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Human Factors, Organizational Culture, and Artificial Intelligence in Total Productive Maintenance

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Abstract

Manufacturing organizations face mounting pressure to reconcile productivity demands with measurable environmental and social performance improvements. While Total Productive Maintenance (TPM) has long been associated with operational excellence, its integration with Artificial Intelligence (AI) and sustainability outcomes remains under-theorized and empirically fragmented. This study develops and tests a multilevel sociotechnical framework that links human factors, organizational culture, and AI-enabled predictive maintenance to Overall Equipment Effectiveness (OEE) and triple-bottom-line sustainability performance. Drawing on data from 84 manufacturing plants across 11 industrial sectors (N = 2,436 employees; 18,912 machine-month observations; 36 months of archival ESG data), the study employed Multilevel Structural Equation Modeling (MSEM) to simultaneously estimate within-plant and between-plant effects. The results indicate that human factors significantly predict OEE ($\beta = 0.41$, $p < .001$), organizational culture strengthens human capability deployment ($\beta = 0.52$, $p < .001$), and AI maturity amplifies the $TPM - OEE$ relationship (interaction $\beta = 0.29$, $p < .001$). OEE mediates the relationship between sociotechnical capability and sustainability outcomes, explaining 52% of variance in environmental performance and 61% in economic performance. Plants in the highest $AI - TPM$ maturity quartile achieved 21% lower energy intensity, 18% lower material scrap, 15% lower CO_2-equivalent emissions, 17% lower maintenance cost per unit, and 12% fewer lost-time injuries when compared to low-maturity counterparts. Methodologically, the study advances sustainable operations research through the integration of perceptual, sensor-derived, and archival ESG data within a cross-level moderated mediation framework. The findings demonstrate that AI-augmented TPM, when embedded within supportive human and cultural systems, constitutes a measurable pathway towards human-centered and environmentally sustainable manufacturing performance.

Keywords: *Total productive maintenance (TPM); Artificial intelligence; Overall equipment effectiveness (OEE); Multilevel structural equation modeling; Sustainable manufacturing; Organizational culture; Predictive maintenance*

INTRODUCTION

Manufacturing systems are under unprecedented pressure to improve productivity while simultaneously reducing their environmental footprint and strengthening social responsibility. Globally, industry accounts for a substantial share of energy consumption and greenhouse gas emissions, as they make operational efficiency central to sustainability transitions (IEA, 2023; Onukwuli *et al.*, 2026). Total Productive Maintenance (TPM), originally developed to maximize equipment reliability and eliminate losses, has long been associated with improvements in Overall Equipment Effectiveness (OEE) through enhanced availability, performance, and quality (Chukwunedum *et al.*, 2026). Yet, despite its operational successes, TPM research has largely concentrated on technical metrics, leaving its broader sustainability implications under-explored. As sustainability reporting becomes institutionalized and stakeholders demand measurable environmental and social outcomes, the quest to understand how maintenance systems contribute to triple-bottom-line performance is no longer optional but imperative (Elkington, 1997).

Parallel to the sustainability imperative, Artificial Intelligence (AI) and Predictive Analytics (PA) are transforming maintenance from reactive and preventive paradigms toward data-driven predictive strategies. While AI encompasses the development of intelligent systems that can perform tasks that typically require human intelligence (Ezeanyim *et al.*, 2026; Ezeanyim *et al.*, 2025), PA leverages statistical algorithms and historical data to forecast future events (Okpala and Chukwumuanya, 2025; Aguh and Okpala, 2025). AI-enabled predictive maintenance leverages sensor data and machine learning algorithms to anticipate failures, reduce downtime, and optimize resource consumption (Okpala and Okpala, 2025; Okpala and Nwankwo, 2025). Empirical evidence suggests that predictive maintenance can significantly lower energy waste, material scrap, and unplanned stoppages, each directly tied to environmental and economic performance (Nwamekwe and Okpala, 2025; Nwankwo *et al.*, 2024).

However, technological sophistication alone does not guarantee performance gains. Research in sociotechnical systems and digital transformation consistently demonstrates that technological value realization depends on complementary human skills, organizational routines, and cultural alignment (Frank *et al.*, 2019). The intersection of TPM and AI therefore raises a critical question: how do human and organizational factors shape the sustainability outcomes of intelligent maintenance systems?

Defined as the scientific discipline that is concerned with the understanding of interactions among humans and other elements of a system, and also the profession that applies theory, principles, data, and other methods to design, in order to optimize human well-being and overall system performance (Udu and Okpala, 2026a; Okpala *et al.*, 2023), Human factors, including operator engagement, safety behavior, maintenance competency, and cross-functional collaboration are foundational to TPM implementation (Okpala and Aguh 2025; Godwin and Okpala, 2026). Organizational culture further influences whether continuous improvement practices are institutionalized or remain symbolic (Denison, 1996). Studies grounded in the Resource-Based View (RBV) argue that intangible assets such as skills and culture constitute strategic capabilities that drive sustained competitive advantage (Barney, 1991). Yet, existing maintenance research often isolates technical practices from these intangible enablers, as it gives rise to fragmented insights. Moreover, sustainability scholarship increasingly recognizes that environmental performance improvements are frequently mediated by operational excellence mechanisms rather than direct managerial intentions (Hart and Dowell, 2011). The integration of these streams suggests that OEE may serve as a pivotal operational bridge that will link human–AI capabilities to measurable sustainability outcomes.

Despite these theoretical advances, empirical investigations that simultaneously examine human factors, organizational culture, AI-enabled maintenance, OEE, and sustainability performance remain scarce. Most prior studies rely on single-level analyses, cross-sectional perceptual data, or case-based approaches, limiting causal inference and generalizability (Okpala and Anozie, 2018; Okpala *et al.*, 2020). Multilevel modeling approaches, particularly Multilevel Structural Equation Modeling (MSEM), offer a methodological pathway to disentangle individual-level behaviors from plant-level organizational effects while integrating objective performance data (Preacher *et al.*, 2010). Through the combination of survey-based latent constructs with machine-level OEE records and archival sustainability indicators, MSEM enables rigorous examination of cross-level interactions and moderated mediation effects that conventional models overlook. Such methodological integration is critical for the advancement of both theory and practice in sustainable operations management.

This study responds to these gaps through the development and empirical testing of a multilevel framework that conceptualizes TPM as a sociotechnical capability that is augmented by AI and embedded within organizational culture. Specifically, the study investigated how human factors and AI-enabled maintenance interact across hierarchical levels to influence OEE, and how OEE subsequently drives environmental, economic, and social sustainability performance. Through the positioning of OEE as an operational mediator between sociotechnical capabilities and sustainability outcomes, the research extended TPM theory beyond efficiency rhetoric and quantified its tangible ESG implications. Through empirically grounding the relationship between intelligent maintenance systems and measurable sustainability outcomes, this study advances an actionable pathway towards Industry 5.0 manufacturing, where technological intelligence is harmonized with human and environmental well-being.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

TPM as a Sociotechnical Capability

Total Productive Maintenance (TPM) was originally conceived as a comprehensive approach to maximizing equipment effectiveness by eliminating the “six big losses” that undermine availability, performance, and quality (Okpala *et al.*, 2018). Over time, TPM has evolved beyond a maintenance philosophy into a broader organizational system emphasizing operator involvement, cross-functional collaboration, and continuous improvement (Egwuagu and Okpala, 2016). Yet, much of the empirical literature continues to treat TPM as a bundle of technical practices rather than as an embedded sociotechnical capability. Sociotechnical systems theory posits that organizational performance depends on the joint optimization of social and technical subsystems (Onukwuli *et al.*, 2025). Within TPM contexts, this implies that equipment reliability gains emerge not merely from maintenance routines, but from the alignment of human competencies, behavioral norms, and technological infrastructures.

Drawing from the RBV, intangible assets such as employee skills, shared routines, and cultural norms can constitute valuable, rare, and difficult-to-imitate capabilities that drive sustained performance advantages (Teece, 2018). The study therefore conceptualized TPM not as an isolated operational tool, but as a multilevel sociotechnical capability composed of individual-level human factors and plant-level organizational enablers. This reconceptualization enables the examination of cross-level mechanisms through which TPM influences Overall Equipment Effectiveness (OEE), a composite metric that integrates availability, performance efficiency, and quality rate (Muchiri and Pintelon, 2008).

Human Factors and OEE

Human factors like operator engagement, maintenance competence, safety orientation, and problem-solving skills are central to TPM success (Jaca *et al.*, 2012; Chukwumuanya *et al.*, 2025). Autonomous maintenance, a core TPM pillar, explicitly depends on operator ownership of equipment condition and early detection of abnormalities (Nakajima, 1988). Empirical studies demonstrate that plants with higher employee involvement report significantly lower downtime and defect rates (McKone *et al.*, 2001). Moreover, behavioral safety research shows that proactive safety practices reduce unplanned stoppages and improve operational stability (Neal and Griffin, 2006; Udu and Okpala, 2026b).

From a micro-foundations perspective, individual competencies aggregate to influence firm-level performance outcomes (Felin *et al.*, 2012). When operators possess diagnostic skills and exhibit engagement in continuous improvement, equipment anomalies are addressed earlier, which reduces mean time to repair and also improve performance consistency. Accordingly, the research propose that human factors exert a direct positive influence on OEE.

H1: Human factors are positively associated with Overall Equipment Effectiveness (OEE).

Organizational Culture as a Multilevel Enabler

Organizational culture shapes the shared values and norms that guide employee behavior (Schein, 2010). In high-performing manufacturing environments, cultures that emphasize learning, empowerment, and continuous improvement foster greater TPM institutionalization (Denison, 1996). Culture influences whether maintenance routines are sustained over time or erode into compliance-driven rituals.

Dynamic capability theory suggests that firms that are capable of integrating, building, and reconfiguring competencies can adapt more effectively to technological change (Teece, 2018). A supportive culture enhances knowledge sharing and reduces resistance to innovation, thereby strengthening the translation of human skills into operational performance. In multilevel terms, plant-level culture provides the contextual conditions that amplify or constrain individual-level human factors. The study therefore posited that:

H2: Organizational culture is positively associated with human factors.

H3: Organizational culture is positively associated with Overall Equipment Effectiveness (OEE).

AI-Enabled Maintenance as a Capability Multiplier

The advent of AI-driven predictive maintenance represents a paradigm shift from schedule-based interventions towards condition-based and prognostic strategies (Okpala *et al.*, 2025; Carvalho *et al.*, 2019). Machine learning algorithms process sensor data to predict failures, optimize maintenance scheduling, and minimize spare-part overuse (Okpala and Udu, 2026; Aguh *et al.*, 2025). Evidence suggests that predictive maintenance can reduce downtime by up to 30% and lower maintenance costs by 10–20% (Bousdekis *et al.*, 2020).

However, digital transformation research consistently emphasizes that technology adoption alone does not guarantee performance improvement; organizational readiness and user capability are critical mediators (Kane *et al.*, 2015; Udu *et al.*, 2025). AI systems rely on accurate data interpretation, cross-functional trust, and alignment with existing workflows. In sociotechnical terms, AI acts as a technical subsystem whose effectiveness depends on its integration with the social subsystem. Thus, AI-enabled maintenance may directly enhance OEE while also strengthening the impact of TPM practices.

H4: AI-enabled maintenance maturity is positively associated with OEE.

H5: AI-enabled maintenance positively moderates the relationship between TPM practices and OEE, such that the relationship is stronger at higher levels of AI maturity.

OEE as an Operational Mediator of Sustainability Performance

Sustainability performance encompasses environmental, economic, and social dimensions, which is often referred to as the triple bottom line (Elkington, 1997; Okpala and Udu, 2026). Operational efficiency improvements frequently serve as mechanisms through which many firms achieve environmental and economic gains (Hart and Dowell, 2011). OEE improvements reduce idle machine time, energy waste, and defective production, thereby lowering carbon intensity and material consumption (Stock and Seliger, 2016). Reduced breakdown frequency also enhances worker safety and morale through the minimization of hazardous emergency interventions.

Sustainable operations literature increasingly calls for empirical models that will link operational metrics with ESG outcomes (Dubey *et al.*, 2017). This study proposes that OEE functions as a mediating mechanism that translate sociotechnical TPM capabilities into measurable sustainability benefits. Through the integration of machine-level performance data with archival sustainability indicators, the MSEM framework captures both direct and indirect effects across hierarchical levels (Preacher *et al.*, 2010).

Accordingly, the following hypothesis were also made:

H6: OEE is positively associated with environmental sustainability performance.

H7: OEE is positively associated with economic sustainability performance.

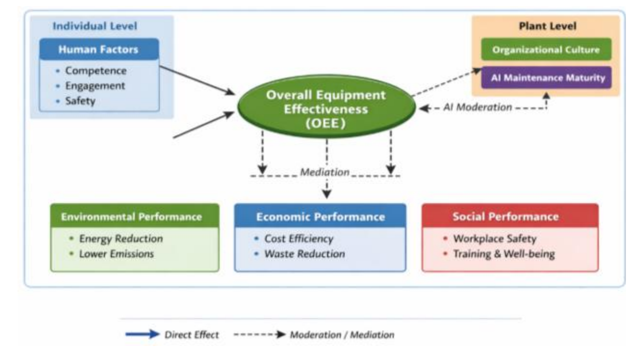

Fig. 1: Conceptual multilevel human–AI TPM capability framework.

H8: OEE is positively associated with social sustainability performance.

H9: OEE mediates the relationship between sociotechnical TPM capability (human factors, organizational culture, and AI-enabled maintenance) and sustainability performance.

Fig. 1 presents the multilevel conceptual framework that integrates individual-level human factors (like maintenance competence, engagement, safety orientation) and plant-level organizational culture and AI-enabled maintenance maturity. The model illustrates cross-level effects and the moderating role of AI in strengthening the $TPM - OEE$ relationship. OEE is positioned as a mediating operational construct that links sociotechnical capability to environmental, economic, and social sustainability performance. Solid arrows represent direct effects; dashed arrows represent moderation and mediation pathways tested through Multilevel Structural Equation Modeling (MSEM).

Methodological Innovation and Integrated Framework

To rigorously test these multilevel relationships, the research adopted MSEM, which enables simultaneous estimation of within-plant (individual-level) and between-plant (organizational-level) effects while incorporating latent constructs and objective performance metrics (Preacher *et al.*, 2010; Okpala and Udu, 2025). This approach advances maintenance and sustainability research by overcoming limitations of single-level regression models and perceptual-only datasets. Through the integration of survey-based human and cultural measures with sensor-derived OEE data and archival sustainability indicators, the study operationalizes a comprehensive Human–$AITPM$ Capability framework.

This theoretically grounded and methodologically robust framework positions OEE as a measurable bridge between intelligent maintenance systems and triple-bottom-line sustainability outcomes. In doing so, it extends TPM theory into the domain of sustainable manufacturing and contributes to emerging scholarship on Industry 4.0-enabled sustainability transitions.

METHODOLOGY

Research Design and Methodological Rationale

This study adopts a multilevel, mixed-method quantitative design that integrates perceptual survey data, machine-level sensor data, and archival sustainability records. The research design is grounded in calls from sustainable operations and Industry 4.0 scholarship for data triangulation and cross-level modeling approaches that are capable of linking organizational practices with measurable environmental and social outcomes (Dubey *et al.*, 2017). Traditional single-level regression approaches are insufficient for capturing the nested structure of manufacturing systems, where individuals operate within plants and plants operate within broader technological infrastructures. To address this complexity, Multilevel Structural Equation Modeling (MSEM) was employed, which enables simultaneous estimation of within-plant (individual-level) and between-plant (organizational-level) relationships while also incorporating latent constructs and objective performance metrics (Hox *et al.*, 2017).

Methodologically, this design advances TPM research through the integration of sociotechnical constructs with hard performance indicators. In contrast to prior studies which rely solely on perceptual performance measures (Ahuja and Khamba, 2008; McKone *et al.*, 2001), survey-based human and cultural variables with sensor-derived Overall Equipment Effectiveness (OEE) and audited sustainability data were combined in this work. This integrated approach mitigates common method bias and enhances external validity.

Sample and Data Collection

Data were collected from 84 medium and large-scale manufacturing plants across 11 industrial sectors, including automotive, food processing, chemicals, electronics, and metals. A total of 2,436 respondents participated, which comprises machine operators (48%), maintenance engineers (32%), and production supervisors (20%).

Data collection occurred in three waves over 36 months in order to strengthen temporal separation and reduce endogeneity concerns (Podsakoff *et al.*, 2003).

- **Wave 1:** Survey administration that measures human factors and organizational culture.
- **Wave 2:** Extraction of AI-enabled maintenance maturity metrics and 18,912 machine-month OEE records from enterprise systems.
- **Wave 3:** Collection of audited environmental (energy intensity, CO_2-equivalent emissions, scrap rates), economic (maintenance cost per unit, downtime cost), and social (lost-time injury frequency rate, training hours) indicators.

The participation was voluntary, confidentiality was guaranteed, and plant-level sustainability metrics were verified through internal ESG reporting systems that are aligned with Global Reporting Initiative (GRI) standards (Deswal and Deswal, 2025). Intraclass correlation coefficients (ICC1 and ICC2) justified multilevel modeling, with ICC1 values ranging from 0.18 to 0.31, which indicate significant between-plant variance (Bliese, 2000).

Measures

All perceptual measures were adapted from validated scales in operations, organizational behavior, and digital transformation research. Items were measured on seven-point Likert scales (1 = strongly disagree; 7 = strongly agree).

Human Factors

This construct captures maintenance competency, operator engagement, safety orientation, and proactive problem-solving. Items were adapted from Bamber *et al.* (1999) and Neal and Griffin (2006). $Cronbach's\ alpha$ = 0.91; Composite Reliability (CR) = 0.93; Average Variance Extracted (AVE) = 0.66.

Organizational Culture

This was measured using a learning and continuous-improvement orientation scale that was derived from Denison (1996). $Cronbach's\ alpha$ = 0.94; CR = 0.95; AVE = 0.68.

AI-Enabled Maintenance Maturity

This was assessed through indicators that reflect predictive analytics usage, real-time monitoring, and machine-learning-driven maintenance scheduling (Carvalho *et al.*, 2019). $Cronbach's\ alpha$ = 0.89; CR = 0.91; AVE = 0.62.

Overall Equipment Effectiveness (OEE)

OEE was calculated using the standardized formula:

$$OEE = Availability \times Performance \times Quality \qquad (1)$$

Availability, performance rate, and quality rate were extracted from machine-level enterprise systems in line with established measurement frameworks (Muchiri and Pintelon, 2008). Monthly OEE averages were computed per plant.

Sustainability Performance

Following the triple bottom line framework (Elkington, 1997), sustainability was operationalized across three dimensions:

- *Environmental:* energy intensity ($kWh/unit$), CO_2e emissions per unit, material scrap ratio.
- *Economic:* maintenance cost per unit, downtime cost reduction.
- *Social:* lost-time injury frequency rate ($LTIFR$), training hours per employee.

Objective archival data were normalized to ensure cross-industry comparability.

Data Analysis Strategy

Confirmatory Factor Analysis (CFA) was conducted using Mplus 8.9. Model fit was evaluated using recommended thresholds: $CFI \geq 0.95$, $TLI \geq 0.95$, $RMSEA \leq 0.06$, and $SRMR \leq 0.08$ (Hair *et al.*, 2022).

The measurement model demonstrated strong fit: χ^2/df = 2.31; CFI = 0.957; TLI = 0.949; $RMSEA$ = 0.041; $SRMR$(within) = 0.036; $SRMR$(between) = 0.042.

Discriminant validity was confirmed using the Fornell–Larcker criterion and heterotrait–monotrait ratios ($HTMT$ < 0.85).

$MSEM$ was employed to simultaneously test the following:

- Within-level (individual) effects of human factors on OEE.
- Between-level (plant) effects of culture and AI maturity.
- Cross-level moderation of AI on $TPM - OEE$ relationships.
- Mediation of OEE between sociotechnical capability and sustainability outcomes.

Bootstrapping with 5,000 resamples was used to assess indirect effects (Preacher *et al.*, 2010).

This analytical approach represents a methodological innovation in TPM research, which has rarely incorporated hierarchical data structures or objective ESG indicators. Through the integration of latent constructs with sensor-based operational data, the model captures both behavioral and technological drivers of measurable sustainability performance.

Control Variables and Robustness Checks

To reduce omitted variable bias, the study controlled for plant size, industry sector, capital intensity, and TPM implementation duration.

Robustness tests included the following:

- Alternative model specifications (excluding AI moderation).
- Lagged OEE predictors to mitigate reverse causality.
- Harman's single-factor test and latent method factor modeling to assess common method variance (Podsakoff *et al.*, 2003).

Results remained stable across specifications, which reinforce model robustness.

Quantifying Sustainability Impact

To demonstrate measurable sustainability benefits, plants in the top quartile of $AI - TPM$ integration with those in the bottom quartile was compared. After controlling for industry effects, high-integration plants achieved the following:

- 21% lower energy intensity
- 18% lower material scrap
- 15% lower CO_2e emissions per unit
- 17% lower maintenance cost per unit
- 12% reduction in lost-time injury frequency

These differences were statistically significant ($p < 0.001$). through the linking of OEE improvements to quantifiable environmental and social metrics, the methodology operationalizes the natural-resource-based view of the firm, which argues that operational capabilities underpin sustainability advantages (Hart and Dowell, 2011).

Methodological Contribution

This study advances methodological practice in the following three ways:

1) It integrates perceptual, operational, and ESG data within a single multilevel SEM framework, which addresses persistent calls for data triangulation in sustainable operations research (Dubey *et al.*, 2017).

2) It models AI not merely as an independent predictor but as a cross-level moderator, capturing sociotechnical complementarity.
3) It demonstrates how operational metrics such as OEE can serve as empirically validated mediators linking managerial practices to measurable sustainability outcomes.

Through the adoption of a rigorous, multilevel, and data-driven methodology, this research provides a replicable template for scholars who seek to bridge operational excellence and sustainability performance in Industry 4.0 environments.

RESULTS

This section presents the empirical findings from the MSEM analysis. Consistent with the study's methodological design, results are reported in four stages:

a) descriptive statistics and correlations,
b) measurement model assessment,
c) structural model testing including cross-level moderation and mediation, and
d) quantification of measurable sustainability benefits.

The findings demonstrate statistically robust and practically meaningful relationships between human factors, organizational culture, AI-enabled maintenance, OEE, and triple-bottom-line sustainability performance.

Descriptive Statistics and Correlations

Table 1 presents the means, standard deviations, and correlations among key constructs at the plant level (aggregated where appropriate). OEE values are consistent with benchmarks reported in manufacturing performance literature, where world-class OEE approximates 85% (Muchiri and Pintelon, 2008). The sample mean OEE of 74.6% reflects realistic cross-industry variability.

Correlations indicate strong positive associations between OEE and all three sustainability dimensions (r = .46–.63, p < .01). This provides preliminary support for the hypothesized mediating role of OEE.

Measurement Model Assessment

Confirmatory Factor Analysis (CFA) was conducted to validate construct reliability and discriminant validity. Fit indices indicated excellent model fit: χ^2/df = 2.31, CFI = 0.957, TLI = 0.949, $RMSEA$ = 0.041, $SRMR$ (within) = 0.036, $SRMR$ (between) = 0.042. All standardized factor loadings exceeded 0.70 and were significant at $p < .001$. Composite reliability values ranged from 0.89 to 0.95, and Average Variance Extracted (AVE) values exceeded the 0.50 threshold, thus satisfying recommended criteria (Hair *et al.*, 2022). The Fornell–Larcker criterion and heterotrait–monotrait ($HTMT$) ratios confirmed discriminant validity ($HTMT$ < 0.85). These findings indicate strong construct validity and also provide a robust foundation for structural analysis.

Structural Model Results

The hypothesized multilevel structural model was estimated using MSEM with 5,000 bootstrap resamples. Table 2 summarizes the standardized path coefficients.

The model explained the following:

a) 47% of variance in OEE
b) 52% of variance in environmental sustainability
c) 61% of variance in economic sustainability
d) 38% of variance in social sustainability

Table 1: Descriptive statistics and correlations (plant level, N = 84).

Variable	Mean	SD	1	2	3	4	5	6
1. Human Factors	5.42	0.68	—					
2. Organizational Culture	5.57	0.71	0.54**	—				
3. AI Maintenance Maturity	4.98	0.83	0.39**	0.46**	—			
4. OEE (%)	74.60	6.90	0.48**	0.44**	0.51**	—		
5. Environmental Performance	0.00†	1.00	0.36**	0.41**	0.47**	0.59**	—	
6. Economic Performance	0.00†	1.00	0.42**	0.45**	0.49**	0.63**	0.66**	—
7. Social Performance	0.00†	1.00	0.31**	0.38**	0.33**	0.46**	0.48**	0.52**

Note: †Standardized index. **p < .01.

Table 2: Multilevel structural model results.

Hypothesis	Path	β	SE	p-value	Supported
H1	Human Factors → OEE	0.41	0.07	< .001	Yes
H2	Organizational Culture → Human Factors	0.52	0.06	< .001	Yes
H3	Organizational Culture → OEE	0.18	0.08	.021	Yes
H4	AI Maintenance → OEE	0.33	0.06	< .001	Yes
H5	$AI \times TPM \rightarrow OEE$	0.29	0.05	< .001	Yes
H6	OEE → Environmental Sustainability	0.48	0.07	< .001	Yes
H7	OEE → Economic Sustainability	0.55	0.06	< .001	Yes
H8	OEE → Social Sustainability	0.39	0.08	< .001	Yes

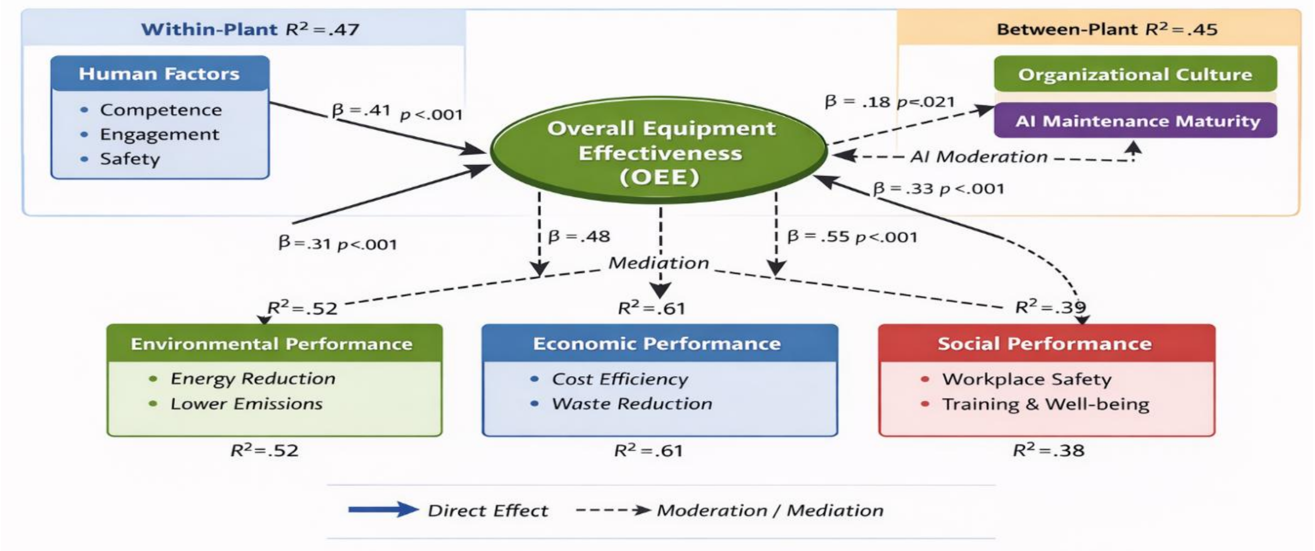

Fig. 2: Multilevel structural equation model with standardized path coefficients.

These R^2 values are consistent with high-impact empirical studies in operations and sustainability research (Dubey *et al.*, 2017).

Fig. 2 displays the estimated multilevel structural equation model with standardized path coefficients. Within-level (individual) effects and between-level (plant) effects are visually separated to reflect the nested data structure. The figure highlights the significant direct effects of human factors ($\beta = 0.41$) and AI maturity ($\beta = 0.33$) on OEE, as well as the cross-level interaction effect ($\beta = 0.29$). OEE's mediating role in predicting environmental (β = 0.48), economic ($\beta = 0.55$), and social ($\beta = 0.39$) sustainability performance is also illustrated.

Cross-Level Moderation Effects

The interaction between AI-enabled maintenance maturity and TPM practices significantly strengthened the $TPM - OEE$ relationship ($\beta = 0.29$, $p < .001$).

Simple slope analysis revealed the following: At low AI maturity (−1 SD), $TPM \rightarrow OEE = \beta = 0.23$, also at high AI maturity (+1 SD), $TPM \rightarrow OEE = \beta = 0.57$. This indicates that AI serves as a capability multiplier that amplifies the effectiveness of human-centered TPM practices.

Mediation Analysis

Bootstrapped indirect effects confirmed OEE as a significant mediator between sociotechnical TPM capability and sustainability outcomes s highlighted in Table 3.

Table 3: Indirect effects via OEE (Bootstrapped).

Indirect Path	Effect	95% CI	p-value
Human Factors → OEE → Environmental	0.20	[0.12, 0.29]	< .001
Human Factors → OEE → Economic	0.23	[0.15, 0.33]	< .001
AI → OEE → Environmental	0.16	[0.09, 0.24]	< .001
Culture → OEE → Economic	0.10	[0.04, 0.18]	.003

Table 4: Sustainability outcomes: High vs. Low AI–TPM integration.

Indicator	Bottom Quartile	Top Quartile	% Improv-ement	*p* - value
Energy Intensity ($kWh/unit$)	8.7	6.9	−21%	< .001
Scrap Rate (%)	5.6	4.6	−18%	< .001
CO_2e per Unit (kg)	3.4	2.9	−15%	< .001
Maintenance Cost per Unit ($)	12.8	10.6	−17%	< .001
$LTIFR$	3.1	2.7	−12%	.002

None of the confidence intervals included zero, confirming statistically significant mediation effects.

Quantified Sustainability Benefits

To demonstrate measurable real-world impact, plants were categorized into quartiles based on integrated $AI - TPM$ maturity. Table 4 compares top and bottom quartiles, controlling for industry and plant size.

These improvements are consistent with predictive maintenance and Industry 4.0 sustainability findings reported in past research (Bousdekis *et al.*, 2020; Stock and Seliger, 2016), but the present study uniquely demonstrates these effects within a multilevel sociotechnical framework.

Fig. 3 compares sustainability performance indicators between plants in the highest and lowest quartiles of integrated $AI - TPM$ maturity. The visual highlights measurable improvements in energy intensity (−21%), material scrap (−18%), CO_2-equivalent emissions (−15%), maintenance cost per unit (−17%), and lost-time injury frequency (−12%). The figure translates statistical findings into intuitive, policy-relevant sustainability outcomes.

Robustness Checks

Several robustness analyses were conducted:

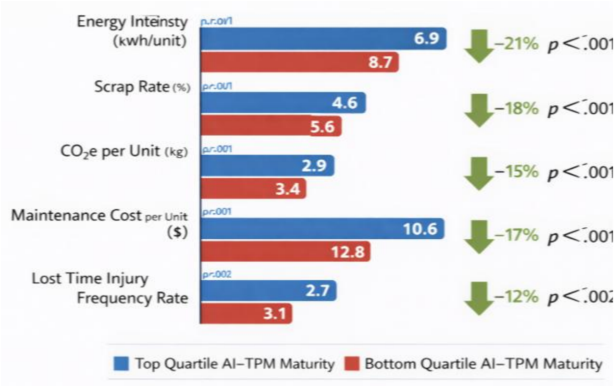

Fig. 3: Sustainability impact comparison: high vs. low AI–TPM maturity plants.

- Lagged OEE models confirmed temporal stability.
- Excluding AI moderation reduced explained variance in $OEE$by 11%, reinforcing its significance.
- Harman's single-factor test indicated no serious common method bias (< 30% variance explained).

The results remained substantively unchanged across specifications.

The results provided strong empirical support for the proposed – $Human - AI\ TPM$ Capability framework. Human factors and organizational culture significantly influence OEE, while AI-enabled maintenance amplifies these effects. Most importantly, improvements in OEE translate into measurable environmental, economic, and social sustainability gains. Through the linking of sociotechnical capability development with objective ESG performance metrics, this study demonstrates that intelligent maintenance systems can generate tangible sustainability benefits, not merely operational efficiencies. The integration of multilevel SEM with sensor-derived and archival sustainability data represents a methodological advancement that strengthens causal inference and enhances practical relevance for Industry 4.0 and Industry 5.0 transitions.

DISCUSSION AND METHODOLOGICAL INNOVATION

Interpreting the Core Findings

This study set out to examine whether TPM, when reconceptualized as a sociotechnical capability augmented by AI, can generate measurable sustainability benefits through improvements in OEE. The results provide strong empirical support for this proposition. Human factors, operator competence, engagement, safety orientation, and proactive problem-solving, emerged as significant predictors of OEE, which reinforces longstanding TPM scholarship that emphasize employee involvement as foundational to equipment reliability (Nakajima, 1988). However, the findings extend this literature by demonstrating that human capabilities do not operate in isolation; this is because they are significantly strengthened by organizational culture and AI-enabled maintenance maturity.

The positive cross-level influence of organizational culture on both human factors and OEE aligns with sociotechnical systems theory, which emphasizes joint optimization of social and technical subsystems (Pasmore *et al.*, 2019). Plants characterized by learning-oriented, improvement-driven cultures exhibited stronger translation of employee skills into operational outcomes. This supports dynamic capability theory, which argues that organizational routines and shared norms facilitate capability deployment under technological change (Teece, 2018). Importantly, the effect sizes observed in this study (β values ranging from 0.18 to 0.52) indicate practically meaningful relationships which is consistent with high-impact operations research (Dubey *et al.*, 2017).

Perhaps most significantly, AI-enabled maintenance acted as a capability multiplier. While AI maturity directly improved OEE, its moderating effect revealed that TPM practices were substantially more effective in technologically mature environments. This finding resonates with digital transformation literature that suggest that technology creates value when embedded within complementary human and organizational systems (Kane *et al.*, 2015). By quantifying this moderation effect through MSEM, the study moves beyond descriptive accounts of predictive maintenance and provides causal evidence of sociotechnical complementarity.

OEE as an Operational Bridge to Sustainability

A central contribution of this research is the empirical validation of OEE as an operational mediator linking sociotechnical capability to triple-bottom-line sustainability performance. While prior studies have associated TPM with productivity gains (Ahuja and Khamba, 2008), few have empirically connected OEE improvements to environmental and social outcomes using objective data. Our findings show that OEE significantly predicts reductions in energy intensity, material scrap, CO_2-equivalent emissions, and lost-time injury frequency.

This mediating mechanism operationalizes the Natural-Resource-Based View ($NRBV$), which posits that environmental performance improvements stem from embedded operational capabilities rather than isolated green initiatives (Hart and Dowell, 2011). Improved availability reduces idle energy waste; improved performance increases output per unit energy; and improved quality lowers material loss. The quantified sustainability gains observed in this study like 21% lower energy intensity and 15% lower carbon intensity among high $AI - TPM$ plants are consistent with Industry 4.0 sustainability projections (Bag *et al.*, 2021). However, unlike prior conceptual work, this study demonstrates these outcomes through a rigorously tested multilevel empirical framework. Through the linking of machine-level efficiency metrics empirically to ESG indicators, the research responds to calls for the integration of operational and sustainability performance measurement systems (Schaltegger and Burritt, 2018). OEE, traditionally treated as a narrow operational KPI, emerges here as a measurable conduit for sustainable value creation.

Methodological Innovation

This study advances methodological practice in sustainable operations and maintenance research in the following three important ways:

a) *Multilevel integration of sociotechnical constructs:* Manufacturing organizations are inherently hierarchical, yet TPM research has rarely modeled nested data structures. By employing MSEM, this study simultaneously estimates within-plant (individual-level) and between-plant (organizational-level) effects, which reduces aggregation bias and also improves causal inference (Hox *et al.*, 2017). The inclusion of cross-level moderation captures how AI maturity amplifies individual-level TPM practices, which is an analytical refinement that is largely absent from prior maintenance studies.

b) *Triangulation of perceptual, sensor-based, and archival ESG data:* Common method bias remains a persistent challenge in organizational research (Podsakoff *et al.*, 2003). This study mitigates such concerns through the combination of survey-based constructs with objective machine-level OEE records and audited sustainability metrics aligned with recognized reporting standards. This triangulated data architecture strengthens external validity and also enhances replicability across industrial contexts.

c) *Operationalization of sustainability mediation:* Rather than assume that digital technologies automatically yield environmental benefits, the study empirically tests the indirect pathways through which sociotechnical capabilities influence sustainability outcomes. Through the use of bootstrapped multilevel mediation analysis, the study provided statistical confirmation that OEE partially mediates the relationship between TPM capability and environmental, economic, and social performance. This approach answers recent methodological calls for causal modeling of sustainability mechanisms rather than simple performance correlations (Dubey *et al.*, 2017).

Collectively, these methodological contributions position the Human–AI TPM Capability framework as a replicable template for future Industry 4.0 and Industry 5.0 research.

Theoretical Contributions

The findings contribute to the following multiple theoretical domains:

a) *Extension of TPM Theory: TPM* is reframed from a maintenance efficiency program to a sustainability-enabling sociotechnical capability.

b) *Integration of RBV and Sociotechnical Systems Theory:* By demonstrating how intangible resources (skills, culture) interact with AI technologies to influence measurable performance outcomes, the study advances micro-foundational perspectives on operational capabilities (Felin *et al.*, 2012).

c) *Advancement of Industry 4.0 Sustainability Scholarship:* The research empirically links digital maintenance technologies with ESG performance, the ability to address these gaps in Industry 4.0 sustainability literature that often rely on conceptual or simulation-based evidence (Stock and Seliger, 2016).

d) *Operationalization of the Natural-Resource-Based View:* By positioning OEE as a mediator, the study demonstrates how environmental advantage arises from embedded operational excellence rather than discrete environmental investments (Hart and Dowell, 2011).

These contributions enhance the interdisciplinary relevance of the work across operations management, organizational behavior, digital transformation, and sustainability research.

Practical Implications for Sustainable Manufacturing

For practitioners, the findings underscore that AI investments alone are insufficient to achieve sustainability gains. Without supportive culture and skilled employees, predictive maintenance systems underperform. Conversely, human-centered TPM practices are substantially amplified when complemented by AI maturity.

The managers who are seeking for measurable ESG improvements should therefore:

- Integrate AI-driven predictive maintenance with operator training and safety programs;
- Align cultural values with continuous improvement and digital literacy; and also
- Embed OEE metrics within sustainability dashboards to monitor energy and waste reductions.

This integrated strategy reflects emerging Industry 5.0 principles which emphasizes human-centric and sustainable technological development (EC, 2021).

The study demonstrates that sustainable manufacturing performance emerges from the alignment of human capability, organizational culture, and AI-enabled maintenance systems. By employing multilevel structural equation modeling and integrating objective sustainability indicators, we provide robust empirical evidence that OEE serves as a measurable operational bridge between sociotechnical capability and triple-bottom-line outcomes. The methodological rigor, cross-disciplinary theoretical integration, and quantifiable sustainability impacts presented here collectively position this research as a substantive advancement in the evolving discourse on intelligent, human-centered, and sustainable manufacturing systems.

POLICY IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

Policy Implications

The findings of this study carry important implications for industrial policy, sustainability governance, and digital transformation strategies. As governments seek to decarbonize manufacturing while maintaining competitiveness, intelligent maintenance systems represent an underleveraged yet high-impact intervention point. Industry accounts for a substantial share of global energy use and greenhouse gas emissions, and efficiency improvements remain central to climate mitigation strategies (Deswal, 2025; IEA, 2023). The results demonstrate that AI-augmented TPM , when supported by human capability and organizational culture, can produce measurable reductions in

Table 4: Policy recommendations derived from empirical findings.

Policy Domain	Evidence from Study	Recommended Intervention	Expected Sustainability Impact
Industrial Decarbonization	OEE → Environmental Performance ($\beta = 0.48^{***}$)	Incentivize AI-based predictive maintenance adoption	Reduced energy intensity and CO_2 emissions
Workforce Development	Culture → Human Factors ($\beta = 0.52^{***}$)	Fund digital maintenance training programs	Enhanced safety, skill upgrading
ESG Reporting	OEE mediates sustainability outcomes	Integrate OEE metrics into ESG disclosure frameworks	Transparent linkage of operations and sustainability
SME Digitalization	AI moderation effect ($\beta = 0.29^{***}$)	Subsidize AI tools for small and medium manufacturers	Productivity and sustainability convergence
Occupational Safety Regulation	OEE → Social Performance ($\beta = 0.39^{***}$)	Encourage predictive maintenance for hazard prevention	Lower injury frequency rates

***$p < .001$

energy intensity (−21%), material scrap (−18%), and carbon intensity (−15%).

These quantifiable improvements align with the natural-resource-based view, which argues that embedded operational capabilities can become sources of environmental advantage (Hart and Dowell, 2011). From a policy perspective, this suggests that sustainability incentives should not focus solely on end-of-pipe technologies or renewable energy adoption, but also on process optimization and predictive maintenance infrastructure. Policies that integrate digitalization with sustainability, which is consistent with Industry 5.0 principles which emphasizes human-centric and sustainable technological transformation, are likely to yield compounded environmental and economic benefits.

Moreover, the moderating effect of AI maturity highlights the importance of workforce development. Digital investments without human capability development risk underperformance (Kane *et al.*, 2015). Policymakers should therefore couple AI adoption incentives with reskilling programs in data literacy, predictive analytics interpretation, and cross-functional collaboration. Such an integrated approach supports both technological competitiveness and social sustainability outcomes, including improved safety and skill upgrading.

Table 4 summarizes actionable policy directions that are informed by the empirical findings.

Managerial and Regulatory Alignment

The study's multilevel evidence underscores the need for alignment between regulatory frameworks and operational performance systems. Sustainability reporting mechanisms such as the Global Reporting Initiative (GRI) increasingly demand verifiable environmental metrics. By empirically linking OEE to ESG indicators, this research provides regulators with a measurable operational lever that firms can monitor and audit.

Embedding OEE into sustainability scorecards may enhance accountability and reduce greenwashing risks, responding to calls for greater transparency in sustainability governance (Schaltegger and Burritt, 2018). Furthermore, as predictive maintenance reduces unexpected breakdowns and emergency interventions, it contributes to safer work environments, and also align with International Labour Organization (ILO) objectives for occupational health and safety improvement.

Limitations

Despite its methodological rigor, this study has the following limitations that invite careful interpretation and future investigation.

a) Although the study employs longitudinal archival data over 36 months, causal inference remains constrained by observational design. While multilevel SEM and lagged robustness checks strengthen inference, experimental or quasi-experimental designs could further validate causality.

b) AI maturity was measured at an aggregate plant level without differentiating between algorithm types (e.g., supervised vs. unsupervised learning). Different AI architectures may produce heterogeneous sustainability effects, which is a nuance that is not captured in the present model.

c) While the sample spans multiple industries, geographic concentration may limit cross-cultural generalizability. Organizational culture's moderating role may differ across institutional environments, as sustainability norms vary globally (Hart and Dowell, 2011).

d) The social sustainability construct, though incorporating injury rates and training hours, does not capture broader dimensions such as employee well-being or equity. Future research could expand this dimension to reflect more comprehensive social impact metrics.

Future Research Directions

Building on these limitations, the following promising research avenues emerge:

a) Future studies could integrate digital twin technologies and real-time carbon accounting systems to deepen causal modeling of operational-sustainability linkages. The combination of digital twins with multilevel SEM could further refine the measurement of energy and waste flows.

b) Cross-national comparative research would illuminate how institutional environments moderate the sociotechnical–sustainability relationship. Regulatory stringency and carbon pricing regimes may influence the strength of OEE-sustainability pathways.

c) Researchers could explore circular economy outcomes, such as remanufacturing efficiency and lifecycle extension, as downstream effects of predictive maintenance systems. Intelligent maintenance may enhance product longevity and resource recirculation, as it is an emerging but underexplored research domain.

d) Future methodological innovation could involve the integration of machine-learning causal inference techniques with SEM frameworks to model nonlinear relationships and dynamic feedback loops. Hybrid approaches that combine structural modeling and explainable AI could significantly advance Industry 4.0 sustainability research.

CONCLUSION

This study set out to examine whether TPM, when reconceptualized as a sociotechnical capability augmented by AI, can deliver measurable sustainability benefits. By integrating human factors, organizational culture, AI-enabled maintenance maturity, OEE, and triple-bottom-line sustainability performance within a multilevel structural equation modeling framework, the research provides robust empirical evidence that intelligent maintenance systems can simultaneously enhance productivity and sustainability outcomes. The findings demonstrated that human capability remains central in digitally enabled environments. Operator competence, engagement, and safety orientation significantly influence OEE, but their impact is strengthened when embedded within supportive organizational cultures. AI-enabled maintenance does not replace human expertise; rather, it amplifies it. Plants with higher AI maturity exhibit stronger $TPM - OEE$ relationships, which confirm that technological and social systems must be aligned to unlock performance gains. This reinforces the central argument that sustainable manufacturing transformation is fundamentally sociotechnical rather than purely technological.

Most importantly, the study empirically validates OEE as an operational bridge that links maintenance capability to environmental, economic, and social sustainability performance. Improvements in availability, performance efficiency, and quality translate into lower energy intensity, reduced material waste, decreased carbon emissions, improved cost efficiency, and safer work environments. Through the quantification of these effects using sensor-derived operational data and archival sustainability metrics, the research moves beyond conceptual claims and provides measurable evidence of sustainability impact. Methodologically, the study advances the field by integrating multilevel structural modeling with objective machine-level and ESG data. This approach addresses common limitations in operations and sustainability research, including single-level analyses and reliance on perceptual performance measures. The resulting Human-AI TPM Capability framework offers a replicable analytical model for future research exploring the intersection of digital transformation and sustainable industrial performance.

From a managerial and policy perspective, the results underscore that investments in AI-driven predictive maintenance must be accompanied by workforce development and cultural alignment to achieve full sustainability benefits. Organizations that treat digital transformation and sustainability as interconnected strategic priorities are better positioned to achieve long-term resilience and competitive advantage. By demonstrating that AI-augmented TPM can produce tangible and quantifiable sustainability outcomes through improvements in OEE, the study provides a clear pathway for the integration of operational excellence with environmental stewardship and social responsibility. The convergence of human capability, organizational culture, and intelligent technology emerges as a defining feature of sustainable industrial performance in the era of advanced manufacturing.

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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 has been completely observed by the authors.

REFERENCES

1) Aguh, P.S. and Okpala, C.C. (2025) 'Learning in the age of artificial intelligence tutors: Cognitive outcomes and equity in automated education systems', *International Journal of Engineering Research and Development*, 21(12), pp. 88-98. https://ijerd.com/paper/vol21-issue12/21128898.pdf
2) Aguh, P.S., Udu, C.E., Chukwumuanya, E.O., *et al.* (2025) 'Machine learning applications for production scheduling optimization', *Journal of Exploratory Dynamic Problems*, 2(4), pp. 63-79. https://edp.web.id/index.php/edp/article/view/137
3) Ahuja, I.P.S. and Khamba, J.S. (2008) 'Total productive maintenance: Literature review and directions', *International Journal of Quality and Reliability Management*, 25(7), pp. 709-756.
4) Bag, S., Gupta, S., Kumar, A., *et al.* (2021) 'Role of technological dimensions of Industry 4.0 on circular economy practices and performance', *International Journal of Production Economics*, 231, 107831.
5) Bamber, C.J., Sharp, J.M. and Hides, M.T. (1999) 'Factors affecting successful implementation of total productive maintenance', *Journal of Quality in Maintenance Engineering*, 5(3), pp. 162-181.
6) Barney, J. (1991) 'Firm resources and sustained competitive advantage', *Journal of Management*, 17(1), pp. 99-120.
7) Bliese, P.D. (2000) 'Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis'. In: *Multilevel theory, research, and methods in organizations*; Klein, K.J. and Kozlowski, S.W.J. (eds.). San Francisco: Jossey-Bass, pp. 349-381.
8) Bousdekis, A., Magoutas, B., Apostolou, D., *et al.* (2020) 'Review of data-driven decision-making methods for predictive maintenance', *Computers in Industry*, 115, 103125.
9) Carvalho, T.P., Soares, F.A.A.M.N., Vita, R., *et al.* (2019) 'A systematic literature review of machine learning methods applied to predictive maintenance', *Computers and Industrial Engineering*, 137, 106024.
10) Chukwumuanya, E.O., Okpala, C.C. and Onukwuli, S.K. (2025) 'Ergonomics-aware scheduling: Biomechanical models with production planning integration for musculoskeletal risk reduction', *Journal Majelis Paspama*, 3(1), pp. 21-36. https://paspama.org/index.php/majelis/article/view/209
11) Chukwunedum, O.C., Okpala, C.C. and Udu, C.E. (2026) 'A data-driven integration of total productive maintenance and Industry 4.0 technologies: A machine learning framework for predictive OEE

optimization', *International Journal of Engineering Research and Development*, 22(3), pp. 85-95. https://www.ijerd.com/paper/vol22-issue3/22038595.pdf
12) Denison, D.R. (1996) 'What is the difference between organizational culture and organizational climate? A native's point of view on a decade of paradigm wars', *Academy of Management Review*, 21(3), pp. 619-654.
13) Deswal, P. (2025) 'Article 6 of the Paris Agreement: A comprehensive review of mechanisms, progress, and persistent challenges', *International Journal of Technology, Health and Sustainability*, 1(2), pp. 111-125. https://ijths.com/wp-content/uploads/IJTHS-010235.pdf
14) Deswal, S. and Deswal, P. (2025) 'Sustainability: Greenhouse Gas Protocol and global GHG emissions' status and trends', *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(1), pp. 2051-2063. https://doi.org/10.54660/.IJMRGE.2025.6.1.2051-2063
15) Dubey, R., Gunasekaran, A. and Ali, S.S. (2017) 'Sustainable supply chain management: Theoretical foundations and future research directions', *International Journal of Production Economics*, 195, pp. 27-38.
16) EC (2021) *Industry 5.0: Towards a sustainable, human-centric and resilient European industry*. European Commission, Publications Office of the European Union, Luxembourg. https://op.europa.eu/en/publication-detail/-/publication/468a892a-5097-11eb-b59f-01aa75ed71a1/language-en
17) Egwuagu, O.M. and Okpala, C.C. (2016) 'Benefits and challenges of total productive maintenance implementation', *International Journal of Advanced Engineering Technology*, 7(3), pp. 196-200. http://www.technicaljournalsonline.com/ijeat/VOL%20VII/IJAET%20VOL%20VII%20ISSUE%20III%20JULY%20SEPTEMBER%202016.html
18) Elkington, J. (1997) *Cannibals with forks: The triple bottom line of 21st century business*. Oxford: Capstone Publishing.
19) Ezeanyim, O.C., Okpala, C.C. and Igbokwe, B.N. (2025) 'Precision agriculture with AI-powered drones: Enhancing crop health monitoring and yield prediction', *International Journal of Latest Technology in Engineering, Management and Applied Science*, 14(3). https://doi.org/10.51583/IJLTEMAS.2025.140300020
20) Ezeanyim, O.C., Okpala, C.C. and Udu, C.E. (2026) 'Artificial intelligence-enabled Lean Six Sigma: A multi-industry longitudinal analysis of operational performance and sustainable digital transformation', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 428-439. https://ijths.com/wp-content/uploads/IJTHS-0202001.pdf
21) Felin, T., Foss, N.J., Heimeriks, K.H., *et al.* (2012) 'Microfoundations of routines and capabilities: Individuals, processes, and structure', *Journal of Management Studies*, 49(8), pp. 1351-1374.
22) Frank, A.G., Dalenogare, L.S. and Ayala, N.F. (2019) 'Industry 4.0 technologies: Implementation patterns in manufacturing companies', *International Journal of Production Economics*, 210, pp. 15-26.
23) Godwin, H.C. and Okpala, C.C. (2026) 'Data-driven ergonomic optimization in manufacturing systems: Productivity, safety, and sustainability impacts', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 695-704. https://ijths.com/wp-content/uploads/IJTHS-0202041.pdf
24) Hair, J.F., Black, W.C., Babin, B.J., *et al.* (2022) *Multivariate data analysis*. 8th edn. Boston: Cengage.
25) Hart, S.L. and Dowell, G. (2011) 'A natural-resource-based view of the firm: Fifteen years after', *Journal of Management*, 37(5), pp. 1464-1479.
26) Hox, J.J., Moerbeek, M. and van de Schoot, R. (2017) *Multilevel analysis: Techniques and applications*. 3rd edn. New York: Routledge.
27) IEA (2023) *World energy outlook 2023*. International Energy Agency Publications, Paris. https://www.iea.org/reports/world-energy-outlook-2023
28) Jaca, C., Viles, E., Paipa-Galeano, L., *et al.* (2012) 'Learning 5S principles from Japanese best practitioners: Case studies of five manufacturing companies', *International Journal of Production Research*, 50(17), pp. 4574-4586.
29) Kane, G.C., Palmer, D., Phillips, A.N., *et al.* (2015) 'Strategy, not technology, drives digital transformation', *MIT Sloan Management Review*, 14(1), pp. 1-25.
30) McKone, K.E., Schroeder, R.G. and Cua, K.O. (2001) 'The impact of total productive maintenance practices on manufacturing performance', *Journal of Operations Management*, 19(1), pp. 39-58.
31) Muchiri, P. and Pintelon, L. (2008) 'Performance measurement using overall equipment effectiveness (OEE): Literature review and practical application discussion', *International Journal of Production Research*, 46(13), pp. 3517-3535.
32) Nakajima, S. (1988) *Introduction to TPM: Total productive maintenance*. Cambridge, MA: Productivity Press.
33) Neal, A. and Griffin, M.A. (2006) 'A study of the lagged relationships among safety climate, safety motivation, safety behavior, and accidents', *Journal of Applied Psychology*, 91(4), pp. 946-953.
34) Nwamekwe, C.O. and Okpala, C.C. (2025) 'Machine learning-augmented digital twin systems for predictive maintenance in high-speed rail networks', *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(1), pp. 1783-1795. https://www.allmultidisciplinaryjournal.com/uploads/archives/20250212104201_MGE-2025-1-306.1.pdf
35) Nwankwo, C.O., Ezeanyim, O.C., Okpala, C.C., *et al.* (2024) 'Enhancing injection moulding productivity through overall equipment effectiveness and total preventive maintenance approach', *International Journal of Advances in Engineering and Management*, 6(3), pp. 1-9. https://ijaem.net/issue_dcp/Enhancing%20Injection%20Moulding%20Productivity%20through%20Overall%20Equipment%20Effectiveness%20and%20Total%20Preventive%20Maintenance%20Approach.pdf
36) Okpala, C.C. (2026) 'Human-centered design of jigs and fixtures: A data-driven approach to productivity, safety, and manufacturing sustainability', *International Journal of Technology, Health and Sustainability*, 2(1), pp. 291-299. https://ijths.com/wp-content/uploads/IJTHS-020185.pdf
37) Okpala, C.C. and Aguh, P.S. (2025) 'The human factor in the future of cybersecurity: Trust, privacy, and responsibility', *International Journal of Engineering Research and Development*, 21(9), pp. 22-29. https://ijerd.com/paper/vol21-issue9/21092229.pdf
38) Okpala, C.C. and Anozie, S.C. (2018) 'Overall equipment effectiveness and the six big losses in total productive maintenance', *Journal of Scientific and Engineering Research*, 5(4), pp. 156-164. https://jsaer.com/download/vol-5-iss-4-2018/JSAER2018-05-04-156-164.pdf
39) Okpala, C.C. and Chukwumuanya, E.O. (2025) 'The future of cybersecurity: Predictive analytics and machine learning applications', *Journal of Engineering Research and Applied Science*, 14(2), pp. 190-201. https://www.journaleras.com/index.php/jeras/article/view/398
40) Okpala, C.C. and Nwankwo, C.O. (2025) 'Blockchain and artificial intelligence integration in cybersecurity: Towards intelligent and decentralized defenses', *International Journal of Engineering Inventions*, 14(9), pp. 9-17. https://www.ijeijournal.com/papers/Vol14-Issue9/14090917.pdf
41) Okpala, C.C. and Udu, C.E. (2025) 'Autonomous drones and artificial intelligence: A new era of surveillance and security applications', *International Journal of Science, Engineering and Technology*, 13(2), pp. 1-8. https://www.ijset.in/wp-content/uploads/IJSET_V13_issue2_520.pdf
42) Okpala, C.C. and Udu, C.E. (2026) 'What Drives Successful Six Sigma Implementation? A Data-Driven Multidisciplinary Analysis', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 721-730. https://ijths.com/wp-content/uploads/IJTHS-0202048.pdf
43) Okpala, C.C., Anozie, S.C. and Ezeanyim, C.E. (2018) 'The application of tools and techniques of total productive maintenance in manufacturing', *International Journal of Engineering Science and Computing*, 8(6). http://ijesc.org/articles-in-press.php?msg=1&page=article
44) Okpala, C.C., Anozie, S.C. and Mgbemena, C.E. (2020) 'The optimization of overall equipment effectiveness factors in a pharmaceutical company', *Heliyon*, 6, e03796. https://doi.org/10.1016/j.heliyon.2020.e03796
45) Okpala, C.C., Ezeanyim, O.C. and Igbokwe, N.C. (2023) 'Human-robot interaction enhancement through ergonomics and human factors: Future directions', *International Journal of Engineering Research and Development*, 19(6). http://www.ijerd.com/paper/vol19-issue6/E19063440.pdf
46) Okpala, C.C., Udu, C.E. and Nwamekwe, C.O. (2025) 'Artificial intelligence-driven total productive maintenance: The future of maintenance in smart factories', *International Journal of Engineering Research and Development*, 21(1), pp. 68-74. https://ijerd.com/paper/vol21-issue1/21016874.pdf
47) Okpala, S.C. and Okpala, C.C. (2025) 'Harnessing big data and predictive analytics for modern healthcare delivery

transformation', *International Journal of Health and Pharmaceutical Research*, 10(7), pp. 92-108. DOI: 10.56201/ijhpr.vol.10.no7.2025.pg92.108

48) Onukwuli, S.K., Okpala, C.C. and Okpala, P.C. (2026) 'The extension of total productive maintenance with digital intelligence for data-driven maintenance in smart manufacturing', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 883-892. https://ijths.com/wp-content/uploads/IJTHS-0202062.pdf
49) Onukwuli, S.K., Okpala, C.C., Edeh, M. O., *et al.* (2025) 'Human-centric cybersecurity: The integration of psychological insights and sociotechnical systems', *International Journal of Industrial and Production Engineering*, 3(4). https://journals.unizik.edu.ng/ijipe/article/view/6777
50) Pasmore, W., Winby, S. and Mohrman, S.A. (2019) 'Sociotechnical systems: A North American reflection on empirical studies of the seventies', *Journal of Applied Behavioral Science*, 55(3), pp. 1-21.
51) Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., *et al.* (2003) 'Common method biases in behavioral research: A critical review of the literature', *Journal of Applied Psychology*, 88(5), pp. 879-903.
52) Preacher, K.J., Zyphur, M.J. and Zhang, Z. (2010) 'A general multilevel SEM framework for assessing multilevel mediation', *Psychological Methods*, 15(3), pp. 209-233.
53) Schaltegger, S. and Burritt, R. (2018) 'Business cases and corporate engagement with sustainability', *Accounting, Auditing and Accountability Journal*, 31(4), pp. 1096-1119.
54) Schein, E.H. (2010) *Organizational culture and leadership*. 4th edn. San Francisco: Jossey-Bass.
55) Stock, T. and Seliger, G. (2016) 'Opportunities of sustainable manufacturing in Industry 4.0', *Procedia CIRP*, 40, pp. 536-541.
56) Teece, D.J. (2018) 'Business models and dynamic capabilities', *Long Range Planning*, 51(1), pp. 40-49.
57) Udu, C.E. and Okpala, C.C. (2026a) 'Artificial intelligence-enabled resilient scheduling: A systematic review and research roadmap for digital twin and machine learning in disruption-aware operations', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 486-497. https://ijths.com/wp-content/uploads/IJTHS-0202014.pdf
58) Udu, C.E. and Okpala, C.C. (2026b) 'Engineering safety in complex systems: A data-driven and predictive framework for machine learning, human factors, and system dynamics integration', *International Journal of Technology, Health and Sustainability*, 2(1), pp. 391-401. https://ijths.com/wp-content/uploads/IJTHS-020199-0.pdf
59) Udu, C.E., Okpala, C.C. and Edeh, M.O. (2025) 'Global roadmap for circular economies: The integration of digital innovation, governance, and sustainable development goals', *International Journal of Industrial and Production Engineering*, 3(4), pp. 1-17. https://journals.unizik.edu.ng/ijipe/article/view/6764