International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(12s) 2026 pp. 899-912
https://doi.org/10.70917/ijcisim-2026-3962
Article

TPM Implementation to Increase OEE of the Winch and Roller Box in a Service Company, Antofagasta 2025

Argeme Gastón Mogollón Chinga[1], Cristian Gen Mogollón Chinga[2], José Pablo Rivera Rodríguez[3]

[1] Universidad César Vallejo, Perú.
Email: amogollonch75@ucvvirtual.edu.pe
ORCID: 0009-0003-3623-8213
[2] Universidad César Vallejo, Perú.
ORCID: 0009-0000-7091-8827
[3] Universidad César Vallejo, Perú.
ORCID: 0000-0002-4578-4588

Abstract: Latin-American industrial service operations depend on hoisting winches and roller boxes whose unplanned stoppages cascade into safety and economic losses, yet the 2024–2026 empirical record on Total Productive Maintenance (TPM) for such mobile critical assets is virtually absent. This study quantifies whether the classical four-phase TPM model — preparation, introduction, implementation and consolidation — increases the Overall Equipment Effectiveness (OEE) of these assets in a transnational service operation in Antofagasta. A pre/post quasi-experimental design tracked a census of 25 critical units (12 winches, 13 roller boxes) over 16 pre- and 16 post-intervention weeks. Aggregate OEE rose from 67,402 % to 86,254 % (Δ = +18,852 pp; $t(15) = 88{,}494$; $p < 0{,}001$; Hedges' $g = 14{,}87$), driven by availability (+11,496 pp) and effectiveness (+8,539 pp); quality stabilised near ceiling. The findings provide first quantitative evidence of TPM transferability to Latin-American mobile transport assets.

Keywords: Availability; Hoisting equipment; Latin America; Overall equipment effectiveness; Pre/post design; Quasi-experimental; Roller boxes; Service sector; Total productive maintenance; Winches.

1. Introduction

Industrial service operations across Latin America — mining, hydrocarbons, construction support — rest on heavy mobile assets whose continuous availability conditions the entire downstream value chain. Hoisting winches and roller boxes are emblematic: when either fails on site, the cost is not limited to a stopped machine but propagates into idle crews, contractual penalties and safety exposure for the operators handling suspended loads. Overall Equipment Effectiveness (OEE), defined as the product of availability, effectiveness and quality, has become the canonical metric for diagnosing such loss structures and benchmarking interventions against the world-class threshold of 85 % [1, 2]. Its decomposability into three multiplicative components is precisely what allows a manager to locate where loss originates and what allows a reviewer to ask whether a reported gain came from where the intervention plausibly acts.

Total Productive Maintenance (TPM), formalised in the Japanese tradition and articulated in the West through the classical four-phase model [3, 4], remains the dominant operational framework for moving OEE [5, 6]. Its empirical record, however, is heterogeneous to a degree that the field has not fully reconciled. In an Indonesian automotive SME, Sumastro et al. [7] report an OEE rise from 67,42 % to 77,80 % (+10,38 pp); in a Peruvian SME combining TPM with 5S and SMED, Quiroz-Flores et al. [8] report a comparable +10,93 pp jump (59,91 % → 70,84 %); in a Bangladeshi cement plant, Irfan et al. [9] report a far more conservative +2,53 pp under TPM and 5S; in a

Peruvian food operation, Castañeda et al. [10] document 79,06 % → 89,37 %. Earlier station-level evidence ranges from station OEE values below 20 % with TPM-driven recoveries of three to seven percentage points [11] to averages persistently below 55 % in the absence of structured rollout [12]. The dispersion is wide enough that the gain attributable to TPM cannot be read off the mean of the published distribution; baseline maturity, intervention scope and sector appear to interact, but no synthesis isolates their respective weights.

Parallel to this classical thread, the maintenance research frontier has shifted toward what the literature labels Maintenance 4.0 and, more recently, Maintenance 5.0: predictive analytics on continuous sensor streams, digital twins of physical assets, machine-learning estimators of remaining useful life and human-centric extensions linked to sustainability [13, 14, 15, 16, 17]. Empirical applications already span ANN-based fault forecasting on heavy machinery [18], ML-driven scheduling architectures [19] and the integration of Industry 4.0 with TPM bundles in manufacturing [20, 21]. The reported performance gains are substantial — Murtaza et al. [14] document breakdown reductions of up to 95 % under predictive frameworks — and the rhetorical effect on the discipline has been to position the classical, paper-based TPM as the legacy benchmark against which more data-intensive approaches measure themselves [22, 23].

Two voids open inside this otherwise active field, and the present study sits at their intersection. The first is sectoral. Systematic reviews of TPM and Industry 4.0 implementations confirm that empirical OEE evidence remains concentrated in continuous, high-volume manufacturing lines, with virtually no 2024–2026 field studies on hoisting and transport equipment in industrial service environments [15, 24]. Adjacent work on rotating machinery has begun to adapt OEE to wind energy assets [25] and to conveyor systems within Lean configurations [26], but neither geometry maps cleanly onto the failure modes of a mobile winch operating on a service contract. The second void is methodological. Pre-experimental single-group designs dominate the literature, yet effect-size reporting, a priori sample-size justification, family-wise error control across OEE components, and explicit handling of weekly autocorrelation are rare [27, 28, 29]. The result is a body of evidence in which magnitudes are reported without the inferential apparatus that would let a reader distinguish a genuine process shift from a baseline anomaly or a low-variance artefact.

A second-order consequence of this configuration is often left implicit. Companies with low digital maturity — and the bulk of Latin-American industrial service operations fall in this category, with sparse on-asset instrumentation and limited automation infrastructure [17] — cannot leap directly to TPM 4.0 architectures. The data layer that predictive maintenance requires presupposes a stabilised operational baseline; instrumenting an unstable process simply produces high-resolution noise. From this angle, the classical four-phase model is not an obsolete competitor of TPM 4.0 but its missing rung on the maturity ladder: it is the intervention that brings variance under control and makes the asset legible to subsequent digital layers [16, 30]. Articulating that role empirically — not as a recommendation but as a quantified pre-post estimate on transport-class machinery — is what the field currently lacks.

The present study addresses both voids on a single dataset. Its objective is to estimate, with full inferential controls, the change in OEE and its three components associated with a structured implementation of the classical four-phase TPM model on a census of 25 critical assets (12 hoisting winches and 13 roller boxes) in a transnational service operation in Antofagasta, monitored weekly over 16 pre- and 16 post-intervention weeks. The contribution claimed is therefore not the novelty of the model but the first quantitative empirical evidence of its transferability from continuous manufacturing to mobile critical transport machinery in the Latin-American industrial service sector, reported with effect sizes, Bonferroni-adjusted contrasts and an explicit assessment of internal-validity threats. The work aligns with Sustainable Development Goal 9 on industry, innovation and infrastructure by documenting how a low-cost, paper-based intervention can stabilise the operational core of asset-intensive services before any digital layer is added.

2 Methodology

2.1 Study design and setting

The study followed a pre/post quasi-experimental design with interrupted-time-series logic, applied without a concurrent control group. The choice was constrained, not preferred: hoisting winches and roller boxes are the income-generating assets of the site and cannot be withdrawn from operation to constitute a parallel control without disrupting contractual obligations and exposing operators to safety risk during load transfers [27]. The interrupted-time-series logic — 16 weekly observations before the intervention and 16 weekly observations after — was adopted as a partial mitigation of this constraint, since a step shift visible against a stable pre-intervention baseline narrows the space of plausible non-intervention explanations more sharply than two isolated measurements [29]. The setting was a transnational industrial service company based in Antofagasta, with more than thirty years of activity supplying heavy mobile assets on contract to mining and hydrocarbon clients.

2.2 *Population, sample and unit of analysis*

The accessible population comprised 33 mechanical assets used in load handling and material transport during the study horizon: 17 roller boxes and 16 hoisting winches. Eligibility was assessed against three inclusion criteria — operational status throughout the observation window, availability of technical specifications and maintenance records covering at least the prior two years, and a documented history of preventive or corrective interventions — and two exclusion criteria: assets in technical retirement and newly commissioned units without an operating history. The resulting census sample contained 25 assets (13 roller boxes, 12 winches), corresponding to 75,8 % of the population. The unit of analysis was the individual machine; the unit of statistical aggregation was the weekly mean across the sample for each OEE component, yielding 16 + 16 paired weekly observations across the intervention boundary.

2.3 *Baseline diagnostic and intervention rationale*

The decision to intervene was anchored on a pre-intervention diagnostic of the fleet's operational state. Mean OEE was 60,16 % for the winches and 62,98 % for the roller boxes — well below the 85 % world-class threshold and consistent with the literature on under-maintained heavy mobile assets in service environments [25, 26]. Figure 1 displays these baseline values disaggregated into availability, effectiveness, quality and aggregate OEE for each asset class, with the 85 % world-class reference line overlaid as a visual anchor. A structured root-cause analysis using Ishikawa categorisation and a Vester matrix was then translated into a Pareto chart of failure causes, summarised in Figure 2, which concentrated 80 % of the cumulative weighted frequency on three causes: absence of maintenance instructions (26,2 % individual weight), insufficient operator monitoring (46,1 % cumulative) and absence of OEE indicators (63,9 % cumulative). The convergence of these causes on instructional, supervisory and metric dimensions — rather than on equipment condition per se — pointed toward the autonomous-maintenance, planned-maintenance and training pillars of classical TPM as the operational lever of choice.

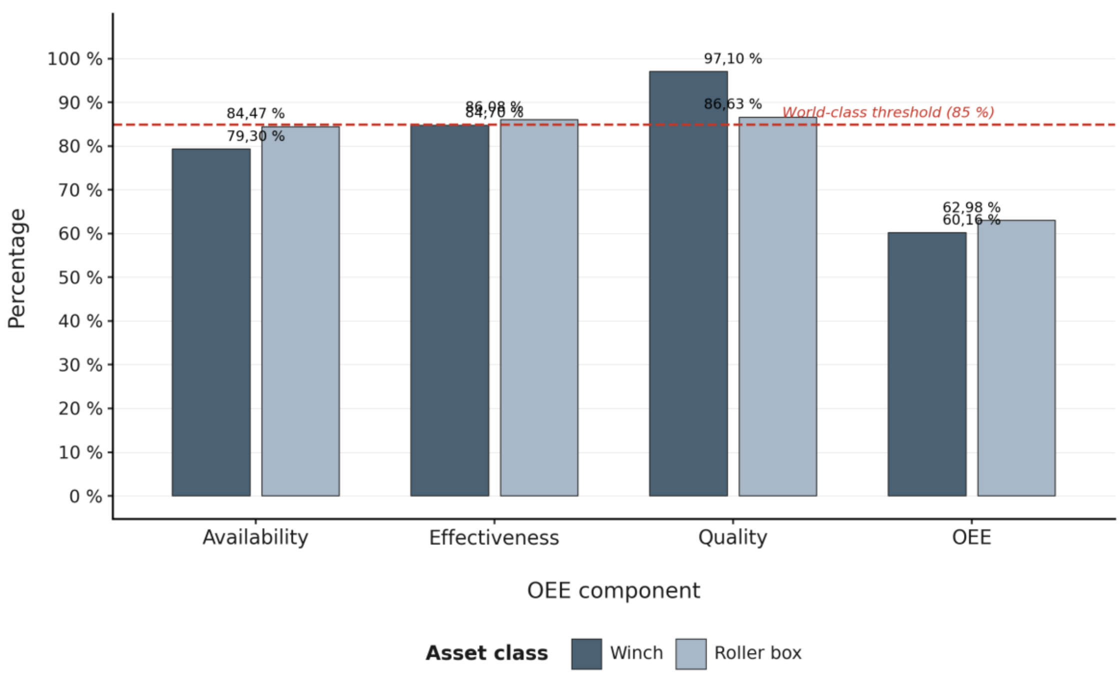

Figure 1. Baseline OEE diagnostic for hoisting winches and roller boxes against the 85 % world-class reference line, January–June 2025. Pre-intervention values of availability, effectiveness, quality and aggregate OEE for each asset class, plotted against the 85 % world-class threshold to make the magnitude of the operational gap directly readable.

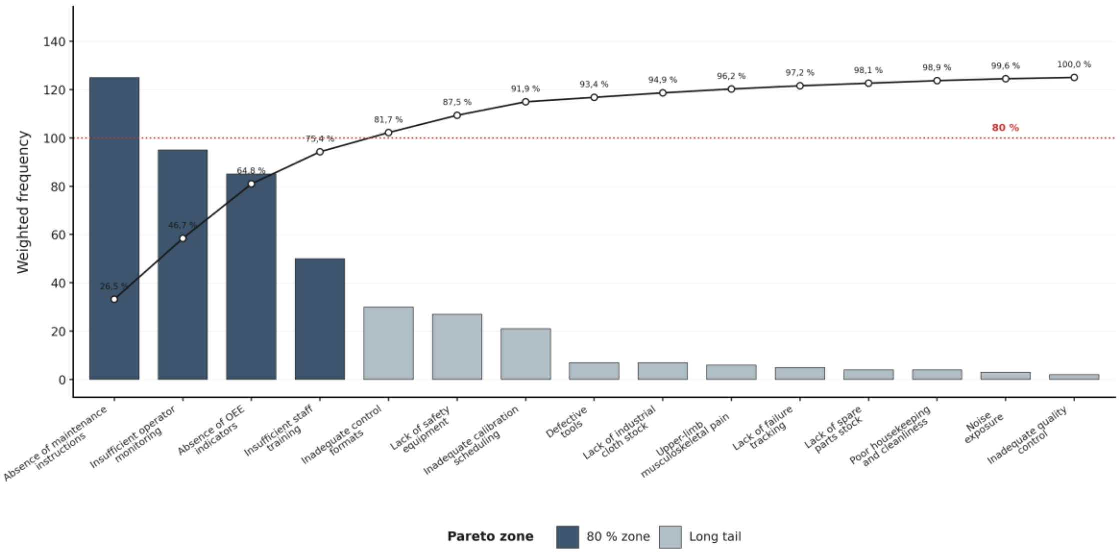

Figure 2. Pareto chart of root causes of low baseline OEE on hoisting winches and roller boxes. The fifteen causes elicited from the Ishikawa diagram are ordered by weighted frequency, with the cumulative-percentage curve overlaid; the three causes located within the 80 % zone define the priority intervention space.

2.4 The classical four-phase TPM intervention

The intervention deployed the four-phase model described by Cuatrecasas and Torrell [4], with pillar content drawn from Mora [3]. The protocol was paper-based throughout — failure logs, autonomous-maintenance checklists, planned-maintenance schedules, quality-maintenance records and training attendance — a configuration consistent with the company's digital-maturity profile and with the Maintenance 4.0 readiness literature that positions paper-anchored TPM as the prerequisite stabiliser before any sensor or twin layer can be added [17, 16]. Table 1 summarises the twelve operational stages distributed across the four phases.

Phase 1 (Preparation) formalised top-management commitment, set up the promotional structure of the TPM committee, drafted basic policies and built the master plan. Phase 2 (Introduction) consisted of the formal launch event communicating objectives, scope and metrics to operators and supervisors. Phase 3 (Implementation) was the operational core and the most extensive of the four; it executed in parallel the autonomous-maintenance routines on the 25 assets, the planned-maintenance schedule, the quality-maintenance procedure, the operator training programme and the early-equipment management routine. Phase 4 (Consolidation) established the control and follow-up mechanisms and raised the operational targets for the subsequent cycle. The intervention spanned the boundary between weeks 16 and 17 of the 32-week observation horizon.

Table 1. Operational stages of the classical four-phase TPM model applied to the 25 critical assets (adapted from Cuatrecasas and Torrell, 2010).

Phase	No.	Stage
Preparation	1	Decision to apply TPM in the company
	2	TPM awareness and information dissemination
	3	Establishment of the TPM promotional structure
	4	Definition of basic TPM objectives and policies
	5	Development of the TPM master plan
Introduction	6	Formal launch of the TPM programme

Implementation	7	Improvement of equipment effectiveness
	8	Development of the autonomous-maintenance programme
	9	Development of the planned-maintenance programme
	10	Training to elevate operational and maintenance capabilities
	11	Early-equipment management
Consolidation	12	TPM consolidation and target elevation

Note. The four phases were deployed sequentially across the 32-week observation horizon (16 pre-intervention + 16 post-intervention weeks). Stages 7–11 operated in parallel within Phase 3, consistent with the classical model's design for simultaneous and progressive execution. All procedures were paper-based, reflecting the company's low digital-maturity profile and the absence of on-asset IoT instrumentation. The intervention boundary between pre- and post-measurement coincided with the transition from Phase 2 to Phase 3.

2.5 Variables, indicators and measurement instrument

The independent variable, TPM, was operationalised through four indices that track adherence to the implementation routines: an autonomous-maintenance index IMA = TAMR / TAMP × 100 (ratio of executed to programmed autonomous-maintenance activities); a preventive-maintenance index IMP = THMP / THEM × 100 (executed preventive-maintenance hours over established hours); a quality-maintenance index IMC = TACR / TACE × 100 (quality activities executed over those established); and a training-plan-compliance index ICPC = THCE / THCP × 100 (executed training hours over those planned) [3]. The dependent variable, Overall Equipment Effectiveness, was computed as OEE = D × E × Q, with availability D = TO / TC, effectiveness E = TORI / TO and quality Q = TOE / TOR, following Cuatrecasas and Torrell [4], where TO is operating time, TC is loading time, TORI is ideal real operating time, TOE is effective operating time and TOR is real operating time.

The measurement instrument was a structured observation form, completed weekly by the maintenance team on a per-asset basis and aggregated to the weekly mean per asset class. Content validity was established through expert judgement by three industrial-engineering specialists evaluating item clarity and pertinence. Inter-rater reliability was not quantified through Cohen's kappa or an intraclass correlation coefficient — a gap that is acknowledged here and revisited in the limitations of the Discussion, since multi-observer field registration on heavy assets without inter-rater calibration introduces an instrumentation-precision threat the present design does not formally rule out [27].

2.6 Statistical analysis

Descriptive statistics for each weekly aggregate of D, E, Q and OEE were summarised by mean, minimum, maximum and standard deviation across the 16 + 16 horizon. Inferential analysis proceeded in three layers, each justified by a design constraint rather than by convenience.

First, normality was assessed on the per-week difference scores — not on the pre and post series separately — using the Shapiro-Wilk test, the most powerful normality procedure for $N < 50$ [28]. Where the differences were compatible with normality, a paired-samples t-test was applied. Where they were not (an outcome anticipated for the quality dimension given its near-ceiling pre-intervention values), the paired t-test was reported as planned and corroborated by the non-parametric Wilcoxon signed-rank test on the same differences.

Second, family-wise error was controlled by Bonferroni correction across the four planned contrasts (OEE, D, E, Q), shifting the per-test significance threshold to $\alpha' = 0{,}0125$. Effect sizes were reported as Hedges' g rather than Cohen's d, since g incorporates the small-sample bias correction relevant at $N = 16$. Their interpretation was framed against empirical effect-size distributions for pre/post operational interventions [31, 32], with an explicit caveat that effect sizes computed against a near-zero pre-intervention variance are mathematically inflated and should be read as evidence of process stabilisation rather than of large material change [33].

Third, the assumption of independence between successive weekly differences was probed through the Durbin-Watson statistic, where $DW \approx 2$ indicates no first-order autocorrelation; deviations were used to qualify, not to invalidate, the inferential conclusions. Ninety-five per cent confidence intervals are reported for every paired mean difference. All computations were performed in SPSS.

2.7 Internal-validity threat assessment

Because the design lacks a concurrent control group, four internal-validity threats were subjected to a structured narrative assessment, with the explicit consequence of replacing causal language ("TPM increased OEE") by associative language ("OEE rose following TPM implementation") throughout the manuscript [27]. The threat of history was probed by reviewing company records of organisational and demand changes within the 32-week horizon. The threat of maturation was examined against the asset-condition trajectory derived from the pre-intervention failure logs. The threat of instrumentation was contained, but not eliminated, by maintaining a single observation form, observer team and aggregation protocol throughout. The threat of testing — the Hawthorne effect arising from operators knowing they were observed — was acknowledged as residually present, since blinding the operators is incompatible with the participative logic of autonomous maintenance itself. Triangulation rested on the alignment between the Ishikawa-Pareto loss attribution at baseline and the post-intervention change pattern across the OEE components, following the mechanism-based causal-reasoning logic recommended for pre-experimental operational research [27, 29].

2.8 Ethical considerations

The study was developed within the ethics framework of the participating university, with the company's written authorisation for data access, anonymised handling of operator-level records, and a similarity check on the final manuscript. Operators were informed of the observation protocol; participation in autonomous-maintenance routines was integrated into the work plan and did not generate identifiable personal data beyond the operator-roster level. Referencing complied with ISO 690-2. The institutional ethics approval number is to be inserted at submission stage.

3 Results

Results are presented in three movements that mirror the analytical question of the study. The first establishes the headline change in the aggregate OEE; the second decomposes that change into the three multiplicative components; the third reports the inferential diagnostics, the dispersion behaviour of the post-intervention series and the position of those series relative to the 85 % world-class threshold. Interpretation of these findings is developed in the Discussion. Throughout this section, weekly OEE is computed per machine and then averaged across the 25-asset sample for each of the 32 weeks; for that reason the mean OEE differs marginally from the product of the mean component values, since the average of products is not algebraically equal to the product of averages.

3.1 Aggregate OEE: magnitude of the post-intervention shift

Across the 32-week observation horizon, the weekly mean OEE of the 25 critical assets rose from 67,402 % in the 16 pre-intervention weeks to 86,254 % in the 16 post-intervention weeks ($\Delta = +18{,}852$ percentage points; 95 % CI 18,398–19,306). The paired-samples t-test on the per-week difference scores yielded $t(15) = 88{,}494$ ($p < 0{,}001$), with the corresponding standardised effect computed as Hedges' $g = 14{,}87$ — a value that, as anticipated by the analytical plan and discussed in §3.3, is amplified by the narrow pre-intervention dispersion (SD = 1,187 %; range 65,8–69,4 %). Significance survived the Bonferroni-adjusted threshold of $\alpha' = 0{,}0125$ set across the family of four planned contrasts. Figure 3 displays the weekly trajectory of the aggregate OEE for the full horizon, with the 85 % world-class reference line overlaid and 95 % confidence bands estimated separately for each phase; the post-intervention series sits entirely above the threshold from the first observation onward and shows no downward drift across the sixteen weeks following the intervention boundary.

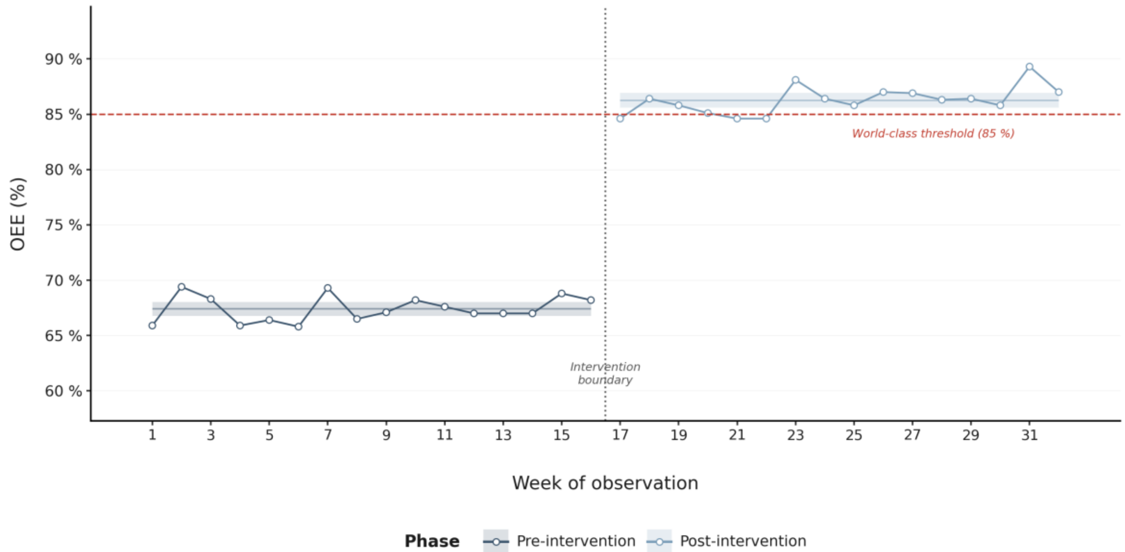

Figure 3. Weekly trajectory of aggregate OEE across the 32-week horizon (16 pre-intervention + 16 post-intervention weeks), with phase-specific 95 % confidence bands and the 85 % world-class reference line. The vertical dotted line marks the intervention boundary between weeks 16 and 17; the post-intervention series sits entirely above the world-class threshold.

3.2 Component decomposition

The +18,852 pp shift in aggregate OEE decomposed asymmetrically across the three multiplicative components. Availability rose from 79,539 % to 91,034 % (Δ = +11,496 pp; 95 % CI 10,442–12,549; t(15) = 23,261; p < 0,001; Hedges' g = 7,35). Effectiveness rose from 87,279 % to 95,819 % (Δ = +8,539 pp; 95 % CI 7,651–9,427; t(15) = 20,491; p < 0,001; Hedges' g = 5,18). Quality rose from 97,089 % to 98,873 % (Δ = +1,784 pp; 95 % CI 1,622–1,945; t(15) = 23,529; p < 0,001; Hedges' g = 8,26). All four contrasts remained significant under the Bonferroni-adjusted threshold α' = 0,0125. Within the additive decomposition of the aggregate shift, availability accounted for the largest share, followed by effectiveness, with quality contributing the smallest absolute change despite displaying the second-largest standardised effect size — a configuration whose mathematical origin is documented in §3.3 and whose substantive reading is taken up in the Discussion. Table 2 consolidates the hypothesis contrasts, confidence intervals and effect sizes for all four variables, and Figure 4 displays the corresponding pre- and post-intervention distributions in four parallel boxplot panels.

Table 2. Paired-samples hypothesis contrasts and Hedges' g effect sizes for OEE and its three components (16 pre-intervention vs. 16 post-intervention weeks; Bonferroni-adjusted threshold α' = 0,0125). Pre-intervention means, post-intervention means, mean differences with 95 % confidence intervals, paired t-statistics with 15 degrees of freedom, exact significance under both the unadjusted and adjusted thresholds and Hedges' g with its small-sample bias correction are reported for each contrast.

Variable	**Mean pre (%)**	**Mean post (%)**	**Δ (pp)**	**95 % CI of Δ**	**t(15)**	**p**	**p Bonf.**	**Hedges' g**
OEE	67,402	86,254	+18,852	[18,398; 19,306]	88,494	< 0,001	< 0,001	14,87
Availability	79,539	91,034	+11,496	[10,442; 12,549]	23,261	< 0,001	< 0,001	7,35
Effectiveness	87,279	95,819	+8,539	[7,651; 9,427]	20,491	< 0,001	< 0,001	5,18
Quality	97,089	98,873	+1,784	[1,622; 1,945]	23,529	< 0,001	< 0,001	8,26 [a]

Note. Decimal comma per SI convention. Exact p-values are reported as < 0,001 rather than 0,000; the four contrasts were planned a priori and the family-wise error rate is controlled by Bonferroni correction at α' = 0,05 / 4 = 0,0125. Hedges' g incorporates the small-sample bias correction relevant for N = 16. Weekly OEE is computed per machine and then averaged across the 25-asset sample; for that reason the mean OEE differs marginally from the product of the mean component values.

[a] The Hedges' g for the Quality contrast is mathematically inflated by the near-zero pre-intervention standard deviation (SD = 0,062 %). This value should be read as evidence of process stabilisation — a consistent upward displacement of the entire distribution — rather than as a large material change in the conventional effect-size sense. The non-parametric Wilcoxon signed-rank corroboration (p = 0,000381) confirms the directional shift without relying on the distributional assumption violated for this variable (Shapiro-Wilk W = 0,732; p < 0,001).

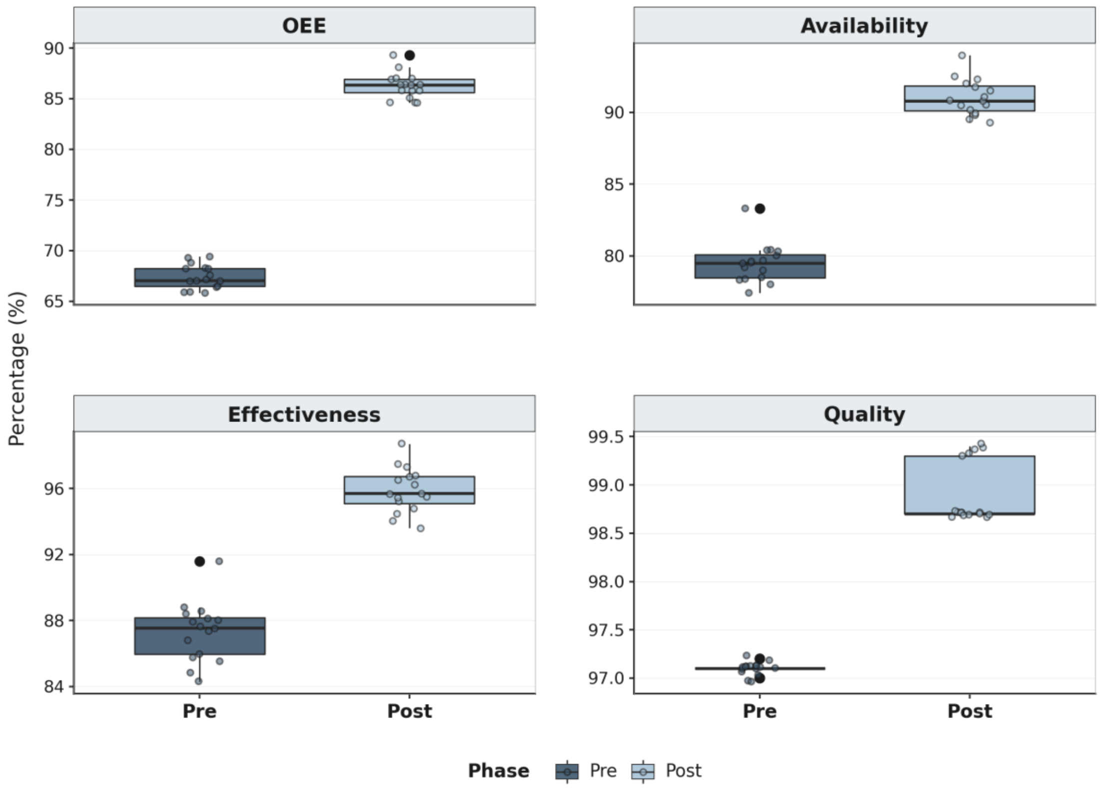

Figure 4. Four-panel boxplots of OEE and its three components — availability, effectiveness and quality — distributed across the 16 pre-intervention and 16 post-intervention weekly observations. The four panels share a common pre/post axis; medians, interquartile ranges, whiskers and any outliers are displayed separately for each variable to expose both the location shift and the dispersion change between phases.

3.3 Stability and inferential diagnostics

Three diagnostic results characterise the inferential robustness of the contrasts reported in §3.1 and §3.2. First, the Shapiro-Wilk test on the per-week difference scores returned W = 0,929; p = 0,236 for OEE, W = 0,889; p = 0,054 for availability and W = 0,972; p = 0,866 for effectiveness — compatible with the normality assumption of the paired-samples t-test in each case. For quality, the corresponding statistic was W = 0,732; p < 0,001, indicating departure from normality; the planned Wilcoxon signed-rank corroboration on the same differences returned p = 0,000381, supporting the same directional conclusion. Second, the Durbin-Watson statistic on the OEE difference series returned DW = 1,585, falling within the band compatible with absence of severe first-order autocorrelation, although the small N qualifies that reading. Third, the four internal-validity threats were addressed through the structured narrative protocol described in §2.7; the outcomes of that assessment are summarised in Table 3.

The dispersion behaviour of the post-intervention series varied by component. The standard deviation of the weekly availability narrowed from 1,624 to 1,397 percentage points and that of weekly effectiveness narrowed from 1,767 to 1,426, while that of the aggregate OEE remained essentially stable at 1,276 against a pre-intervention 1,187. The quality series exhibited a different pattern: weekly dispersion expanded from 0,062 to 0,292 percentage points, although both values remained at least one order of magnitude below the dispersion observed for the other three variables. The near-zero pre-intervention standard deviation of the quality series is the mathematical origin of the inflated Hedges' g value (g = 8,26) reported in Table 2 for the quality contrast; this point is taken up substantively in the Discussion.

Table 3. Internal-validity diagnostics and inferential robustness checks across the four contrasts. Diagnostic outputs for normality on the difference scores, non-parametric corroboration where required, first-order autocorrelation and the structured assessment of the four internal-validity threats considered in §2.7.

Panel A. Inferential diagnostics

Diagnostic	Statistic	Outcome
Shapiro-Wilk on OEE differences	W = 0,929; p = 0,236	Compatible with paired t-test
Shapiro-Wilk on Availability differences	W = 0,889; p = 0,054	Borderline; normality not rejected at α = 0,05
Shapiro-Wilk on Effectiveness differences	W = 0,972; p = 0,866	Compatible with paired t-test
Shapiro-Wilk on Quality differences	W = 0,732; p < 0,001	Non-normal; paired t retained per plan; Wilcoxon reported as corroboration
Wilcoxon signed-rank on Quality differences	p = 0,000381	Corroborates the paired-t directional conclusion without distributional assumption
Durbin-Watson on OEE difference series	DW = 1,585	No evidence of severe first-order autocorrelation; interpret with caution given N = 16

Panel B. Internal-validity threat assessment

Threat	Assessment protocol	Outcome
History	Review of company records for organisational, demand or staffing changes within the 32-week horizon	No documented concurrent change; threat cannot be fully ruled out from external sources
Maturation	Examination of the pre-intervention failure-log trajectory for gradual improvement	Pre-intervention series shows stable oscillation with no upward drift; the abrupt step shift at week 16–17 is inconsistent with gradual maturation
Instrumentation	Verification that the observation form, observer team and aggregation protocol remained constant throughout	Constant instrument confirmed; inter-rater reliability was not quantified (limitation acknowledged)
Testing (Hawthorne)	Assessment of operator awareness of the observation protocol	Residually present; blinding operators is incompatible with the participative logic of autonomous maintenance

Note. Exact p-values are reported as < 0,001 rather than 0,000. The Wilcoxon signed-rank test on the Quality differences serves as a non-parametric corroboration of the planned paired t-test, given the departure from normality detected by the Shapiro-Wilk statistic. The Durbin-Watson statistic falls within the 1,5–2,5 band conventionally associated with absence of severe first-order autocorrelation, although the small series length (N = 16) reduces the power of this diagnostic. The structured internal-validity assessment supports the use of associative language throughout the Discussion: TPM implementation was associated with the observed shifts, not causally proven to have produced them.

Taken together, the position of the post-intervention OEE series above the 85 % world-class threshold across all sixteen weeks, the magnitude and statistical significance of the four planned contrasts under the Bonferroni-adjusted threshold, the survival of the quality contrast under the non-parametric corroboration, and the absence of severe first-order autocorrelation in the difference series jointly establish the empirical pattern that the Discussion will place inside the contemporary debate on OEE elasticity and on the transferability of classical TPM to mobile critical assets.

4 Discussion

4.1 Magnitude inside the OEE Elasticity Paradox

The first finding to interpret is the magnitude itself. A +18,852 pp shift in aggregate OEE, observed over a 16-week post-intervention horizon following a paper-based deployment of the classical four-phase model, is roughly seven times larger than the +2,53 pp reported by Irfan et al. [9] under a TPM + 5S protocol in cement manufacturing, 1,8 times larger than the +10,38 pp reported by Sumastro et al. [7] in an Indonesian automotive SME, 1,7 times larger than the +10,93 pp reported by Quiroz-Flores et al. [8] under a TPM + 5S + SMED combination in a Peruvian SME, and 1,8 times larger than the +10,31 pp documented by Castañeda et al. [10] in a Peruvian food operation. The dispersion of published gains has a name in the contemporary literature — the OEE Improvement Elasticity Paradox [28] — and the present estimate sits at the upper end of its distribution.

Three reconciling factors are advanced, not as conclusions but as hypotheses available for replication. The first is baseline maturity. Pre-intervention OEE was 67,402 % and decomposed into an availability of 79,539 %, an effectiveness of 87,279 % and a quality of 97,089 %; comparable studies operating from higher baselines have less arithmetic headroom and necessarily report smaller absolute gains [34, 2]. The second is the configuration of the intervention. Where Quiroz-Flores et al. [8] combined TPM with 5S and SMED, and where Irfan et al. [9] layered 5S over an autonomous-maintenance pillar, the present study deployed the four-phase classical model alone, on a census of 25 critical assets, with no parallel operational change. A single, structurally aligned intervention executed across the entire fleet plausibly produces a more concentrated effect than partial rollouts diluted by competing methodologies — though this proposition itself awaits empirical confirmation. The third is the dispersion structure of the weekly series. Pre-intervention OEE oscillated within a 3,6 pp band (65,8–69,4 %) with a weekly standard deviation of 1,187 pp, an unusually narrow window that mathematically tightens the standard error of the paired mean difference and amplifies the t-statistic to $t(15) = 88{,}494$ [33].

The honest reading of the third factor is that the inflated t-statistic does not invalidate the +18,85 pp estimate, but it does invite caution about reading the confidence interval [18,398; 19,306] as a measure of physical, machine-level precision. The interval describes how stably the weekly fleet-average behaved, not how precisely individual assets shifted. The strongest design counterpart to this concern would have been a concurrent control series on similar hoisting equipment at another site, which the operational constraints of the participating company precluded; the consequence is that history, maturation and regression-to-the-mean explanations remain logically open even after the inferential battery of §3.3 has been applied. The interrupted-time-series logic narrows the space of plausible alternatives — gradual maturation does not produce step shifts of this size, and the documented absence of organisational or demand changes within the 32-week horizon makes a coincident historical confounder improbable — but it cannot mathematically eliminate them. The argument the data support is therefore associative, not causal, and is framed accordingly throughout the remainder of this section.

4.2 Availability as the dominant driver: a service-sector inversion

Of the +18,852 pp shift in aggregate OEE, availability contributed +11,496 pp — close to 61 % of the total movement, the largest single share of any component by a wide margin. This pattern inverts the modal pattern of the manufacturing literature, where effectiveness typically leads. In Singh et al. [11], the post-intervention gain on a metal-industry rolling station was concentrated in the speed and minor-stop dimensions of performance rather than in uptime; in Sumastro et al. [7], the +10,38 pp gain in an automotive SME similarly leaned on effectiveness reductions in micro-stoppages and idling rather than on unplanned-stoppage reduction.

Two mechanisms are proposed to make sense of the inversion. The first is structural: in a service operation the critical asset is idle when not under contract, so unplanned stoppages constitute the dominant loss because they cannot be absorbed by the buffer inventory that manufacturing lines use to insulate downstream throughput from upstream failure [25, 26]. The planned-maintenance pillar of classical TPM, which targets unplanned stoppages by converting them into scheduled interventions, therefore has the highest marginal leverage in this context — even when its execution is paper-based. The second mechanism is metric-induced. The Pareto diagnosis of §2.3 identified the absence of OEE indicators as the third-ranked cause of low baseline performance; instrumenting the metric itself improves measured availability because previously untracked stoppages are now recorded and therefore acted upon. The two mechanisms are confounded in the present design — the planned-maintenance pillar and the OEE-indicator deployment were introduced simultaneously, both within Phase 3 — and the data cannot adjudicate their relative contributions. An independent telemetered availability signal would be required to separate them; that signal was not available on the paper-based instrumentation of the participating company.

The practical implication, stated as a hypothesis for the field rather than as a recommendation derived from a single study, is that generic 'apply all pillars equally' guidance may not transfer cleanly across sectors. A TPM rollout in a service operation may yield disproportionate returns from the planned-maintenance pillar and from the visual-management routines that produce the indicator architecture, with the autonomous-maintenance and quality pillars contributing through different multipliers than they do in continuous manufacturing. The argument requires multi-sector replications before it can graduate from hypothesis to claim.

4.3 Effectiveness, operator engagement and the assumption of digital prerequisites

The effectiveness component rose from 87,279 % to 95,819 % (+8,539 pp; Hedges' g = 5,18), a magnitude that becomes interpretively interesting only when placed against the contemporary Maintenance 4.0 and Maintenance 5.0 literature. Recent frameworks position predictive analytics, condition-monitoring sensor networks, digital twins and machine-learning estimators of remaining useful life as the technologies through which substantial gains in heavy-equipment effectiveness are now expected to be obtained [13, 14, 15, 18, 19]. Murtaza et al. [14] document breakdown reductions of up to 95 % in cyber-physical systems under predictive frameworks; Samadhiya et al. [20] argue that the integration of Industry 4.0 with TPM bundles is the operative pathway for further productivity gains; Tortorella et al. [21] show that digital maintenance adoption is the empirical correlate of TPM maturity in their cross-sectoral sample.

The present finding offers a counterpoint that the field should be invited to absorb. An 8,5 pp gain in effectiveness was obtained without sensors, without a digital twin, without any predictive layer — through the autonomous-maintenance pillar of the classical model, executed on paper, on a workforce that received structured training in basic inspection, cleaning, lubrication and minor-defect recognition. The proposed mechanism is operator engagement as a transferable causal lever: when operators are explicitly given responsibility for the condition of their asset, the population of small, sub-failure deviations that drag effectiveness downward — micro-stoppages, speed losses from incipient wear, brief manual adjustments — is detected and corrected earlier in its life cycle than under a centralised maintenance regime [35, 36].

The strategic reading is dual. Organisationally, operator engagement appears to be a lever that does not require digital infrastructure to activate; this is encouraging for the bulk of Latin-American industrial service operations, where Folgado et al. [17] document a sparse on-asset instrumentation profile that places digital-twin deployment several investment cycles away. Strategically, the finding sharpens the maturity-ladder argument introduced at the close of the Introduction: a process whose effectiveness oscillates within a 7,3 pp band before stabilisation is a poor candidate for predictive instrumentation, because the signals that predictive models train on are dominated by operational variance rather than by the degradation signature the analyst is attempting to forecast [16, 22, 23]. The classical four-phase model is not an obsolete competitor of TPM 4.0; it is the intervention that compresses variance enough to make the asset legible to a subsequent digital layer.

This reading is contingent on the assumption that operator engagement, once activated, persists beyond the observation horizon. The available evidence covers 16 post-intervention weeks. Whether the engagement effect decays once the Hawthorne attention recedes, and whether the consolidation phase of the model produces the cultural anchoring that Cuatrecasas and Torrell [4] describe as its purpose, are questions a longitudinal replication extending beyond a single annual cycle would be required to answer.

4.4 Quality: from causal magnitude to process stabilisation

The smallest absolute shift among the four contrasts is the quality component, which rose from 97,089 % to 98,873 % (+1,784 pp). The standardised effect size — Hedges' g = 8,26 — is the artefact in the analysis that demands the most careful interpretive handling. Both Hollaar et al. [33] and Panjeh et al. [31] have documented that effect sizes computed against a near-zero pre-intervention standard deviation are mathematically inflated and should not be interpreted against Cohen's conventional 0,2 / 0,5 / 0,8 thresholds. The pre-intervention quality series in this study had SD = 0,062 %, an order of magnitude below the dispersion of any other component, which mechanically generates a g value that overstates the practical magnitude of the underlying material change.

The honest reading is that the gain is best described as process stabilisation in the statistical-process-control sense, rather than as a defect-rate reduction in the strict manufacturing sense. The entire post-intervention distribution shifted upward; the median moved from 97,1 % to 98,7 %; the minimum of the post-series (98,7 %) exceeded the maximum of the pre-series (97,2 %). What the data communicate is that the quality-maintenance pillar of the model held the process inside a tighter band around a higher central tendency, not that defects were eliminated in a transformative sense. This reframing is itself part of the contribution of the present manuscript to the wider literature on pre-experimental OEE evaluation: it operationalises the warning that Hollaar et al. [33] issue at the meta-analytic level — that standardised effect sizes in pre/post designs with near-zero baseline dispersion must be reported alongside the dispersion that produced them, and that the substantive interpretation should track the displacement of the full distribution rather than the magnitude of the g value [32].

The limitation attached to this finding is that the quality indicator captures the proportion of effective operating time within real operating time, not an absolute defect count per shift; near-ceiling values therefore have a hard upper bound that compresses the room for interpretable change. Whether the additional 1,8 pp of quality translates into financial returns proportional to the inferential precision is a question the present study is not equipped to answer and that would require operational cost data outside the scope of the observation form.

4.5 Synthesis: the maturity-ladder argument and SDG 9 closure

Taken together, the four findings recompose into a single empirical statement: the structured deployment of the classical four-phase TPM model on a census of 25 critical hoisting and transport assets in a Latin-American industrial service operation was associated with a substantial, statistically significant and dimensionally decomposable shift in OEE, with the largest absolute contribution coming from availability, a methodologically interesting contribution from effectiveness obtained without digital instrumentation, and a quality gain best read as process stabilisation. The double void identified in the Introduction — sectoral and methodological — is partially closed by the magnitude estimate itself and by the inferential apparatus that surrounds it.

The strategic implication is the one anticipated by the narrative arc of this manuscript: in the contemporary Maintenance 4.0 / 5.0 discourse, the classical four-phase model is not the dated alternative against which advanced approaches are measured, but the missing rung of the maturity ladder on which the advanced approaches will eventually be built [24, 30]. A company whose mobile asset fleet oscillates within an 18 pp window of variability cannot extract useful signal from a predictive model; the model will fit the noise. The intervention this study describes is the variance-reduction step that creates the data substrate on which any later digital layer can be built.

The residual limitations that have not already been embedded above can be stated briefly. The design lacks a concurrent control group, leaving regression-to-the-mean and history threats logically unresolved. The inter-rater reliability of the observation form was not quantified, which leaves a small residual instrumentation-precision risk. The post-intervention horizon of 16 weeks does not demonstrate sustainability of the gains beyond a single quarter. Future work would test the present findings against a stepped-wedge cluster design across multiple service sites, with a telemetered availability channel acting as an independent reference series, and would then layer IoT instrumentation onto the stabilised baseline to estimate the incremental contribution of digital maintenance over the classical floor.

The work closes by returning to the framing introduced at the start. Sustainable Development Goal 9 calls for inclusive, resilient infrastructure and innovation; in resource-constrained service operations, the structured deployment of a paper-based TPM model is the kind of low-cost, organisationally tractable intervention that can stabilise the operational core before any subsequent investment in digitalisation. The empirical evidence presented here suggests that this stabilisation is achievable, and quantifiable, on critical mobile transport machinery — the asset class that the 2024–2026 literature had documented as a gap.

5 Conclusion

The structured implementation of the classical four-phase Total Productive Maintenance model on a census of 25 critical hoisting and transport assets — 12 winches and 13 roller boxes — operating in a transnational industrial service operation in Antofagasta was associated with a shift in aggregate OEE from 67,402 % to 86,254 %, a paired difference of +18,852 pp under inferential controls that included Bonferroni adjustment, Hedges' g effect-size reporting and Durbin-Watson autocorrelation diagnostics. Availability and effectiveness carried the largest absolute contributions to the shift, while the smaller absolute gain in quality is best read as a process-stabilisation outcome rather than as a defect-rate reduction in the strict sense. The finding constitutes the first quantitative empirical evidence of the transferability of the classical four-phase model from continuous manufacturing to mobile critical transport machinery in the Latin-American industrial service sector, and positions the classical model as the variance-reduction prerequisite on which any subsequent Maintenance 4.0 or 5.0 architecture will, in this asset class, eventually depend.

References

1. ABDULLAH, Jonayed, RIFAT, Al Hossain y RAY, Avirup. Enhancing overall equipment effectiveness (OEE) of a selected machine in a light manufacturing factory in Bangladesh. Journal of Engineering and Technology for Industrial Applications [en línea]. 2025, vol. 11, n.° 52. ISSN: 2447-0228. Disponible en: https://doi.org/10.5935/jetia.v11i52.1579
2. ABEDIN, Ahsanul. Improvement of overall equipment efficiency with root cause analysis and TPM strategy: a case study. International Journal of Research in Industrial Engineering [en línea]. 2023, vol. 12, n.° 3, págs. 205-220. ISSN: 2717-2937. Disponible en: https://doi.org/10.22105/riej.2023.393216.1388
3. MORA, Alberto. Mantenimiento: Planeación, ejecución y control. México: Alfaomega Grupo Editor, 2009. ISBN: 978-607-7686-44-6.
4. CUATRECASAS, Lluís y TORRELL, Francesc. TPM en un entorno Lean Management: Estrategia competitiva. Barcelona: Profit Editorial, 2010. ISBN: 978-84-96998-31-5.
5. RATHI, S. S., KUMAR, Mithilesh y KUMAR, Sanjeev. Implementation of Total Productive Maintenance to Improve Productivity of Rolling Mill. Indian Journal of Engineering & Materials Sciences [en línea]. 2023, vol. 30, n.° 6, págs. 543-551. ISSN: 0975-1017. Disponible en: https://doi.org/10.56042/ijems.v30i6.3158
6. SAXENA, Mudit. Total productive maintenance (TPM) as a vital function in manufacturing systems. Journal of Applied Research in Technology & Engineering [en línea]. 2022, vol. 3, n.° 1, págs. 43-54. Disponible en: https://doi.org/10.4995/jarte.2022.15934
7. ALMASHAQBEH, Sahar y HERNÁNDEZ, Eduardo. Evaluation and Improvement of a Plastic Production System Using Integrated OEE Methodology: A Case Study. Management Systems in Production Engineering [en línea]. 2024, vol. 32, n.° 3, págs. 145-155. Disponible en: https://doi.org/10.2478/mspe-2024-0042
8. BISWAS, Joyeshree. Total Productive Maintenance: An In-depth Review with a Focus on Overall Equipment Effectiveness Measurement. International Journal of Research in Industrial Engineering [en línea]. 2024, vol. 13, n.° 4, págs. 312-328. Disponible en: https://doi.org/10.22105/riej.2024.453380.1436
9. BURGOS, Anthony. Implementación de una propuesta de mejora en la eficiencia global de los equipos, aplicando la metodología TPM, para reducir los costos de mantenimiento en la línea de envasado de la empresa La Molina E.I.R.L. Trujillo, 2021 [en línea]. Tesis de licenciatura, Universidad Privada del Norte, 2022. Disponible en: https://hdl.handle.net/11537/31463
10. CANAHUA, Nohemy. Implementación de la metodología TPM-Lean Manufacturing para mejorar la eficiencia general de los equipos (OEE) en la producción de repuestos en una empresa metalmecánica. Industrial Data [en línea]. 2021, vol. 24, n.° 1, págs. 49-62. ISSN: 1810-9993. Disponible en: https://doi.org/10.15381/idata.v24i1.18402
11. SINGH, S., et al. Implementation of Total Productive Maintenance Approach: Improving Overall Equipment Efficiency of a Metal Industry. Inventions [en línea]. 2022, vol. 7, n.° 4, pág. 119. Disponible en: https://doi.org/10.3390/inventions7040119
12. GIANFRANCO, Joshua, MUHAMMAD, Iqbal, FEBRI, Hariadi y MUCHAMMAD, Fauzi. Pengukuran total productive maintenance (TPM) menggunakan metode overall equipment effectiveness (OEE) pada mesin reaktor produksi. Jurnal Lebesgue: Jurnal Ilmiah Pendidikan Matematika, Matematika dan Statistika [en línea]. 2022, vol. 3, n.° 1, págs. 1-12. Disponible en: https://www.researchgate.net/publication/367711318_PENGUKURAN_TOTAL_PRODUCTIVE_MAINTENANCE_TPM_MENGGUNAKAN_METODE_OVERALL_EQUIPMENT_EFFECTIVENESS_OEE_PADA_MESIN_REAKTOR_PRODUKSI
13. PSAROMMATIS, Foivos, MAY, Gökan y AZAMFIREI, Victor. Envisioning maintenance 5.0: Insights from a systematic literature review of Industry 4.0 and a proposed framework. Journal of Manufacturing Systems [en línea]. 2023, vol. 68, págs. 376–399. ISSN: 0278-6125. Disponible en: https://doi.org/10.1016/j.jmsy.2023.04.009
14. CASTAÑEDA, Sair, RODRÍGUEZ, Sharon, YILDIZ, Orkun, ARANDA, Duilio y ÁLVAREZ, José. Increase of the Availability of Machinery in a Food Company Applying the TPM, SMED and RCM Methodologies. International Journal of Engineering Trends and Technology [en línea]. 2024, vol. 72, n.° 8, págs. 145-155. Disponible en: https://doi.org/10.14445/22315381/IJETT-V72I8P114
15. CASTRO, Armando y PÉREZ, Joel. Application of total productive maintenance in a manufacturing process of cardboard boxes under lean six sigma dmaic methodology. South African Journal of Industrial Engineering [en línea]. 2025, vol. 35, n.° 4, págs. 112-124. Disponible en: https://doi.org/10.7166/35-4-3068
16. CHUMBIMUNI, Milagros, GIL, Elías y CÉSPEDES, Carlos. Integrated Model of TPM, SMED, Poka Yoke, and 5S to Improve OEE in Pole Production in Peru. Proceedings of the Latin American and Caribbean Consortium of Engineering Institutions [en línea]. 2025. Disponible en: https://doi.org/10.18687/LACCEI2025.1.1.2288
17. CHUNDHOO, Vickram, CHATTOPADHYAY, Gopinath, KARMAKAR, Gour y KAHANDAWA, Gayan. Embedding risk in total productive maintenance model. International Journal of System Assurance Engineering and Management [en línea]. 2025, vol. 16, n.° 4, págs. 543-556. Disponible en: https://doi.org/10.1007/s13198-025-02736-1
18. CONTRERAS-RIOS, Valerie, et al. Process Optimization through the Implementation of SLP, Kanban, Poka-Yoke and TPM to Improve Efficiency in a Metalworking SME. International Journal of Engineering Trends and Technology [en línea]. 2025, vol. 73, n.° 6. Disponible en: https://doi.org/10.14445/22315381/IJETT-V73I6P122
19. DA MOTTA, José, WERDERITS, Dayana, DE SOUZA, Nilo, MEDEIROS, José, SANTOS, Gilberto, & MOTTA, Luís. (2025). Analysis of results of a pilot implementation of total productive maintenance in a Brazilian industry. Proceedings on Engineering Sciences, 7(3). https://doi.org/10.24874/PES07.03.009

20. DURAN, Francisco y GUERRERO, Luis. (2025). Overall Equipment Effectiveness (OEE): Una herramienta clave para la eficiencia en la producción. Ciencia Latina Revista Científica Multidisciplinar, 9(3). https://doi.org/10.37811/cl_rcm.v9i3.18236
21. GONZALES-VERA, Rolando, RODRIGUEZ-BARRIENTOS, Karol, CASTRO-RANGEL, ÁLVAREZ, Percy, & LEPORE, Robert. (2025). Improvement Model of OEE in the Production Process of Cardboard Boxes Through SMED, TPM, Automation, and IoT. SSRG International Journal of Mechanical Engineering, 12(6). https://doi.org/10.14445/23488360/IJME-V12I6P104
22. HERRERA-URIBE, José, RIVERO-DAVILA, Diana, & SÁENZ-MORÓN, Martín. (2023). Model based on TPM to increase the overall efficiency of equipment in an oil company. Proceedings of the Latin American and Caribbean Consortium of Engineering Institutions. https://doi.org/10.18687/LACCEI2023.1.1.1050
23. Ibarra, A., Pérez, H., & Beltrán, C. (2024). Impacto del TPM aplicado en empresa “Fabricación y Mantenimiento Kiko Pérez” en Capilla de Guadalupe, Altos Jalisco. Scientia Tecnológica, 1(2). Available from: https://revista.scientiatecnologica.com.mx/index.php/inicio/article/view/27
24. Irfan, M. T. H., Rafiquzzaman, M., & Manik, Y. A. (2025). Productivity improvement through lean tools in cement industry – A case study. Heliyon, 11(3), e42057. https://doi.org/10.1016/j.heliyon.2025.e42057
25. Jurewicz, D., Dąbrowska, M., Medyński, D., Motyka, P., & Kolbusz, K. (2023). Implementation of Total Productive Maintenance (TPM) to Improve Overall Equipment Effectiveness (OEE): A Case Study. In: Intelligent Systems in Production Engineering and Maintenance. Cham: Springer, págs. 543-561. https://doi.org/10.1007/978-3-031-44282-7_42
26. LUCANTONI, Laura, ANTOMARIONI, Sara, CIARAPICA, Filippo Emanuele y BEVILACQUA, Maurizio. A data-driven framework for supporting the total productive maintenance strategy. Expert Systems with Applications [en línea]. 2025, vol. 268, pág. 126283. ISSN: 0957-4174. Disponible en: https://doi.org/10.1016/j.eswa.2024.126283
27. OLALERE, Isaac O. y RAMDASS, Kem. Assessing the impact of quality improvement on production defectiveness: a case study on an automotive manufacturing industry. Cogent Engineering [en línea]. 2024, vol. 11, n.° 1, pág. 2392636. ISSN: 2331-1916. Disponible en: https://doi.org/10.1080/23311916.2024.2392636
28. VÁSQUEZ-CAYCHO, Yoselin R., REYES-GUZMÁN, Katherine R. y VEGA-CAYCHO, Merly M. Implementación TPM para incrementar el OEE en el sector manufactura: revisión sistemática de literatura. Aibi Revista de Investigación, Administración e Ingeniería [en línea]. 2025, vol. 13, n.° 2, págs. 45-56. ISSN: 2346-030X. Disponible en: https://doi.org/10.15649/2346030X.4097
29. MARES, Armando y RAMÍREZ, Joel. Application of total productive maintenance in a manufacturing process of cardboard boxes under Lean Six Sigma DMAIC methodology. South African Journal of Industrial Engineering [en línea]. 2024, vol. 35, n.° 4, págs. 112-125. Disponible en: https://sajie.journals.ac.za/pub/article/view/3068
30. ORTEGA, Mercedes y TARAZONA, Jack. Aplicación del TPM para incrementar el OEE en las unidades de transportes de carga de la empresa Heavy Load Corporation SAC, Ate, 2022 [en línea]. Tesis de licenciatura, Universidad César Vallejo, 2022. Disponible en: https://hdl.handle.net/20.500.12692/108652
31. QUIROZ-FLORES, Juan, REYNAGA-VÁSQUEZ, Bryan y CHÁVEZ-REVOREDO, Enrique. Empirical Study on OEE Optimization in a Peruvian Flexographic Printing SME: A Lean-TPM Model Integrating 5S and SMED. Proceedings of the Latin American and Caribbean Consortium of Engineering Institutions [en línea]. 2025. Disponible en: https://doi.org/10.18687/LACCEI2025.1.1.1716
32. HERNÁNDEZ, Roberto y MENDOZA, Christian. Metodología de la investigación: Las rutas cuantitativa, cualitativa y mixta. México: McGraw-Hill Education, 2018. ISBN: 978-1-4562-6096-5.
33. SAHRI, Zineb y EL ABBADI, Laila. The evolution of Kaizen in the industry: Systematic Literature Review. International Journal of Production Management and Engineering [en línea]. 2024, vol. 12, n.° 2, págs. 89-102. Disponible en: https://doi.org/10.4995/ijpme.2024.21143
34. ORTIZ, José, et al. Modelo de gestión basado en el mantenimiento productivo total (TPM) y Six Sigma para aumentar la efectividad global de los equipos (OEE) en una empresa de confecciones de Lima, Perú. Industrial Data [en línea]. 2024, vol. 27, n.° 2, págs. 145-162. ISSN: 1810-9993. Disponible en: https://doi.org/10.15381/idata.v27i2.26975
35. AICHOUNI, Ahmed Baha Eddine, SILVA, Cristóvão y FERREIRA, Luís Miguel D. F. A Systematic Literature Review of the Integration of Total Quality Management and Industry 4.0: Enhancing Sustainability Performance Through Dynamic Capabilities. Sustainability [en línea]. 2024, vol. 16, n.° 20, pág. 9108. ISSN: 2071-1050. Disponible en: https://doi.org/10.3390/su16209108
36. SHARMA, Ashutosh K. y SHARMA, Sanjay. An Implementation Case of Training and Education Pillar of TPM for Grinding Operations. In: Lecture Notes in Mechanical Engineering [en línea]. Cham: Springer, 2024, págs. 241-252. Disponible en: https://doi.org/10.1007/978-981-97-3173-2_28