



From loss diagnosis to predictive control: A critical review of Total Productive Maintenance implementation for Overall Equipment Effectiveness enhancement in process industries

Sandeep Kumar Prajapati¹, Dr. Ranjeet Singh Thakur²

¹ Department of Mechanical Engineering, Infinity Management & Engineering College, Madhya Pradesh, India

² Guide, Department of Mechanical Engineering, Infinity Management & Engineering College, Madhya Pradesh, India

Abstract

Overall Equipment Effectiveness (OEE) has become the de facto performance measure through which Total Productive Maintenance (TPM) programmes are justified, monitored and audited. Yet the metric and the programme were both formalised for discrete, repetitive assembly environments, whereas the process industries — cement, chemicals, pharmaceuticals, pulp and paper, sugar, food and beverage — operate coupled, continuous or semi-continuous plants in which availability is constrained by campaign scheduling, cleaning and changeover validation, thermal inertia and upstream–downstream buffering. This review addresses the resulting mismatch. Its objective is to establish, through a critical and comparative synthesis rather than a descriptive summary, how TPM-to-OEE research has evolved, which methodologies and data sources dominate, what is robustly established, and what remains unresolved for continuous-process settings. A structured search of Scopus-, Web of Science- and PubMed-indexed sources was executed over the period 2021–2026, supplemented by seminal earlier work, and the retrieved corpus was organised around four themes: metric formalisation and its variants, single-site diagnostic case studies, structured design and deployment frameworks, and the digital, statistical and sustainability extensions of TPM. Two peer-reviewed Elsevier studies are adopted as base papers and dissected in depth: a Design for Lean Six Sigma (DMADV) TPM and reliability framework deployed in an Active Pharmaceutical Ingredient plant, and a lean-tools productivity study in a cement plant. The synthesis yields three principal findings. First, reported OEE gains are almost entirely attributable to availability recovery, while performance-rate losses — the dominant loss class in continuous plants — remain under-diagnosed. Second, the evidential base is overwhelmingly single-site, pre–post and uncontrolled, so effect sizes cannot be separated from concurrent demand, feedstock and seasonal variation. Third, no published framework links individual TPM pillars quantitatively to specific OEE components in a process-industry setting, which leaves pillar sequencing a matter of practitioner judgement rather than evidence. Two defensible gaps are formalised from these findings — a methodological–causal gap and a process-industry contextualisation and generalisability gap — and a conceptual research framework is proposed that couples loss-stratified OEE measurement with reliability statistics and a pillar-to-component attribution model, evaluated through a controlled multi-period, multi-line design. The review distinguishes throughout between what the literature has established and what is advanced here as a recommendation.

Keywords: Total Productive Maintenance, Overall Equipment Effectiveness, process industry, six big losses, autonomous maintenance, reliability-centred maintenance, Lean Six Sigma

Introduction

Maintenance has migrated over four decades from a cost centre to a determinant of manufacturing competitiveness. Total Productive Maintenance (TPM), codified by Nakajima^[1], reframed equipment care as a company-wide activity built on operator ownership, small-group improvement and the systematic elimination of six categorised losses, and it introduced Overall Equipment Effectiveness (OEE) as the composite indicator of the availability, performance and quality dimensions of that loss structure. The arithmetic simplicity of OEE — the product of three ratios, each bounded by unity — is the main reason for its diffusion, and it remains the single most cited maintenance key performance indicator in the operations-management literature^[3].

That simplicity is also its principal weakness. Muchiri and Pintelon^[2] showed that the original formulation embeds assumptions about planned production time, ideal cycle time and defect attribution that do not survive translation across manufacturing archetypes, and traced the emergence of derivative metrics — total equipment effectiveness performance, production equipment effectiveness, overall factory effectiveness, overall plant effectiveness and overall

asset effectiveness — each created to repair a specific inadequacy. The systematic review by Ng Corrales *et al.*^[3], covering 186 screened articles, confirmed that these modifications proliferated precisely because the base model was being applied outside the discrete-assembly context for which it was designed.

The process industries expose this tension most sharply. In a cement kiln line, an Active Pharmaceutical Ingredient (API) train, a sugar mill or a paper machine, equipment is functionally coupled: the effectiveness of one asset is conditioned on the state of those upstream and downstream of it, so an isolated machine-level OEE can rise while plant throughput falls. Ideal cycle time is not a fixed engineering constant but a function of feedstock quality, grade recipe and thermal state. Cleaning, sterilisation, campaign changeover and regulatory validation consume calendar time that is neither a breakdown nor value-adding production, and its classification materially changes the availability term. Empirical work confirms the consequence: Tsarouhas^[9] found, across fifteen months of failure and repair data from a continuous croissant line, that the binding constraint was not availability but the interaction of minor

stoppages and speed losses, which conventional shop-floor reporting systematically under-records.

The research problem addressed by this review follows directly. A large and growing body of work reports OEE improvement after TPM deployment in process plants, but the reported effect sizes are heterogeneous, the loss diagnostics behind them are shallow, and the causal attribution from a specific TPM pillar to a specific OEE component is almost never established. Practitioners are therefore offered a programme with eight pillars and no evidence-based guidance on which pillar to deploy first in a continuous plant, while researchers accumulate case studies that are individually plausible and collectively non-cumulative.

The motivation for a review at this juncture is threefold. The literature has shifted markedly since 2021 towards digital and statistical extensions of TPM [6, 7, 19], creating a discontinuity with the earlier descriptive case-study tradition that has not yet been critically reconciled. The process industries have simultaneously come under energy and emissions pressure that makes equipment effectiveness a sustainability variable and not only a productivity one [18], [20]. And two recent, methodologically contrasting studies in Elsevier journals — Shannon *et al.* [4] in an API plant and Irfan *et al.* [5] in a cement plant — now provide a natural pair against which the field's methodological range can be calibrated.

The objectives of this review are to:

- Trace the evolution of the OEE construct and of TPM deployment practice, distinguishing metric-level from programme-level developments;
- Classify the dominant methodologies, data sources and evaluation metrics used in TPM-to-OEE studies and assess their internal validity;
- Critically compare two contrasting base studies conducted in process environments;
- Formalise the two most consequential research gaps for the process-industry context and propose a conceptual framework that addresses them.

The contribution of this review is threefold: a thematic rather than chronological synthesis that separates established findings from recurrent but unverified claims; an explicit internal-validity critique of the pre-post single-site design that dominates the field; and a proposed measurement-and-attribution framework that converts the identified gaps into testable constructs. The remainder of the paper is organised as follows. Section 2 states the review

methodology. Section 3 develops the conceptual background. Section 4 presents the thematic literature review. Section 5 dissects the two base papers. Section 6 tabulates comparative evidence. Sections 7 and 8 formalise the gaps and future directions. Section 9 proposes the research framework, and Sections 10 and 11 discuss and conclude.

Review Methodology

The review followed a structured, reproducible protocol adapted from the systematic-review procedure applied to the OEE domain by Ng Corrales *et al.* [3]. Searches were executed across Scopus, Web of Science, ScienceDirect, Emerald Insight, Taylor & Francis Online, SpringerLink, MDPI and PubMed/PubMed Central. The core Boolean string combined the programme term, the metric term and the sector term: ("total productive maintenance" OR TPM) AND ("overall equipment effectiveness" OR OEE) AND ("process industry" OR cement OR pharmaceutical OR chemical OR "pulp and paper" OR sugar OR "food and beverage" OR continuous). Complementary strings substituted "autonomous maintenance", "planned maintenance pillar", "six big losses", "reliability centred maintenance" and "maintenance 4.0" for the programme term.

Inclusion was restricted to peer-reviewed journal articles and indexed book chapters published between 2021 and 2026, written in English, reporting either an empirical OEE measurement, a deployment framework, or a systematic synthesis. Seminal pre-2021 works were retained only where they define a construct still in active use — principally [1, 2, 10]. Records were excluded where the venue was not indexed in Scopus or Web of Science, where OEE was mentioned without being measured, where the study duplicated an earlier dataset by the same authors, or where the reported improvement was asserted without a stated baseline. Backward and forward citation chaining was applied to the two base papers and to the three synthesis studies [3, 6, 7]. Bibliographic metadata — authorship, year, volume, pagination and DOI — was verified against the publisher record for every reference cited in Section 12; no reference is included on the basis of a secondary citation alone. Fig. 1 summarises the protocol. The review is interpretive and critical in character; no meta-analytic pooling was attempted, because the heterogeneity of OEE operationalisation across the corpus, documented in Section 4, makes effect sizes formally incommensurable.

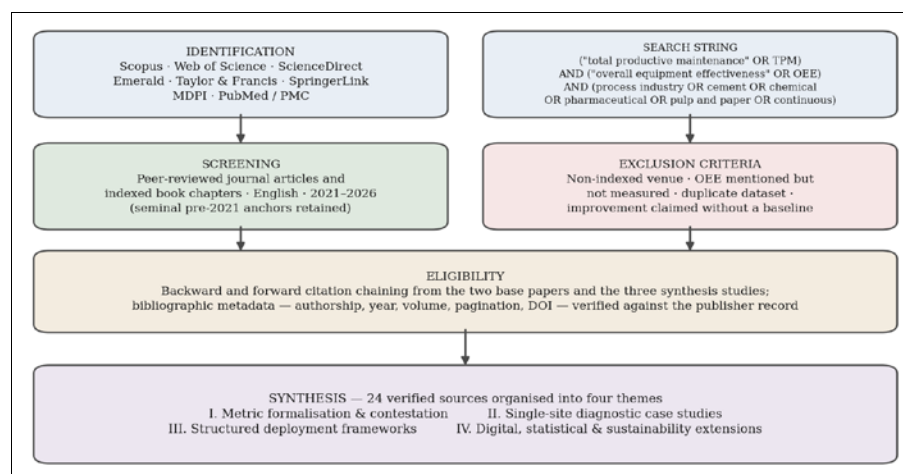


Fig 1: Review protocol: identification, screening, eligibility and thematic synthesis of the reviewed corpus.

Conceptual and Theoretical Background

TPM is conventionally represented as a set of eight interdependent pillars — autonomous maintenance, focused improvement, planned maintenance, quality maintenance, early equipment management, education and training, office TPM, and safety, health and environment — resting on a 5S foundation^[13]. The pillars are not independent instruments but a sequenced programme: autonomous maintenance transfers routine cleaning, lubrication and inspection to operators, which both frees maintenance capacity for the planned-maintenance pillar and generates the abnormality data on which focused improvement depends. Bamber *et al.*^[10] established early that the cross-functional team is the operative mechanism linking these pillars to measured OEE, a finding that later frameworks have repeatedly re-derived.

OEE decomposes equipment loss into three multiplicative terms, as set out in Fig. 2. Availability captures downtime losses, conventionally breakdown and setup/adjustment; performance rate captures speed losses, conventionally idling/minor stoppages and reduced speed; and quality rate captures defect losses, conventionally process defects and reduced yield at start-up^[1, 2]. The multiplicative form is consequential: because the terms compound, a plant with three individually respectable ratios of 0.90 records an OEE of 0.729, and — more importantly for diagnosis — a one-point improvement in the smallest term yields a larger absolute OEE gain than the same improvement in the largest. This property is widely acknowledged but rarely exploited as a prioritisation rule in the applied literature.

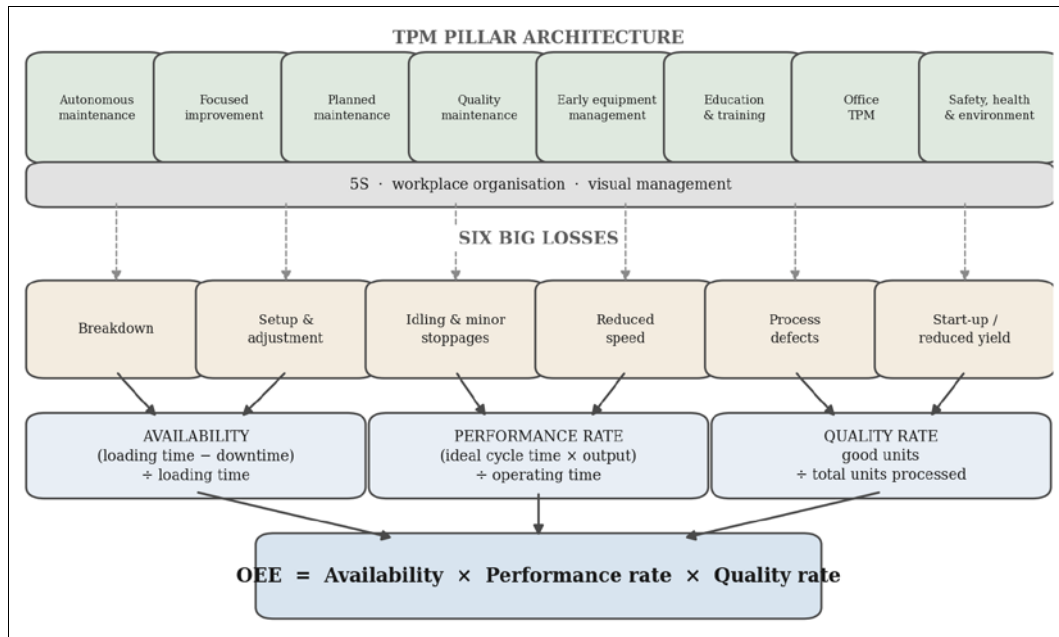


Fig 2: Structural relationship between the TPM pillar architecture, the six big losses and the three multiplicative components of OEE, after Nakajima^[1] and Muchiri and Pintelon^[2].

Three theoretical qualifications matter for process plants. First, the loss taxonomy is not sector-neutral; Muchiri and Pintelon^[2] demonstrated that the placement of planned stoppages, cleaning and validation inside or outside the loading-time denominator can move reported OEE by tens of points without any physical change in plant behaviour, which is why cross-study comparison of absolute OEE values is unsound. Second, the machine-level scope of OEE is inadequate for coupled lines, which motivated the line-, factory- and plant-level extensions catalogued in^[2, 3] and the process-oriented indicators later proposed by Ng Corrales *et al.*^[23]. Third, TPM's theoretical status has broadened: Samadhiya and Agrawal^[18] situate it within the resource-based view, modelling TPM as a bundle of firm-specific, path-dependent capabilities rather than a toolkit, and validate the resulting structural model on 326 survey responses. That repositioning is significant because it predicts — correctly, on the evidence of Section 4 — that transplanting TPM tools without the accompanying organisational capability yields small and non-durable OEE gains. Adjacent methodologies increasingly co-occur with TPM. Reliability-Centred Maintenance contributes criticality-based task selection and failure-mode logic; Lean Six Sigma

contributes the DMAIC and DMADV process architectures that impose measurement discipline on improvement projects^[4]; and Maintenance 4.0 contributes condition monitoring, predictive analytics and digital-twin representations^[6, 7]. Singh *et al.*^[8] specifically analysed the integration of OEE with such strategic tools and concluded that OEE functions best as the common dependent variable across them rather than as a standalone improvement method — a position this review adopts.

Thematic Literature Review

1. Theme I — Formalisation and contestation of the effectiveness metric

The earliest and most cumulative strand concerns the metric itself. Muchiri and Pintelon^[2] provide the reference critique, showing how OEE evolved into a family of derivative indicators as practitioners encountered line-level, factory-level and asset-portfolio-level questions the original could not answer. Ng Corrales *et al.*^[3] extended this into a formal systematic review, reporting that academic interest accelerated markedly over the preceding five years and that the keyword structure of the field had shifted from measurement towards implementation and optimisation. The same group subsequently proposed and implemented an

operation-level lean indicator intended to capture effectiveness in process rather than equipment terms ^[23], which is directly relevant to continuous plants where the unit of analysis is a transformation step rather than a machine. Singh *et al.* ^[8], writing in a process-mechanical-engineering venue, mapped the integration of OEE with other strategic improvement tools and identified the absence of standardised loss-classification conventions as the central obstacle to comparability.

The methodological character of this theme is analytical and review-based rather than empirical; its data sources are bibliographic databases and its evaluation criteria are construct validity and comparability rather than measured improvement. Its principal advantage is conceptual rigour; its principal limitation is that the proposed variants are seldom validated on industrial data, so the field possesses many candidate metrics and little evidence on which performs better under which plant topology. The trend is clearly towards process- and system-level effectiveness constructs.

2. Theme II — Single-site diagnostic case studies

This is numerically the dominant theme and methodologically the weakest. The canonical design collects production and downtime records for a baseline window, computes availability, performance and quality, ranks loss causes using Pareto and cause-and-effect analysis, deploys a subset of TPM tools, and recomputes OEE. Irfan *et al.* ^[5] follow exactly this template in cement. Tsarouhas ^[9] represents the more rigorous variant, analysing fifteen months of failure and repair data from a continuous croissant line at daily resolution with descriptive statistics of scheduled and unscheduled interruptions — a temporal depth rarely matched. Marinho *et al.* ^[16] applied a tool-selection framework to equipment malfunctions in the cork industry, and Jurewicz *et al.* ^[11] analysed the causes of low OEE and designed a revised maintenance and overhaul plan for a machinery fleet, identifying the building and vulcanising stations as the process bottleneck. Khalili *et al.* ^[12] examined planned preventive maintenance effects on OEE in a Malaysian batching-plant context using SPSS-based analysis, and is notable in the corpus for reporting an outcome that did not conform to expectation, which the majority of case studies do not.

Datasets in this theme are almost invariably proprietary plant records — shift logs, computerised maintenance management system (CMMS) work orders and production returns — of between three and eighteen months' duration, for a single site and frequently a single line. Evaluation is confined to OEE and its three components, occasionally supplemented by breakdown-hour counts. The advantages are ecological validity and immediate managerial relevance. The limitations are severe and structural: absent control lines or control periods, pre-post differences confound the intervention with demand, feedstock, grade-mix and seasonal effects; sample sizes at the plant level are one; and the interventions are typically bundles, so no individual pillar's contribution is identifiable. Reported gains cluster in the low single digits to the low tens of percentage points, and — critically — are attributed predominantly to availability recovery, which is the loss class most visible in existing reporting systems and therefore the one most susceptible to measurement-driven rather than physical improvement.

3. Theme III — Structured deployment and evaluation frameworks

A smaller but methodologically stronger strand imposes an explicit design architecture on deployment. Shannon *et al.* ^[4] applied the Define–Measure–Analyse–Design–Verify sequence of Design for Lean Six Sigma to construct a combined TPM and reliability programme for an API plant, using OEE as the designated measure in the Measure phase, Pareto analysis of runtime and downtime for current-state characterisation, and semi-structured voice-of-the-customer interviews across local and global engineering teams for requirement elicitation. Iqbal *et al.* ^[24] subsequently extended the same DMADV architecture with an explicit sustainability lens in a pharmaceutical setting. Mohad *et al.* ^[19] contribute the most statistically grounded work in the corpus, positioning statistical reliability analysis as the formal support for the planned-maintenance pillar — that is, deriving maintenance intervals from failure-time distributions rather than from calendar convention. Turanoglu Bekar ^[17] proposed a four-phase TPM performance-measurement system evaluated through an integrated fuzzy COPRAS and data envelopment analysis method, thereby treating TPM effectiveness as a multi-criteria efficiency problem rather than a single-ratio one. The distinguishing feature of this theme is that its outputs are transferable procedures rather than site-specific results, and that its evaluation extends beyond OEE to planned- and corrective-maintenance hours, cleaning time, availability hours and multi-criteria efficiency scores. Its limitation is the mirror image of its strength: the frameworks are verified through pilot deployment at a single site, often on a single critical asset, and their designers explicitly acknowledge the resulting constraint on generalisability ^[4]. Longitudinal evidence on whether the designed state persists after the project team disbands is absent across the entire theme.

4. Theme IV — Digital, statistical and sustainability extensions

Since 2021 the field's centre of gravity has moved towards the integration of TPM with Industry 4.0 capability. Tortorella *et al.* ^[6] surveyed 335 practitioners across sixteen countries and identified sixty-seven statistically significant pairings of Industry 4.0 technologies with TPM practices, controlling for socio-economic context, technological intensity and firm size; fostering operator ownership and the standardisation of autonomous-maintenance checks emerged among the practices most consistently coupled to digital adoption. Mouhib *et al.* ^[7] combined bibliometric mapping with systematic review to characterise digital TPM, identified the Internet of Things, artificial intelligence, digital twins and augmented reality as the principal enablers, and concluded that the decisive obstacle is the absence of a standardised, cross-industry model — existing approaches being fragmented or excessively context-specific. Wolska *et al.* ^[13] provide a consolidated account of implementation prerequisites and barriers.

In parallel, prediction has begun to replace retrospective measurement. Dobra and Jósvali ^[21] applied machine-learning models to forecast OEE in assembly processes, demonstrating that the indicator is amenable to short-horizon prediction rather than only to after-the-fact computation. Pavloudakis *et al.* ^[22] applied OEE as a productivity driver for continuous mining systems, one of the few treatments of a genuinely continuous,

environmentally coupled operation. On the sustainability axis, Chen *et al.* ^[20] examined TPM and lean manufacturing as antecedents of sustainable manufacturing, Samadhiya and Agrawal ^[18] validated TPM's relationship with economic, social and environmental performance through partial least squares structural equation modelling, and Zehra *et al.* ^[14] integrated OEE into a holistic efficiency-and-sustainability assessment in automotive manufacturing. Gupta and Vardhan ^[15] had earlier established the joint optimisation of OEE, productivity and production cost through TPM, anchoring the economic argument.

This theme uses the widest range of data: multi-country practitioner surveys, bibliometric corpora, sensor and machine-log time series, and structural-model survey instruments. Its evaluation metrics correspondingly diversify to include partial correlations, path coefficients, prediction error and multi-criteria efficiency scores. Its advantage is methodological plurality and larger effective

sample sizes; its limitation is that the empirical work is concentrated in discrete manufacturing and in firm-level perceptual data, so the predictive and structural results have not been demonstrated on continuous-process plant data. The unresolved challenge the theme itself names is standardisation ^[7].

Critical Review of the Two Base Papers

The two base studies are both peer-reviewed Elsevier articles set in process plants and both report OEE outcomes, yet they occupy opposite positions on the methodological spectrum identified in Section 4 — one a design-science framework study, the other a diagnostic pre–post case study. Comparing them therefore exposes the field's structural trade-off between transferability and simplicity. Table I sets out the comparison, and Fig. 3 plots the plant-level trajectory reported by Base Paper B.

Table 1: Critical Comparison of the Two Base Papers

Criterion	Base Paper A — Shannon, Trubetskaya, Iqbal & McDermott (2023), <i>Heliyon</i> 9(10), e20516	Base Paper B — Irfan, Rafiquzzaman & Manik (2025), <i>Heliyon</i> 11(3), e42057
Research objective	To establish the requirement for, and the relationship between, TPM and Reliability-Centred Maintenance in an Active Pharmaceutical Ingredient plant, and to design and verify a deployable maintenance framework with OEE as its governing measure.	To diagnose why a cement plant's OEE sits well below the 85% world-class benchmark, identify and prioritise the dominant production-loss causes, and raise productivity using lean tools.
Methodology	Design for Lean Six Sigma executed through the DMADV cycle. Pareto analysis of runtime and downtime in the Measure phase; semi-structured voice-of-the-customer interviews with local and global engineering teams; design and pilot verification on a critical asset.	Diagnostic-then-intervention lean case study. Cause-and-effect diagrams and Pareto charts to rank root causes of inefficiency, operator training, then deployment of TPM together with 5S and recomputation of OEE machine by machine.
Dataset	Process runtime, downtime and plant availability metrics for a single API site, combined with qualitative interview data; centrifuge area used as the pilot bed.	Plant production and breakdown records: baseline OEE of 65.57% (Sept 2022) and 65.43% (Oct 2022); post-intervention OEE of 67.75% (Nov 2023) and 68.49% (Dec 2023); Pareto breakdown data for the vertical roller mill and ball mill.
Experimental design	Design-science single-site deployment with a verification phase; no control asset or control period; qualitative and quantitative strands triangulated.	Uncontrolled pre–post comparison of two baseline months against two post-intervention months separated by more than a year; no control line.
Reported results	33% reduction in planned maintenance activities; 70% reduction in corrective maintenance; 50% reduction in cleaning for maintenance; 20% OEE increase in the centrifuge pilot area; plant availability increased by 206 hours.	Average OEE raised from approximately 65.5% to approximately 68.5%; machine-level breakdown time reduced after TPM implementation; root causes ranked as motor damage, bearing damage, vibration and absent 5S practice.
Strengths	Transferable procedural architecture; OEE embedded as a designed measure rather than an afterthought; multi-dimensional outcome set spanning maintenance labour, cleaning and availability; explicit integration of reliability logic; regulated continuous-process setting closely analogous to other process industries.	Transparent, reproducible diagnostic chain from Pareto ranking to intervention; machine-resolved OEE reporting; genuinely heavy continuous-process context; open access with usable baseline figures for benchmarking.
Weaknesses	Requirement elicitation is process-industry dependent and therefore exposed to respondent bias; the headline 20% OEE gain is reported for one pilot asset and not for the plant; no statistical testing of the pre–post difference; loss decomposition is not carried to the level of the six loss classes.	Only two of the eight TPM pillars are meaningfully exercised (effectively autonomous maintenance and workplace organisation); the six big losses are not decomposed; no reliability metrics such as MTBF or MTTR; no cost–benefit or energy analysis; the absolute gain of roughly three percentage points leaves OEE far from benchmark.
Limitations acknowledged / inferred	The authors explicitly identify the single-site case-study design as the limiting condition on generalisability.	Baseline and post-intervention windows are separated by more than twelve months, leaving demand, feedstock, grade-mix and seasonal effects uncontrolled; sustainability of the gain is unverified.
Resulting research gap	The framework is designed and verified but not replicated across sites or sectors, not sustained longitudinally, and does not model which pillar drives which OEE component; condition-monitoring data streams are not integrated.	TPM is applied as a toolkit rather than a sequenced programme; no formal model, no loss-class attribution, no failure-time analysis, and no forecasting or interval optimisation.
Potential improvements	Replicate the DMADV architecture across multiple process sectors; substitute quantitative loss decomposition and criticality analysis for the interview-heavy Analyse phase; test pillar-to-component linkages statistically; extend verification over several production campaigns.	Extend to a phased multi-pillar roadmap; adopt a controlled, multi-period longitudinal design; integrate CMMS and sensor data for condition-based triggers; quantify economic and specific-energy impact alongside OEE.

Three observations follow from the comparison. First, the two studies are not competing explanations of the same phenomenon but complementary halves of an incomplete method: Paper A supplies a deployment architecture without deep loss diagnostics, while Paper B supplies loss diagnostics without a deployment architecture. Neither delivers both, and the literature reviewed in Section 4 contains no study that does. Second, the magnitude asymmetry between the two — a 20% pilot-asset OEE gain

against a three-point plant-level gain — is not evidence that DMADV is superior, because the units of analysis differ; conflating pilot-asset and plant-level effect sizes is a recurrent interpretive error in this literature and is one reason cross-study comparison remains unsound [2]. Third, both studies report availability-side improvements far more confidently than performance-rate improvements, reproducing at the level of the base papers the corpus-wide bias identified in Section 4.2.

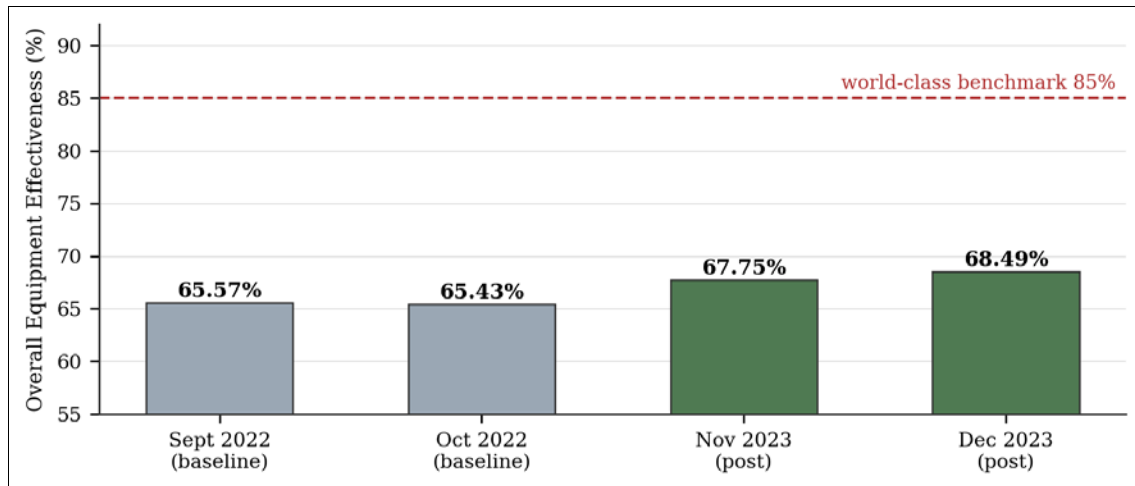


Fig 3: Plant-level OEE reported by Base Paper B before and after lean and TPM deployment in a cement plant, set against the conventional 85% benchmark. Data from Irfan *et al.* [5]; the baseline and post-intervention windows are separated by more than twelve months, which is the study's principal internal-validity constraint.

On the balance of transferability, methodological explicitness and multi-dimensional measurement, Paper A [4] is the stronger foundation for extension, and Paper B [5] serves as the process-industry benchmark and counterfactual against which a more rigorous design can be contrasted.

Comparative Analysis of Existing Studies

Table II consolidates the principal empirical and synthesis studies discussed in Section 4. Fig. 4 summarises the resulting profile of the corpus. The heterogeneity visible across the Evaluation-metrics column is itself a finding: only a minority of studies report anything beyond OEE and its three components, and almost none report both an effectiveness measure and a reliability measure for the same asset.

Table 2: Comparative Analysis of Representative Studies (2021–2026, with Seminal Anchors)

Author / Year	Method	Dataset / source	Variables & features	Evaluation metrics	Main results	Limitations
Nakajima (1988) [1]	Conceptual codification of TPM and OEE	Japanese plant practice	Six big losses; eight pillars	OEE ($A \times P \times Q$)	Established the loss taxonomy and the 85% benchmark still in use	Discrete-assembly origin; no statistical validation
Muchiri & Pintelon (2008) [2]	Critical literature review and application discussion	Published OEE literature	Loss classification; time-base definitions	Construct validity; metric comparability	Traced OEE's evolution into TEEP, PEE, OFE, OPE and OAE variants	No primary empirical data
Ng Corrales <i>et al.</i> (2020) [3]	PRISMA systematic review and bibliometrics	186 screened articles from WoS and Scopus	Keywords; author and country networks	Publication and citation counts	Confirmed rapid growth and a shift from measurement to implementation themes	Bibliometric only; no plant-level validation
Tsarouhas (2019) [9]	Longitudinal failure and repair data analysis	15 months of daily data, continuous croissant line	Scheduled vs unscheduled interruptions	A, P, Q and daily OEE	Identified maintenance-improvement potential with speed and minor-stoppage losses dominant	Single line; observational, no intervention
Tortorella <i>et al.</i> (2021) [6]	Practitioner survey with partial correlation analysis	335 respondents, 16 countries	I4.0 technologies $\times$ TPM practices; firm size, sector, context	Partial correlations under controls	67 significant technology–practice pairs; operator ownership and standardised AM checks prominent	Perceptual firm-level data; no OEE measurement
Marinho <i>et al.</i> (2021) [16]	Tool- and framework-selection case study	Cork-industry SME equipment data	Equipment malfunction modes; stoppage causes	OEE; equipment availability	Selected a framework to evaluate malfunctions and raise OEE in an SME setting	SME-specific; limited generalisability

Singh <i>et al.</i> (2021) ^[8]	Analytical review of OEE integration	Published OEE and improvement literature	OEE linkages to strategic improvement tools	Construct integration criteria	OEE best used as a common dependent variable across improvement tools	Conceptual; no empirical test
Khalili <i>et al.</i> (2023) ^[12]	Pre-post statistical case study (SPSS, Excel)	Batching-plant breakdown records, Malaysia	Breakdown time; A, P, Q	OEE before and after PPM	Demonstrated PPM effects on availability, performance efficiency and quality rate	Single firm; non-conforming outcome not fully explained
Turanoglu Bekar (2023) ^[17]	Fuzzy COPRAS integrated with DEA	TPM performance-measure set	Novel TPM performance measures across four phases	Multi-criteria efficiency scores	Proposed a four-phase TPM performance-measurement system	Method-centric; limited industrial replication
Shannon <i>et al.</i> (2023) ^[4] (Base A)	Design for Lean Six Sigma, DMADV	API plant runtime, downtime, availability; engineering interviews	Planned vs corrective maintenance; cleaning time; reliability and criticality	OEE; maintenance hours; availability hours	33% less planned and 70% less corrective maintenance; 20% OEE gain on pilot asset; +206 availability hours	Single site; interview-dependent; no statistical testing
Mohad <i>et al.</i> (2024) ^[19]	Statistical reliability analysis of the planned-maintenance pillar	Equipment failure-time records	Failure distributions; maintenance intervals	Reliability functions; operational excellence indicators	Positioned statistical reliability as formal support for planned maintenance	Pillar-specific; OEE linkage not fully modelled
Samadhiya & Agrawal (2024) ^[18]	PLS-SEM, resource-based view	326 survey responses, manufacturing firms	TPM constructs; economic, social, environmental performance	Path coefficients; model fit	Validated TPM's relationship with multi-dimensional sustainability performance	Perceptual data; no equipment-level measurement
Dobra & J3svai (2024) ^[21]	Supervised machine learning	Assembly-process production data	Historical OEE and process features	Prediction error on forecast OEE	Showed OEE is predictable at short horizon rather than only retrospective	Discrete assembly; not validated on continuous plants
Pavloudakis <i>et al.</i> (2024) ^[22]	OEE-driven productivity analysis	Continuous mining system operating data	Availability, utilisation and productivity of continuous systems	OEE; system productivity	Applied OEE as a productivity driver in a continuous, coupled operation	Sector-specific; limited transfer to process manufacturing
Irfan <i>et al.</i> (2025) ^[5] (Base B)	Lean diagnostic case study (Pareto, cause-effect) with TPM and 5S	Cement plant production and breakdown records, 2022 and 2023	Motor and bearing damage; vibration; 5S practice; A, P, Q	Plant and machine-level OEE; breakdown hours	OEE raised from about 65.5% to about 68.5%; breakdown time reduced per machine	Uncontrolled pre-post windows over a year apart; only two pillars exercised
Mouhib <i>et al.</i> (2025) ^[7]	Bibliometric analysis plus systematic review	58 relevant publications on digital TPM	IoT, AI, digital twin and AR enablers; pillar transformation	Thematic and network indicators	Identified enablers and proposed a four-pillar TPM 4.0 deployment framework	Framework not empirically deployed; standardisation still open

Read across the table, three patterns are robust. Studies with large samples measure perceptions rather than equipment ^[6, 18]; studies that measure equipment have samples of one ^[4, 5, 9, 12, 16]. Predictive and multi-criteria methods have matured

but remain untested on continuous-process data ^[17, 21]. And no row reports a quantified link between an individual TPM pillar and a specific OEE component.

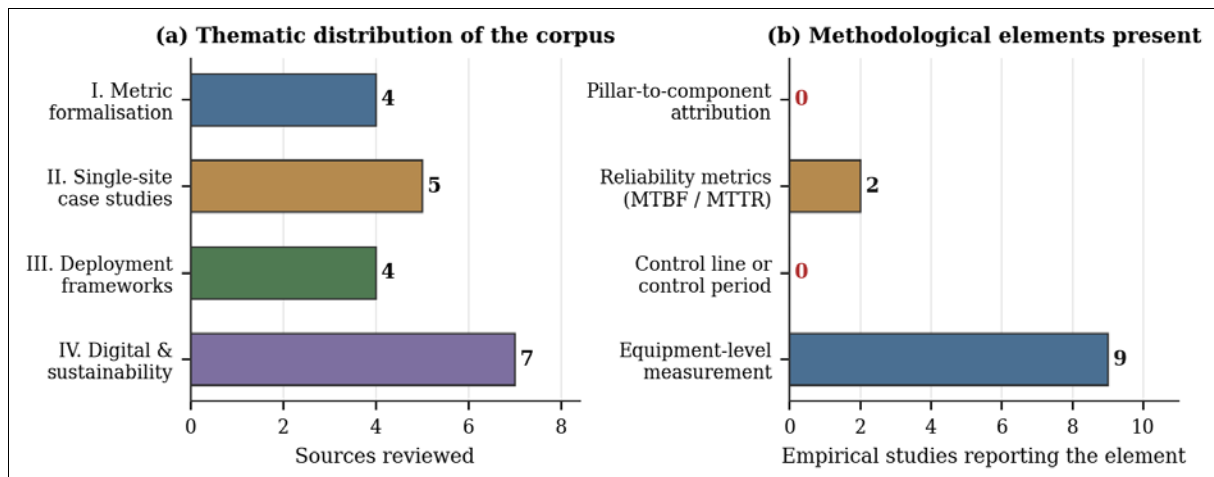


Fig 4: Profile of the reviewed corpus: (a) distribution of sources across the four themes of Section 4; (b) count of the empirical studies in Table II reporting each methodological element. The two zero counts correspond directly to the gaps formalised in Section 7.

Research Gaps

Of the several deficiencies exposed above, two are both specific enough to be actionable and central enough to the present research title to warrant formal statement.

Gap 1 — Methodological and causal-attribution gap

The prevailing evidence for TPM's effect on OEE rests on uncontrolled, single-site, pre–post comparisons in which a bundle of interventions is deployed simultaneously and a composite indicator is recomputed afterwards. This design cannot separate the intervention effect from concurrent variation in demand, feedstock quality, product mix and season, and the problem is acute where baseline and post-intervention windows are widely separated in time, as in [5]. It equally cannot attribute the observed change to any individual pillar, because autonomous maintenance, 5S, planned maintenance and training are introduced together [4, 5, 16]. The literature consequently offers practitioners no evidence-based sequencing rule, and the theoretically motivated prioritisation implied by OEE's multiplicative structure — attack the smallest term first — is never operationalised. Statistical reliability analysis has been advanced for one pillar in isolation [19] and structural modelling has been applied to firm-level perceptions [18], but no study joins equipment-level loss data to a pillar-attribution model. This is a methodological gap with a causal-inference core, and it is the reason the field's case studies do not accumulate.

Gap 2 — Process-industry contextualisation and generalisability gap

OEE's loss taxonomy, time-base conventions and machine-level scope were formalised for discrete repetitive production [1, 2], and the derivative metrics developed since have been validated principally in that setting [3, 23]. Process plants violate the underlying assumptions: assets are functionally coupled so machine-level effectiveness is not additive to plant throughput; ideal cycle time varies with grade, feedstock and thermal state rather than being constant; and cleaning, campaign changeover and regulatory validation occupy calendar time whose classification materially determines the reported availability [2, 4]. The digital and predictive advances that now define the frontier have been demonstrated on discrete assembly data [21] and on perceptual firm-level surveys spanning mixed sectors [6], while the one synthesis explicitly devoted to digital TPM names the absence of a standardised, cross-industry model as the field's decisive obstacle [7]. The result is a generalisability gap in two directions: process-industry findings are too site-specific to transfer, and the methodological frontier is too discrete-manufacturing-specific to import. Continuous-process evidence exists only in isolated pockets [5, 9, 22].

Future Research Directions

The directions below follow from the two gaps and are advanced as recommendations, not as established findings.

- Quasi-experimental designs for maintenance research. Interrupted time-series, difference-in-differences across parallel lines, or stepped-wedge rollouts across production units would allow the TPM effect to be separated from exogenous variation, without requiring randomisation that industrial settings cannot support.
- Pillar-to-component attribution modelling. Treating availability, performance rate and quality rate as separate dependent variables and pillar-maturity scores as predictors — through panel regression or structural models of the kind used at firm level by Samadhiya and Agrawal [18] — would convert pillar sequencing from practitioner judgement into an estimable question.
- Process-native effectiveness constructs. The line-, plant- and process-level extensions catalogued in [2, 3] and implemented in [23] should be validated against plant throughput in coupled continuous systems, with an explicit and published convention for classifying cleaning, changeover and validation time.
- Loss-resolved instrumentation of performance-rate losses. Because minor stoppages and speed losses dominate in continuous lines [9] yet are the least reliably captured by manual reporting, automated capture from SCADA, MES and CMMS streams is the prerequisite for credible performance-rate diagnostics [7].
- Transfer of predictive OEE methods to continuous plants. Short-horizon OEE forecasting demonstrated in assembly [21] should be re-estimated on process-plant time series, where autocorrelation, campaign structure and grade transitions alter the modelling problem substantively.
- Joint effectiveness–sustainability evaluation. Given the established TPM–sustainability relationship [18, 20] and the energy intensity of cement, chemical and pharmaceutical production, specific energy consumption and emissions per tonne should be reported alongside OEE rather than separately from it [14].
- Longitudinal persistence studies. No reviewed study re-measures OEE after the improvement team disbands; multi-year follow-up would test whether designed states are sustained and would discriminate genuine capability building from project-period effects [4, 18].

Proposed Research Framework

The proposed framework is a four-stage architecture that retains the deployment discipline of Base Paper A while supplying the loss-diagnostic depth and causal identification that both base papers lack. Fig. 5 presents its architecture; it is a conceptual design to be tested, not a validated result.

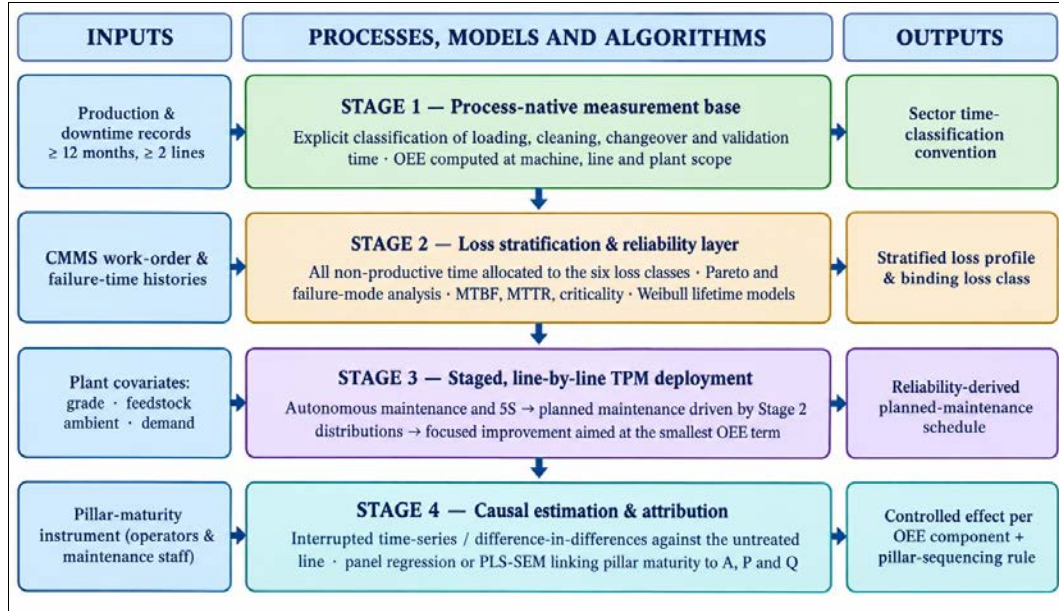


Fig 5: Proposed four-stage research framework linking input data streams, staged methods and models, and the resulting outputs. Stages 2 and 4 supply the loss resolution and causal identification absent from both base papers.

Inputs: Three streams are required: (i) historical production and downtime records at shift or hourly resolution for at least twelve months across two or more parallel or comparable process lines, providing both the baseline and the control series; (ii) CMMS work-order histories yielding failure and repair times for reliability estimation; and (iii) plant context variables — grade or campaign identity, feedstock quality indicators, ambient conditions and demand loading — to serve as covariates. A pillar-maturity instrument, administered periodically to operators and maintenance staff, supplies the predictor series.

Processes and Methods: Stage 1 establishes a process-native measurement base: loading time, cleaning, changeover and validation time are classified against an explicitly published convention, and OEE is computed at machine, line and plant level so that coupling effects are visible [2, 3, 23]. Stage 2 performs loss stratification, allocating all non-productive time to the six loss classes and computing MTBF, MTTR and criticality per asset, which supplies the reliability layer advocated by Mohad *et al.* [19] and absent from Base Paper B. Stage 3 deploys TPM in a staged, line-by-line sequence — autonomous maintenance and 5S first, then planned maintenance informed by the Stage 2 failure-time distributions, then focused improvement targeted at the smallest OEE term — following the DMADV discipline of Base Paper A [4] but with quantitative rather than interview-led analysis. Stage 4 performs causal estimation.

Models and Algorithms: Pareto and failure-mode analysis for loss ranking; Weibull or comparable lifetime models for failure-time characterisation and maintenance-interval derivation [19]; interrupted time-series or difference-in-differences estimation with the untreated line as control for the treatment effect; panel regression or PLS-SEM relating pillar-maturity scores to each OEE component separately

[18]; and, as an extension, short-horizon OEE forecasting to test whether process-plant series are predictable in the manner demonstrated for assembly [21].

Variables and features: Dependent — availability, performance rate, quality rate and composite OEE at three scopes. Independent — pillar-maturity scores, autonomous-maintenance task compliance, planned-maintenance adherence, training hours and 5S audit scores. Reliability — MTBF, MTTR and asset criticality. Covariates — grade, feedstock, ambient and demand variables. Economic and environmental — maintenance cost, specific energy consumption and yield.

Outputs: A published time-classification convention for the sector; a stratified loss profile identifying which loss class binds the plant; a reliability-derived planned-maintenance schedule; a controlled estimate of the TPM effect on each OEE component; and an evidence-based pillar-sequencing recommendation.

Evaluation Metrics: Absolute and relative change in each OEE component with confidence intervals; the difference-in-differences estimate against the control line; MTBF and MTTR shifts; explained variance and path significance in the attribution model; forecast error for the predictive extension; and maintenance cost and specific energy consumption per tonne of saleable output.

Expected Contribution: If the framework performs as designed, it would deliver the first controlled, loss-resolved estimate of TPM's effect on individual OEE components in a continuous-process plant, together with an empirically grounded pillar-sequencing rule — addressing Gap 1 — and a process-native measurement convention that makes results comparable across process sites, addressing Gap 2. The contribution is methodological as much as empirical: it

converts a literature of non-cumulative case reports into a design that other plants can replicate and against which their results can be compared.

Discussion

Synthesising across the four themes, the field displays a characteristic and instructive asymmetry. Its conceptual layer is mature: the loss taxonomy, the multiplicative structure of OEE and the pillar architecture of TPM are stable, well-theorised and now embedded in a resource-based account of capability^[18]. Its methodological layer is not. The modal study remains an uncontrolled pre–post case report, and the accumulation of such reports has produced breadth without cumulative knowledge, because effect sizes computed under incompatible time-base conventions cannot be pooled^[2] and interventions deployed as bundles cannot be decomposed.

A second implication concerns where improvement is actually being found. Across the corpus, gains are reported predominantly on the availability axis, which is also the axis best served by existing shop-floor reporting. Tsarouhas^[9] and the metric-critique literature^[2, 8] both indicate that in continuous production the binding constraint is more often the performance rate, where minor stoppages and speed losses accumulate invisibly. The reasonable inference — advanced here as an interpretation rather than a demonstrated result — is that the literature's availability bias is partly an artefact of measurement capability rather than a property of process plants, and that instrumented performance-rate capture would relocate a substantial share of the improvement opportunity.

Third, the digital turn has changed the field's claims faster than its evidence. Tortorella *et al.*^[6] establish that Industry 4.0 technologies and TPM practices are jointly adopted in a structured way, and Mouhib *et al.*^[7] map the enabling technologies comprehensively, but both are synthesis or survey studies; the demonstrated gains remain concentrated in discrete manufacturing. For a process plant, the practical implication is that digital augmentation should be introduced as an instrumentation layer supporting classical loss diagnosis, not as a substitute for the organisational work of autonomous maintenance — a reading consistent with the finding that operator ownership and standardised autonomous-maintenance checks are precisely the practices most tightly coupled to successful digital adoption^[6].

Finally, the sustainability linkage has strengthened the case for TPM without yet altering how effectiveness is measured. Established results connect TPM to environmental and economic performance at firm level^[18, 20] and integrate OEE into broader efficiency assessments^[14], yet effectiveness and energy intensity are still reported in separate studies. In energy-intensive process sectors this separation is untenable, since availability recovery achieved through more frequent hot restarts can raise OEE and specific energy consumption simultaneously. Joint reporting is therefore recommended, and it is a recommendation rather than a finding: no reviewed study has yet tested the trade-off directly.

Conclusion

This review examined how TPM implementation has been linked to OEE enhancement in process industries, organising the evidence thematically around metric formalisation, single-site diagnostics, structured deployment frameworks and digital, statistical and sustainability extensions. The established findings are clear in outline: TPM deployment is consistently associated with reduced breakdown time and improved availability across sectors^[4, 5, 11, 12, 16]; structured design architectures such as DMADV produce more transferable and multi-dimensional outcomes than tool-led interventions^[4, 17, 19]; and TPM is now credibly theorised as an organisational capability with measurable sustainability consequences rather than as a maintenance toolkit^[18, 20].

The unresolved problems are equally clear. The dominant research design cannot support causal inference or pillar-level attribution, and the measurement conventions underpinning OEE were not built for coupled continuous plants, which together constitute the methodological–causal gap and the process-industry generalisability gap formalised in Section 7. Against these, the proposed framework contributes a staged, controlled and loss-resolved design that couples process-native OEE measurement with reliability statistics and an explicit pillar-to-component attribution model, evaluated across multiple lines and periods with sustainability indicators reported alongside effectiveness.

The expected contribution is to move the field from demonstrating that TPM improves OEE — which the literature has amply established — to explaining which pillar improves which component, by how much, under what plant conditions, and for how long. That shift is what would make process-industry TPM research cumulative. The framework and the directions in Sections 8 and 9 are proposals awaiting empirical test, and are stated as such.

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