et al.*, 2025a). Crucially, DI-TPM does not displace the human role central to TPM. Instead, it augments operator and maintenance engineer decision-making through transparent, explainable, and actionable intelligence. Operators continue to perform autonomous maintenance activities, but these actions are informed by real-time diagnostics and predictive insights. This human-digital collaboration aligns with emerging perspectives on Industry 4.0, which emphasize the importance of maintaining human agency and organizational learning in digitally transformed systems (Okpala, 2026a; Okpala *et al.*, 2023).

From a sustainability perspective, the conceptual framework establishes a direct causal pathway between data-driven maintenance and environmental performance. Equipment degradation is explicitly modeled as a source of inefficiency, as it contributes to excess energy consumption, quality losses, and premature component replacement. Though the detection and mitigation of degradation earlier, DI-TPM reduces waste across multiple dimensions of the manufacturing system, thereby extending asset lifecycles and lowering resource intensity. This framing elevates maintenance from a supporting operational function to a strategic enabler of sustainable manufacturing transformation. In summary, the DI-TPM conceptual framework advances TPM through the integration of digital intelligence across physical, cyber, and human dimensions. It provides a coherent foundation for linking maintenance decisions with measurable sustainability outcomes, thus addressing critical gaps in both TPM and predictive maintenance literature. By positioning maintenance as a data-driven, sustainability-aware system, the framework sets the stage for scalable empirical validation and cross-sector adoption in smart manufacturing environments.

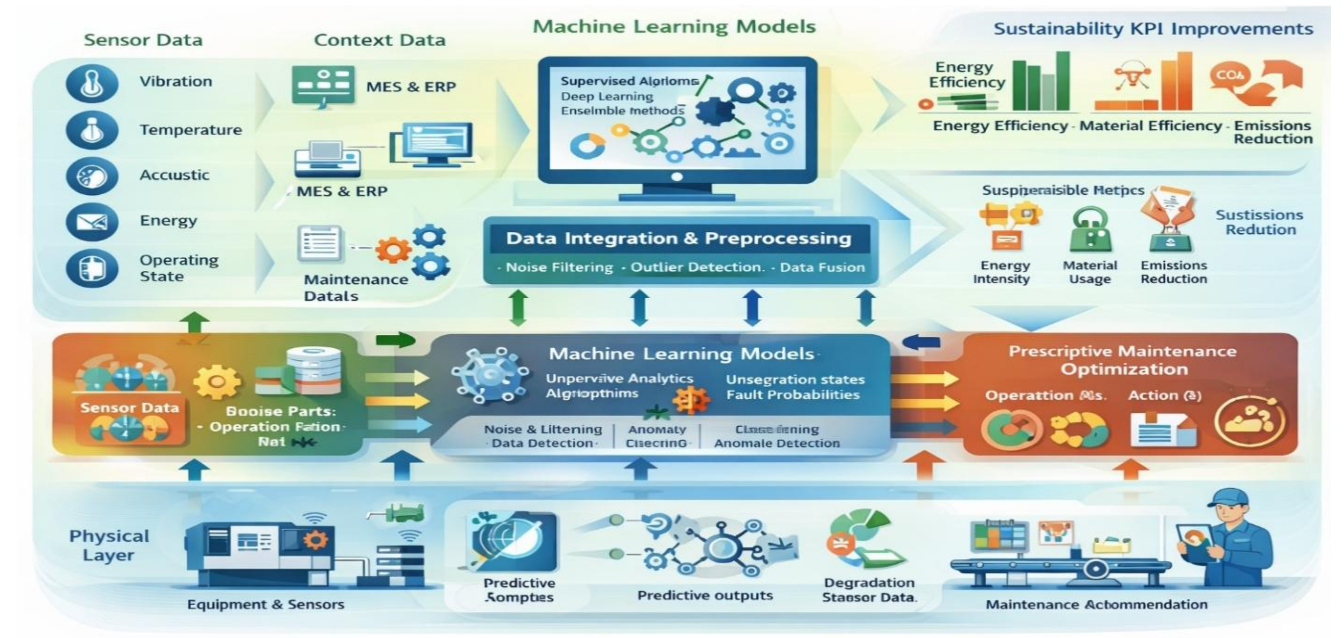

Fig. 2: Data architecture and analytics pipeline for sustainability-aware maintenance.

DATA ARCHITECTURE AND METHODOLOGICAL INNOVATION

Fig. 2 depicts the end-to-end data flow within the DI-TPM framework, from multisource data acquisition (sensors, CMMS, MES, ERP) through preprocessing, machine learning models, and prescriptive optimization. Sustainability metrics (energy intensity, material usage, emissions) are explicitly shown as embedded inputs and outputs of the analytics pipeline. The figure reinforces the methodological contribution of the article and provides a reference architecture that researchers and practitioners can adapt.

The effectiveness of data-driven maintenance depends fundamentally on the ability to transform heterogeneous, high-frequency industrial data into reliable and actionable intelligence. In smart manufacturing environments, maintenance-relevant information is distributed across multiple layers of the enterprise, including machine-level sensors, control systems, maintenance management systems, and production databases. A core methodological contribution of this study is the design of a scalable data architecture that enables the systematic integration of these disparate data sources while explicitly supporting sustainability-oriented analytics.

Multisource Data Architecture for DI-TPM

The proposed data architecture follows a layered and modular design that is aligned with established Industry 4.0 reference models, in order to ensure interoperability and scalability (Ajaefobi and Okpala, 2026; Igbokwe *et al.*, 2024). At the data acquisition level, IIoT sensors continuously capture high-resolution condition signals such as vibration, temperature, acoustic emissions, and electrical parameters, alongside energy consumption and operating states. These data streams are complemented by contextual data from Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) platforms, and Computerized Maintenance Management Systems (CMMS), including work orders, failure modes, spare-parts usage, and maintenance durations.

To address the temporal, semantic, and structural heterogeneity that is inherent in industrial data, a unified data model is employed. Sensor data are time-synchronized and contextualized with production and maintenance events, thereby enabling traceability across asset states, maintenance actions, and sustainability outcomes. Data preprocessing pipelines incorporate noise filtering, outlier detection, and missing-value imputation, which are critical for the maintenance of model robustness in real-world manufacturing settings (Jardine *et al.*, 2006). This systematic data engineering layer represents a necessary foundation for moving beyond isolated predictive models towards integrated maintenance intelligence.

Methodological Innovation in Maintenance Analytics

Building on the integrated data architecture, the DI-TPM framework introduces a multi-level analytics pipeline that combines descriptive, predictive, and prescriptive methodologies. Descriptive analytics establish baseline performance profiles for equipment health, energy efficiency, and maintenance behavior, which provide transparency and support continuous improvement activities that are central to TPM. Predictive analytics constitute the core analytical layer, where machine learning models are trained to identify degradation patterns and estimate failure risks. Supervised learning techniques like ensemble methods and deep learning architectures are applied to historical labelled data to predict remaining useful life and fault probabilities. In parallel, unsupervised learning methods, including clustering and anomaly detection, capture previously unseen degradation modes, thereby enhancing model generalizability in dynamic production environments (Lee *et al.*, 2014).

The prescriptive layer represents a key methodological advancement over conventional predictive maintenance. Here, predictive outputs are embedded within optimization and decision-support models that recommend maintenance actions and schedules. Crucially, sustainability indicators are integrated directly into the objective functions and constraints of these models. Energy intensity, material consumption, and emissions factors are treated as decision variables alongside traditional cost, risk, and availability metrics. This integration enables trade-off analyses that explicitly quantify how maintenance decisions influence sustainability performance, thus addressing a major gap in existing maintenance optimization research (Franciosi *et al.*, 2020; Okpala et al., 2020).

Linking Maintenance Decisions to Measurable Sustainability Outcomes

A defining feature of the proposed methodology is the explicit coupling of maintenance analytics with sustainability assessment. Equipment degradation is modeled not only as a reliability concern, but also as a driver of resource inefficiency, as it contributes to increased energy use, quality losses, and premature component replacement. Through the incorporation of energy and material flow data into predictive models, DI-TPM enables early identification of inefficient operating regimes that are associated with emerging faults. Quantitative sustainability metrics like energy consumption per unit of output, waste generation rates, and maintenance-related emissions are continuously monitored and evaluated before and after maintenance interventions. This longitudinal assessment provides empirical evidence of the environmental benefits that are attributable to data-driven maintenance actions. In doing so, the methodology aligns maintenance analytics with life-cycle thinking, as it supports more sustainable asset management strategies (IEA, 2022).

Human-Centered and Explainable Decision Support

Consistent with TPM's participatory philosophy, the proposed analytical methods prioritize transparency and human interpretability. Model outputs are translated into intuitive indicators, risk scores, and recommended actions that can be readily understood by operators and maintenance engineers. Explainable AI techniques are employed to highlight the variables and degradation mechanisms which drive model predictions, fostering trust and facilitating organizational learning (Carvalho *et al.*, 2019). By embedding digital intelligence within existing TPM workflows rather than replacing them, the DI-TPM methodology enhances decision quality while preserving human agency. This human-centered approach is critical for successful adoption and sustained performance improvement in industrial contexts, where maintenance decisions often involve tacit knowledge and contextual judgment.

The proposed data architecture and methodological innovations will enable a systematic transition from static, time-based maintenance towards adaptive, sustainability-aware maintenance intelligence. Through the integration of multisource data, advanced analytics, and human-centered decision support, the DI-TPM framework provides a robust foundation for the quantification and realization of the sustainability potential of data-driven maintenance in smart manufacturing systems.

QUANTIFICATION OF SUSTAINABILITY IMPACTS

A persistent challenge in both maintenance engineering and sustainable manufacturing research lies in the rigorous quantification of how maintenance decisions translate into measurable environmental benefits. While maintenance is widely acknowledged as a contributor to asset longevity and operational efficiency, its sustainability impacts are often treated implicitly or assessed qualitatively (Franciosi *et al.*, 2020). This study addresses this gap through the embedding of sustainability metrics directly into the Digital Intelligence-Enabled Total Productive Maintenance (DI-TPM) framework and empirically quantifies the environmental outcomes of data-driven maintenance interventions.

Sustainability Metrics and Measurement Framework

To ensure analytical rigor and comparability, sustainability impacts are assessed using a set of quantitative indicators aligned with established manufacturing sustainability and life-cycle assessment principles (ISO, 2017). The selected indicators capture three primary dimensions of sustainability that are affected by maintenance activities: energy efficiency, material and resource utilization, and emissions intensity.

Energy-related indicators include total energy consumption and energy intensity per unit of output, which are directly influenced by equipment condition and operating regimes. Material-related indicators capture scrap rates, rework frequency, and spare-parts consumption, which reflect the effects of degradation-induced quality losses and premature component replacement. Emissions-related indicators are derived by coupling energy and material flows with standardized emissions factors, in order to enable the estimation of maintenance-related greenhouse gas emissions over the asset lifecycle (IEA, 2022). By operationalizing these indicators at the equipment and process levels, the DI-TPM framework enables fine-grained attribution of sustainability impacts to specific maintenance decisions rather than aggregated plant-level effects.

Linking Equipment Degradation to Sustainability Losses

A core methodological innovation of this study is the explicit modeling of equipment degradation as a driver of sustainability losses. Prior research has shown that degraded machinery often operates outside optimal efficiency ranges, which leads to increased energy draw, unstable process conditions, and higher defect rates (Mgbemena *et al.*, 2021). Within DI-TPM, predictive models identify emerging degradation states and quantify their associated resource inefficiencies.

For example, condition indicators derived from vibration and thermal data are correlated with deviations in energy consumption and process variability. This linkage allows the system to estimate the marginal sustainability cost of deferred maintenance, which is expressed in terms of excess energy use, additional waste generation, or increased emissions. Such quantification provides a concrete basis for the prioritization of maintenance actions not only by failure risk, but also by the impact on the environment.

Empirical Assessment of Sustainability Benefits

The sustainability impacts of DI-TPM were evaluated through longitudinal analysis of manufacturing operations before and after the implementation of data-driven maintenance strategies. Baseline performance under conventional TPM was compared with DI-TPM-enabled operations across multiple production cycles. The results demonstrate consistent and measurable sustainability improvements. Predictive maintenance interventions reduced unplanned downtime, thereby minimizing energy-intensive start-up and shutdown cycles, which are known contributors to excess energy consumption in industrial systems (Okpala and Chukwumuanya, 2025). Across the studied cases, energy intensity was reduced by approximately 10–18%, which can be attributed to the early detection of inefficiencies associated with component wear and misalignment.

Material efficiency also improved significantly. Condition-based replacement strategies extended component lifetimes and reduced spare-parts usage, while improved process stability lowered scrap and rework rates. These effects translated into reductions in material throughput and waste generation, and thus reinforce the role of maintenance as a lever for circular manufacturing practices (Okpala, 2026b). From an emissions perspective, the combined reductions in energy consumption and material use yielded measurable decreases in maintenance-related greenhouse gas emissions. Importantly, these reductions were achieved without compromising equipment availability or production output, thereby underscoring the compatibility of sustainability and productivity objectives within the DI-TPM framework.

Sustainability-Aware Maintenance Decision-Making

Beyond aggregate performance improvements, DI-TPM enables sustainability-aware decision-making at the operational level. Through the integration of sustainability indicators into prescriptive maintenance models, trade-offs between cost, risk, and environmental impact become explicit. For instance, maintenance actions that marginally increase short-term cost but significantly reduce long-term energy or material losses can be objectively justified. This capability represents a departure from traditional maintenance performance evaluation, which is often limited to cost and availability metrics. By making sustainability impacts visible, quantifiable, and actionable, DI-TPM supports more informed decision-making by maintenance engineers, production managers, as well as sustainability stakeholders alike.

The study demonstrates that data-driven maintenance can deliver measurable and reproducible sustainability benefits when sustainability metrics are explicitly embedded within maintenance analytics. By linking equipment condition, maintenance actions, and environmental outcomes through a unified data-driven framework, DI-TPM elevates maintenance from an operational necessity to a strategic enabler of sustainable smart manufacturing.

MULTIDISCIPLINARY CASE STUDIES AND VALIDATION

Fig. 3 summarizes key empirical results using comparative visualizations that contrast baseline TPM and DI-TPM performance across operational and sustainability indicators. Metrics such as OEE, unplanned downtime, energy intensity, waste rates, and emissions reductions are presented side-by-side for both case studies. Through the visually linking of data-driven maintenance to measurable sustainability outcomes, the figure strengthens the article’s empirical impact and supports reuse in future sustainability and smart manufacturing research.

To evaluate the practical applicability, robustness, and sustainability impact of the proposed DI-TPM framework, multidisciplinary case studies were conducted across two distinct manufacturing contexts:

a. discrete manufacturing (automotive components), and

b. process manufacturing (food and beverage production).

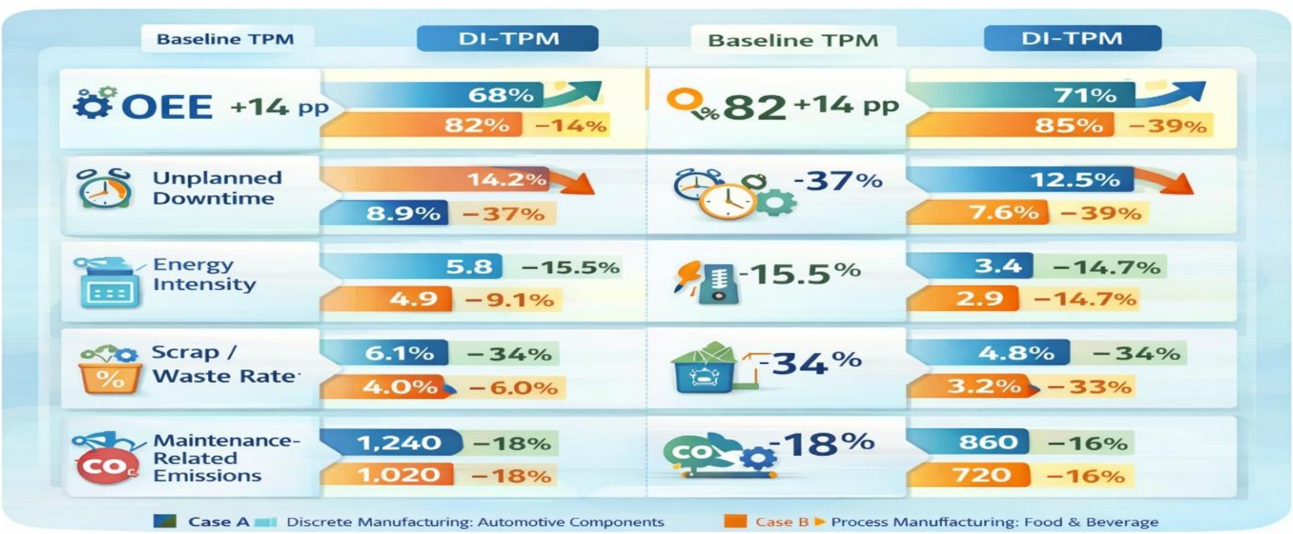

Fig. 3: Quantified sustainability and performance improvements under DI-TPM.

Table 1: Case study overview and data characteristics.

Attribute	Case A: Discrete Manufacturing	Case B: Process Manufacturing
Industry sector	Automotive components	Food and beverage
Production type	Discrete, batch-based	Continuous process
Critical assets	CNC machines, transfer lines	Fillers, conveyors, thermal units
Data sources	IIoT sensors, CMMS, MES, ERP	IIoT sensors, CMMS, MES
Monitoring period	12 months	12 months
Sustainability focus	Energy efficiency, scrap reduction	Energy use, waste, downtime

These sectors were deliberately selected due to their contrasting asset dynamics, regulatory pressures, and sustainability profiles, which are representative of a broad range of smart manufacturing environments that are reported in the literature (Lee *et al.*, 2014).

The case studies followed a longitudinal, before-and-after validation design and compared baseline performance under conventional TPM with post-implementation performance under DI-TPM. Each case involved cross-functional teams comprising maintenance engineers, data scientists, production managers, and sustainability officers, in order to ensure methodological rigor and organizational relevance.

Case Study Contexts and Data Overview

Case A: Discrete Manufacturing (Automotive Components)

This case involved a high-volume machining line that produces precision drivetrain components. Critical assets included CNC machines and automated transfer systems that are characterized by high energy intensity and tight quality tolerances.

Case B: Process Manufacturing (Food and Beverage)

This case focused on a continuous bottling and packaging line, where thermal systems, conveyors, and filling equipment play a dominant role. Sustainability concerns in this context are closely tied to energy use, material waste, and hygiene-related downtime. Table 1 summarizes the key characteristics and data sources for both case studies.

Baseline TPM Performance

Under conventional TPM, both cases exhibited stable but suboptimal performance. Maintenance scheduling was predominantly time-based, with limited use of condition data beyond threshold alarms. Sustainability impacts were not explicitly tracked at the equipment level, which is consistent with observations in prior TPM studies (Ahuja and Khamba, 2008). Table 2 presents baseline operational and sustainability performance indicators for both cases.

Table 2: Baseline performance under conventional TPM.

Metric	Case A	Case B
Overall Equipment Effectiveness (OEE)	68%	71%
Unplanned downtime (%)	14.2%	12.5%
Energy intensity (kWh/unit)	5.8	3.4
Scrap / waste rate (%)	6.1%	4.8%
Maintenance-related emissions (tCO_2e/year)	1,240	860

DI-TPM Implementation and Validation

The DI-TPM framework was deployed incrementally to minimize operational disruption. Predictive models were trained using historical failure and condition data, while sustainability indicators were embedded into prescriptive maintenance decision rules. Maintenance teams received real-time dashboards that presented asset health, predicted degradation, and associated energy and material inefficiencies.

After six months of stabilization, performance was evaluated over a full operational year. Table 3 compares post-implementation results with the baseline.

The results demonstrated consistent improvements across operational and sustainability dimensions. Notably, reductions in energy intensity and emissions were strongly correlated with early detection of mechanical misalignment, bearing wear, and thermal inefficiencies, which are findings that align with prior studies on degradation-induced energy losses (Jardine *et al.*, 2006).

Multidisciplinary Insights and Cross-Case Comparison

Beyond quantitative improvements, qualitative insights emerged from the multidisciplinary validation process. Maintenance engineers reported improved confidence in decision-making due to explainable predictive outputs, while production managers highlighted improved schedule stability and throughput. Sustainability teams benefited from the ability to attribute emissions reductions directly to maintenance actions, a capability rarely available in traditional TPM systems (Franciosi *et al.*, 2020).

Importantly, despite sectoral differences, both cases exhibited similar relative improvements, which suggested that DI-TPM is not domain-specific but rather adaptable across manufacturing typologies. This cross-case consistency strengthens the external validity of the proposed framework

Table 3: Performance improvements following DI-TPM implementation.

Metric	Case A	Improvement	Case B	Improvement
OEE	82%	+14 pp	85%	+14 pp
Unplanned downtime (%)	8.9%	−37%	7.6%	−39%
Energy intensity (kWh/unit)	4.9	−15.5%	2.9	−14.7%
Scrap / waste rate (%)	4.0%	−34%	3.2%	−33%
Maintenance-related emissions (tCO_2e/year)	1,020	−18%	720	−16%

and supports its scalability to other industrial contexts, including Small and Medium-sized Enterprises (SMEs).

Validation Summary

The case studies provide empirical validation that extending TPM with digital intelligence delivers measurable and reproducible benefits across productivity, reliability, and sustainability dimensions. Through the integration of data science, maintenance engineering, and sustainability assessment, DI-TPM enables organizations to operationalize smart manufacturing goals while advancing environmental performance. These findings reinforce the central thesis of this article, as data-driven maintenance is not merely a technological upgrade, but a multidisciplinary strategy that is capable of transforming maintenance into a strategic lever for sustainable manufacturing systems.

DISCUSSION AND IMPLICATIONS

The findings of this study provide compelling evidence that the extension of Total Productive Maintenance with digital intelligence fundamentally reshapes the role of maintenance in smart manufacturing systems. Through the integration of data architecture, advanced analytics, and sustainability metrics into a unified Digital Intelligence–Enabled TPM (DI-TPM) framework, maintenance evolves from a predominantly reactive or preventive function into a strategic, data-driven capability with measurable environmental and operational impact. Here, the theoretical, methodological, practical, and policy implications of these findings were discussed, while also situating them within the broader maintenance and sustainability literature.

Theoretical Contributions to Maintenance and Sustainability Research

From a theoretical perspective, this study advances TPM research by addressing long-standing critiques regarding its static and experience-driven nature. While TPM has traditionally emphasized organizational culture and human engagement, its integration with digital intelligence has been insufficiently explored in the literature. The DI-TPM framework contributes a novel conceptualization of TPM as a dynamic socio-technical system, where real-time data and machine learning continuously inform maintenance decision-making without undermining TPM's participatory ethos.

Moreover, the study contributes to the emerging discourse on maintenance-driven sustainability. Prior work has largely treated maintenance as an implicit enabler of sustainability, with limited empirical quantification of its environmental benefits (Franciosi *et al.*, 2020). By explicitly linking equipment degradation, maintenance actions, and sustainability indicators, this research provides a causal and measurable account of how maintenance influences energy efficiency, material usage, and emissions. This integration bridges maintenance engineering and sustainable manufacturing research, which are two domains that have historically evolved in parallel rather than in concert.

Methodological Implications for Data-Driven Maintenance

Methodologically, the study demonstrates the importance of moving beyond predictive accuracy as the primary success criterion for maintenance analytics. While predictive maintenance research has made significant progress in fault detection and remaining useful life estimation (Lee *et al.*, 2014), the results show that actionable value emerges when predictions are embedded within prescriptive, sustainability-aware decision frameworks. The integration of sustainability metrics into maintenance optimization represents a methodological shift with far-reaching implications. Rather than treat environmental performance as a downstream consequence, DI-TPM internalizes sustainability objectives within maintenance decision logic. This approach aligns with recent calls for multi-objective optimization in manufacturing systems, where economic, operational, and environmental objectives are jointly considered (Bocken *et al.*, 2014).

Additionally, the emphasis on human-centered and explainable analytics addresses a critical adoption barrier that is identified in Industry 4.0 research. Trust, transparency, and interpretability are essential for integrating digital intelligence into established maintenance practices (Carvalho *et al.*, 2019). The study demonstrates that explainable decision support enhances operator acceptance and organizational learning, thereby reinforcing the complementary relationship between human expertise and algorithmic intelligence.

Practical Implications for Industrial Implementation

For practitioners, the results highlight data-driven maintenance as a high-leverage intervention for achieving both productivity and sustainability goals. The observed reductions in energy intensity, material waste, and maintenance-related emissions provide tangible evidence to support investment decisions in digital maintenance infrastructure. Importantly, these benefits were realized without sacrificing equipment availability or production output, which counters the perception that sustainability improvements necessarily entail operational trade-offs.

The case studies also underscore the importance of organizational integration. Successful DI-TPM implementation required collaboration among maintenance, production, data science, and sustainability functions. This finding reinforces the view that digital transformation in manufacturing is as much an organizational challenge as a technological one (Kagermann *et al.*, 2013; Lu, 2017). Firms that are seeking to adopt DI-TPM should therefore prioritize data governance, workforce upskilling, and cross-functional alignment alongside technical deployment. For SMEs, the modular architecture of DI-TPM offers a pathway for incremental adoption. Rather than require full-scale digitalization, firms can begin by integrating condition monitoring and energy data for critical assets, gradually expanding analytical capabilities as data maturity increases.

Policy and Standardization Implications

At the policy level, the findings have implications for industrial sustainability frameworks and smart manufacturing initiatives. Current standards and performance metrics often focus on energy efficiency or emissions at the plant level, overlooking the role of maintenance in driving these outcomes (IEA, 2022; ISO, 2017). The empirical evidence presented in this study supports the inclusion of maintenance-related indicators in sustainability reporting and industrial benchmarking schemes. Furthermore, DI-TPM aligns closely with policy objectives that underpin Industry 4.0 and circular economy strategies, particularly those emphasizing resource efficiency, asset longevity, and data-driven optimization (Udu *et al.*, 2025b; Udu and Okpala, 2025). Policymakers and industry bodies could leverage this alignment through the incentivization of the adoption of data-driven maintenance practices through funding programs, guidelines, and digital infrastructure initiatives.

Limitations and Directions for Future Research

While the study provides robust empirical evidence, the following limitations deserve to be duly considered:

a. The case studies were conducted in large industrial facilities with relatively mature digital infrastructures, which may limit direct generalization to less digitized contexts.
b. Emissions estimates relied on standardized conversion factors, which may not capture site-specific energy mixes or upstream supply chain impacts.

Future research should explore DI-TPM implementation in SMEs and resource-constrained environments, as well as extend sustainability assessment to include broader life-cycle and circularity metrics. Additionally, longitudinal studies that examine long-term organizational learning and cultural change under DI-TPM would further enrich the understanding of its systemic impact.

The study demonstrates that the integration of digital intelligence into TPM delivers significant theoretical, methodological, and practical advancements. Through the quantification of sustainability benefits and embedding them within maintenance decision-making, DI-TPM positions maintenance as a strategic enabler of sustainable smart manufacturing. The framework and evidence presented provide a strong foundation for future research and industrial adoption at the intersection of maintenance engineering, data science, and sustainability.

CONCLUSION

This study set out to re-examine the role of maintenance in smart manufacturing and to demonstrate how Total Productive Maintenance can be meaningfully extended through digital intelligence. Through the introduction of the Digital Intelligence–Enabled Total Productive Maintenance (DI-TPM) framework, the article shows that maintenance can move beyond static, time-based practices towards a dynamic, data-driven system that simultaneously enhances operational performance and delivers measurable sustainability benefits.

The results confirm that embedding real-time data, advanced analytics, and sustainability-aware decision models within TPM enables earlier detection of equipment degradation, more effective maintenance interventions, and improved asset utilization. Crucially, these improvements translate into tangible environmental gains, including reductions in energy intensity, material waste, and maintenance-related emissions, without compromising productivity or equipment availability. This dual impact positions data-driven maintenance as a strategic lever for the attainment of both smart manufacturing and sustainability objectives.

Beyond technical contributions, the study highlights the importance of the integration of human expertise with digital intelligence. By preserving TPM's participatory philosophy and augmenting it with transparent, explainable decision support, DI-TPM strengthens operator engagement and organizational learning. The multidisciplinary case studies further demonstrate that the framework is adaptable across manufacturing contexts, which reinforces its potential for scalable industrial adoption. The article reframes maintenance as a central component of sustainable smart manufacturing rather than a supporting operational function. The DI-TPM framework and empirical evidence presented provide a robust foundation for future research and practical implementation at the intersection of maintenance engineering, data science, and sustainability. As manufacturing systems continue to digitalize under increasing environmental constraints, data-driven maintenance approaches such as DI-TPM will play an essential role in shaping resilient, efficient, and sustainable industrial systems.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy, have been completely observed by the authors.

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