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Advanced Machine Performance Management Using OEE and Deep-Loss Analysis: A Framework for Saudi Manufacturing Competitiveness under Vision 2030

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Abstract*- Saudi Arabia's manufacturing ambitions under Vision 2030 require factories to convert installed capacity into reliable, high-quality and resource-efficient output rather than depend mainly on additional capital equipment. Overall Equipment Effectiveness (OEE) remains one of the most widely used measures for exposing availability, performance and quality losses, yet the literature shows that an aggregate OEE score can conceal the mechanisms that actually create lost capacity [1–4]. This review develops an advanced machine performance management framework that combines OEE with deep-loss analysis, defined here as a structured decomposition of OEE losses into event, duration, frequency, causal, economic and operational layers. Thirty sources published from 2020 to 2025 were critically synthesized, covering OEE theory, total productive maintenance, Lean 4.0, predictive maintenance, digital twins, machine learning, real-time shop-floor monitoring and Saudi industrial transformation [5–30]. The review finds that effective performance management depends on three transitions: from periodic OEE reporting to trusted event-level data; from six-loss categorization to causal and value-weighted prioritization; and from isolated corrective actions to closed-loop learning supported by analytics and governance. The proposed framework links machine signals, standardized OEE calculation, loss trees, causal analysis, intervention portfolios and verification of sustained gains. It is tailored to Saudi manufacturing by connecting factory-level outcomes to productivity, localization, quality, resilience and advanced-manufacturing objectives under Vision 2030. and workforce capability development at scale.

Keywords: overall equipment effectiveness; deep-loss analysis; machine performance management; total productive maintenance; predictive maintenance; Lean 4.0; Saudi manufacturing; Vision 2030

I. INTRODUCTION

Manufacturing competitiveness is increasingly determined by how effectively plants convert time, equipment, materials and technical knowledge into saleable output. In high-capital industries, relatively small losses in machine availability or cycle performance can propagate into missed delivery windows, overtime, excessive work-in-process and poor return on invested assets. OEE addresses this problem by combining availability, performance and quality into a single indicator and by linking those dimensions to the familiar categories of equipment loss [1,2]. Research since 2020 nevertheless shows that the usefulness of OEE depends less on the percentage itself than on the discipline used to define time states, collect data, interpret losses and convert findings into improvement action [2,3]. Inconsistent definitions, manual recording and arbitrary exclusions can make two plants with similar physical performance report materially different OEE values.

The recent literature therefore shifts attention from OEE as a retrospective score toward OEE as part of a broader performance-management system. Studies have extended OEE into cost-sensitive, value-added and resource-oriented measures, while others combine it with machine learning, energy analytics, digital twins and real-time monitoring [14,18–24]. These approaches respond to a practical weakness of aggregate measurement: a low score indicates that effectiveness is being lost, but it does not by itself explain which event patterns, operating conditions or organizational decisions are responsible. Even the six traditional loss categories can remain too coarse when breakdowns, micro-stops, reduced speed or defects have multiple subcauses with different recurrence rates and economic consequences.

This review uses the term deep-loss analysis for a multi-layer diagnostic process that drills beneath OEE and conventional loss categories. The concept does not replace OEE. Instead, it treats OEE as the performance boundary and then decomposes each loss into equipment state, event code, duration, frequency, product, shift, operating condition, causal mechanism and value impact. Such decomposition is increasingly feasible because connected shop-floor systems can combine PLC signals, machine-state data, maintenance records, quality results, energy traces and production context [19,22,23]. The managerial challenge is to prevent data abundance from producing dashboard abundance without operational learning.

The Saudi context makes this challenge strategically important. Vision 2030 emphasizes a more competitive industrial base, localization, higher-value manufacturing and adoption of advanced production technologies [29,30]. National initiatives are encouraging factories to adopt automation, analytics and Fourth Industrial Revolution capabilities. These investments create value only when they improve stable throughput, quality, cost and resilience. An OEE-centered framework enriched by deep-loss analysis can translate digital investment into measurable operational priorities, while also supporting disciplined capability building across maintenance, production, quality and engineering functions.

It also offers a common performance language across plant hierarchies: operators can act on events, engineers can investigate mechanisms, managers can allocate resources by value at risk, and executives can connect equipment performance to capacity, service and competitiveness.

II. AIM AND OBJECTIVES

The aim of this review is to develop a rigorous machine performance management framework that integrates standardized OEE measurement with deeper causal analysis of manufacturing losses and aligns improvement priorities with Saudi industrial competitiveness under Vision 2030. Rather than asking only how OEE can be increased, the study examines how loss information can be made more diagnostic, economically meaningful and actionable across technical and managerial levels.

Four objectives guide the review. First, it evaluates recent evidence on OEE measurement, extensions and implementation limitations, including ambiguity in time-state definitions and the risk of treating benchmark values as universal targets [1–4]. Second, it synthesizes methods for decomposing availability, performance and quality losses into granular causal structures using TPM, root-cause analysis, lean methods and digital analytics [13–20]. Third, it identifies the roles of real-time monitoring, predictive maintenance, machine learning, digital twins and data-oriented shop-floor management in moving from loss reporting toward anticipation and control [21–28]. Fourth, it translates these findings into a Saudi-oriented implementation framework that links machine-level improvement to productivity, localization, resource efficiency, resilience and workforce capability [29,30].

III. REVIEW METHODOLOGY

A structured integrative review was adopted because the research question spans performance measurement, maintenance, industrial engineering, digital manufacturing and national industrial policy. The design combines literature synthesis, thematic classification and contextual interpretation to construct an analytical framework, while avoiding claims of new causal evidence because no primary survey data are generated directly within this review. Searches focused on literature published from 2020 through 2025, consistent with the requested recency window. Search concepts combined "overall equipment effectiveness", "OEE", "six big losses", "total productive maintenance", "machine performance", "Lean 4.0", "predictive maintenance", "digital twin", "machine learning", "shop-floor analytics", "Saudi manufacturing" and "Vision 2030". Sources were retained when they made a direct contribution to at least one of four analytical domains: OEE definition or measurement; loss identification and improvement; digital or predictive performance management; or Saudi industrial transformation. Priority was given to peer-reviewed journal articles with methods and operational implications. Official

Saudi strategy and industrial-development sources were included only to contextualize national objectives, not to substitute for technical manufacturing evidence. Studies outside the 2020–2025 publication window, papers with only incidental mention of OEE, and sources lacking sufficient methodological or bibliographic information were excluded from the analytical set. The final synthesis uses the thirty references listed in this paper.

Analysis proceeded in four stages. First, evidence was coded according to OEE measurement, loss structure, improvement method, digital enabler and outcome. Second, recurring limitations were compared, including inconsistent time definitions, excessive aggregation, weak causal attribution, static benchmarking and poor linkage between losses and financial value [1–4,14,18]. Third, enabling approaches were grouped into intervention families: TPM and lean routines, statistical and causal analysis, machine-learning prediction, digital-twin simulation and real-time data architectures [5–28]. Finally, the findings were integrated with Saudi industrial priorities to build a framework linking measurement, diagnosis, prioritization, execution and sustainment [29,30]. Because this is a review and conceptual synthesis, no new production data, experimental effect sizes or causal claims are introduced. Conclusions are limited to patterns supported by the reviewed sources. This approach preserves a distinction between evidence strength and framework design. Empirical case studies inform mechanisms, reviews establish research themes, and policy documents define contextual relevance. Where studies use different OEE conventions or sector-specific extensions, the synthesis compares their underlying logic rather than forcing equivalence across settings.

IV. OEE AS THE PERFORMANCE FOUNDATION

OEE remains valuable because it expresses three fundamentally different routes through which productive capacity disappears. Availability represents the proportion of scheduled production time during which equipment is capable of running; performance compares actual production speed with the ideal rate; and quality represents the share of output produced correctly the first time. Their multiplicative relationship prevents a strong result in one dimension from masking weakness in another [1,2]. The same logic maps naturally to the six classic equipment losses: breakdowns and setup losses affect availability; minor stops and reduced speed affect performance; and process defects and startup losses affect quality [8,13,15].

Recent research, however, cautions against using OEE as a universal ranking number. Schiraldi and Varisco show that even formal manufacturing standards can create ambiguity if equipment states and time categories are not defined coherently [2]. Cheah et al. similarly argue that OEE improvement requires an integrated implementation framework rather than isolated calculation [3]. Case evidence confirms that OEE is most useful when the factors are connected to explicit operational losses and improvement routines [4,8,13]. Accordingly, a credible system begins with a loss-accounting constitution: planned production time, excluded time, ideal cycle time, good-count rules, changeover boundaries, micro-stop thresholds and downtime reason codes must be governed consistently.

A second limitation is aggregation. A monthly OEE of 70% can result from very different patterns: one catastrophic failure, hundreds of short stops, chronic slow cycles, excessive setup duration or high rework. These patterns have different owners, risks and remedies. Hung et al. extend this argument by showing that conventional OEE can overlook hidden capacity embedded in the assumed ideal cycle and propose a value-added perspective [14]. Stefana et al. add a cost dimension, demonstrating the usefulness of translating equipment losses into monetary consequences and resource consumption [18]. Such work indicates that the next generation of performance management should preserve the interpretability of OEE while making losses traceable to value.

For Saudi manufacturers, this distinction matters because rapid industrial expansion may create pressure to add capacity before existing capacity is fully understood. A disciplined OEE layer provides a consistent baseline for utilization and loss visibility. Deep-loss analysis then determines whether improvement should focus on maintenance, setup engineering, cycle optimization, quality control, operator capability, material flow or system design. OEE therefore functions best as the front door to diagnosis, not as the final diagnosis itself.

Measurement discipline protects programs from gaming. If teams can redefine time, ideal speed or quality when results deteriorate, the metric loses comparability and accountability. Stable definitions ensure changes in OEE reflect operations rather than reporting. practices.

V. FROM SIX LOSSES TO DEEP-LOSS ANALYSIS

The six-loss structure is a useful decomposition because it links OEE factors to operational phenomena. Its weakness is that each category can contain different mechanisms. A breakdown may be caused by bearing wear, sensor contamination, software faults, poor lubrication, unstable utilities, incorrect operation or delayed maintenance response. Minor stops may originate from feed interruptions, guarding interlocks, product misalignment, material variation or upstream starvation. Reduced speed can reflect conservative settings, tool degradation, thermal instability, operator behavior or a bottleneck outside the measured asset. Treating these events as one category can lead to broad actions that improve reporting discipline without eliminating the dominant mechanism.

Deep-loss analysis extends the hierarchy in five directions. The first layer is event granularity. Every loss should be described by a standardized reason hierarchy that separates symptom, subsystem and mechanism. A "machine stop" code, for example, has little diagnostic value; a hierarchy such as stop–feed system–sensor false trigger creates a pathway for ownership and recurrence analysis. The second layer concerns temporal structure. Duration alone can mislead: a single 120-minute breakdown and 120 one-minute micro-stops produce the same lost time but require different countermeasures. Frequency, mean duration, recurrence interval, time-of-shift and sequence position should accompany total minutes.

The third layer is contextual segmentation. Losses should be analyzed by product family, tooling, recipe, shift, crew, raw-material lot, ambient condition and preceding machine state where relevant. Research on human performance and new technology adoption shows that learning and configuration effects can influence apparent equipment effectiveness [7]. Machine-learning work demonstrates that patterns hidden in production data can support OEE prediction and assembly-performance analysis [20]. Contextual segmentation prevents the organization from blaming the machine for variation produced by surrounding process conditions.

The fourth layer is causal depth. Root-cause analysis should distinguish correlation from mechanism and should move from Pareto ranking toward testable causal statements. Raju et al. demonstrate value in separating availability, performance and quality losses, while TPM research shows how association rules and network analysis can expose relationships between OEE factors and operational variables [13,27]. A practical sequence is to identify the dominant loss, stratify it, test likely mechanisms with engineering evidence, implement a targeted countermeasure and verify whether the event signature changes. This avoids the common failure mode in which teams generate long lists of possible causes but do not establish which causes explain the observed pattern.

The fifth layer is value weighting. Minutes of lost capacity are not economically equal. A ten-minute stop on a constrained line during peak demand may matter more than a longer stop on a non-bottleneck asset. Quality losses may also carry scrap, rework, warranty or customer-service consequences that exceed their direct time effect. Cost-oriented OEE extensions and hidden-capacity research support integrating loss duration with throughput constraint, conversion cost, energy, material loss and service risk [14,18]. Deep-loss prioritization should rank opportunities by a combination of recoverable capacity, recurrence probability, economic impact, implementation effort and strategic importance.

This approach changes the management question from "Why is OEE low?" to "Which recurring mechanisms destroy the most recoverable value, under which conditions, and which intervention will remove them without creating another loss?" That question is more demanding, but it creates a bridge between measurement and engineering action. It also enables learning across machines: once loss signatures, causal mechanisms and proven countermeasures are codified, factories can reuse knowledge instead of repeatedly solving the same problem locally.

Table 1. Deep-loss expansion of conventional OEE loss categories.

OEE dimension	Conventional loss	Deep-loss variables	Diagnostic emphasis	Typical improvement levers
Availability	Breakdowns	Subsystem, fault code, duration, recurrence, condition trend	Failure mechanism and response latency	Basic conditions, preventive/predictive maintenance, spares, redesign
Availability	Setup and adjustment	Product change, tool, step time, first-cycle stability	Internal vs external setup and adjustment source	SMED, presetting, tooling, standard work, parameter control
Performance	Minor stops	Event frequency, duration bands, sensor/interlock, starvation/blockage	Chronic micro-loss patterns and sequencing	Sensor correction, material flow, autonomous maintenance, logic changes
Performance	Reduced speed	Actual/ideal cycle, product, operator, tool wear, temperature	Speed loss by context and constraint position	Process optimization, tooling, training, control limits
Quality	Process defects	Defect mode, parameter window, material lot, machine state	Causal links between process condition and defect	Quality-at-source, parameter control, predictive quality, mistake proofing
Quality	Startup/yield loss	Warm-up, first-off count, changeover, stabilization time	Ramp-up learning and process stabilization	Startup standards, recipe control, training, engineering changes

VI. DIGITAL ENABLERS FOR MACHINE PERFORMANCE MANAGEMENT

Digitalization strengthens OEE only when data architecture improves the reliability, speed and depth of loss decisions. Mouhib et al. propose real-time OEE monitoring as a digital framework in which production and quality data are collected continuously, calculated consistently and presented to relevant users [22]. Data-oriented shop-floor research likewise emphasizes automated acquisition, accessibility and timely KPI visualization [23]. These capabilities address a long-standing problem with manual OEE systems: event duration may be estimated, short stops may go unrecorded, reason codes may be entered after the event, and production context may not be synchronized with machine state.

A robust architecture separates raw signals from governed performance semantics. PLC states, counters, alarms, cycle signals, energy meters and condition sensors form the event layer. Manufacturing execution, maintenance and quality systems provide contextual records such as work order, product, shift, tool, defect and maintenance action. A semantic layer then converts these sources into standardized equipment states and OEE calculations. This separation is important because raw connectivity does not guarantee trustworthy KPIs; the same sensor event can be interpreted differently if business rules are inconsistent.

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Predictive maintenance adds an anticipatory dimension. Reviews of Industry 4.0 maintenance show that machine learning can support fault detection and prognosis, but practical performance depends on data quality, integration, latency, scalability and context awareness [5,6]. Instead of using prediction as a separate maintenance project, the proposed framework connects predictive signals to the OEE loss tree. A rising failure probability should be translated into expected availability loss, production exposure and an intervention decision. This allows maintenance optimization to compete for resources on the same value basis as setup, speed or quality improvements.

Digital twins offer a complementary capability. Reviews describe digital twins as synchronized virtual representations that support monitoring, simulation and optimization of industrial operations [9–12]. For OEE management, their strongest role is not decorative visualization but counterfactual testing: managers can examine how altered maintenance intervals, buffers, speeds, changeover rules or failure scenarios may affect equipment and system performance before changing the physical process. Recent research specifically links digital-twin integration with OEE and Lean 4.0 [24]. Used with disciplined data governance, these tools can shift performance management from reporting what was lost toward predicting what may be lost and testing how best to prevent it.

Machine learning can also support prioritization after losses occur. Pattern discovery across event combinations, shifts, products and operating ranges can reveal interactions that are difficult to detect through isolated Pareto charts. However, model output should remain subordinate to engineering validation, because predictive accuracy without interpretability can direct action toward proxies rather than mechanisms.

VII. INTEGRATED OEE–DEEP-LOSS MANAGEMENT FRAMEWORK

The framework organizes machine performance management as a closed loop. Figure 1 summarizes six linked layers: data foundation, OEE measurement, loss decomposition, causal diagnosis, intervention management and sustained control. Skipping a layer creates predictable failure modes: poor data produces disputed OEE, aggregated OEE produces vague priorities, untested causes produce generic actions, and unverified actions produce temporary gains.

The data foundation establishes machine-state integrity. Automated signals should capture run, stop, idle, fault, setup and production counts while contextual systems supply product, order, shift, maintenance and quality information. Reason-code design should minimize free text and encourage rapid classification at the point of work. Governance should specify ownership for the data dictionary, ideal cycle-time master, planned-time rules and code changes. This creates a stable measurement contract across production, maintenance, quality and finance.

The OEE layer converts governed events into availability, performance, quality and composite OEE. The objective is to identify the magnitude and location of losses. The next layer expands the result into a structured loss tree. Each OEE factor is decomposed into loss families, equipment subsystems, event codes and contextual segments. Frequency-duration matrices are useful because they distinguish chronic micro-losses from infrequent catastrophic events. A Pareto of minutes should be supplemented by counts, variability, recoverable capacity and value impact.

Causal diagnosis then tests why dominant losses occur. Methods can include five-why analysis, fault trees, change-point analysis, statistical comparison, process capability studies, association-rule mining and predictive models, Lucantoni et al. demonstrate how association rules and network analysis can reveal hidden relationships within OEE factors and support TPM prioritization [27]. Predictive-quality and predictive-maintenance research adds tools for identifying degradation or process conditions before the loss becomes visible in output [5,6,17].

Intervention management translates validated causes into an improvement portfolio. Actions should be classified by control type: restore basic conditions, eliminate source causes, reduce exposure, detect earlier, automate response or redesign the process. Each action should specify owner, expected loss

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reduction, implementation effort, operational risk and verification metric. Lean, SMED and TPM practices remain relevant because many losses are organizational or mechanical rather than algorithmic [3,4,16,27,28]. Digital technologies should augment these routines by improving visibility, prediction and feedback rather than replacing disciplined problem solving.

Finally, sustained control compares post-action loss signatures with the baseline. Improvement is accepted only when the targeted loss decreases without transferring loss into another OEE factor or downstream process. Control charts, recurrence monitoring, standard-work audits and model-drift checks can support sustainment. Proven countermeasures are then codified into maintenance standards, setup parameters, training materials and engineering specifications. This feedback converts local problem solving into organizational knowledge and progressively raises the performance baseline.

Figure 2 translates the closed loop into a four-stage maturity roadmap for Saudi factories. Stage one establishes trusted data and definitions. Stage two creates loss visibility and accountable daily management. Stage three integrates predictive and causal analytics. Stage four connects machine performance to network capacity, cost, energy and strategic manufacturing goals. The roadmap allows plants to sequence investment according to operational maturity instead of purchasing advanced technology before foundational measurement practices are stable. This makes decisions auditable, repeatable and comparable across factories over time.

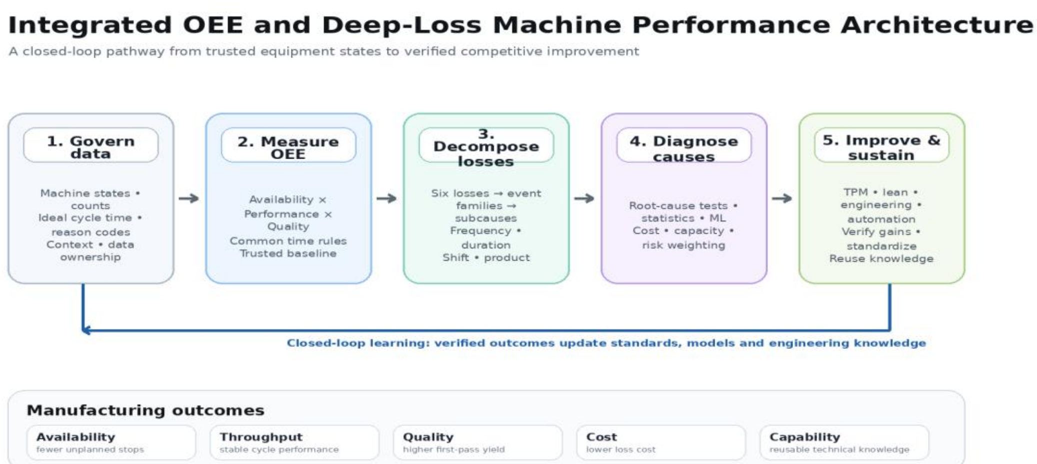

Figure 1. Integrated OEE and deep-loss machine performance management architecture.

VIII. SAUDI MANUFACTURING COMPETITIVENESS UNDER VISION 2030

Saudi industrial policy gives machine performance management a wider strategic meaning than plant-level efficiency alone. The Vision 2030 Annual Report highlights localization, industrial capability, automation and high-value manufacturing as central elements of a more competitive industrial base [29]. Complementary national initiatives promote advanced manufacturing, digital transformation and Fourth Industrial Revolution adoption, including programs intended to move traditional factories toward smarter operating models [30]. These priorities imply that productivity improvement should not be treated only as cost reduction; it is also a mechanism for releasing capacity, improving quality, strengthening delivery reliability and building technical capabilities that support localization.

OEE provides a useful bridge because it translates technical losses into a common operational language. Availability improvement supports resilience and asset utilization. Performance improvement raises throughput without necessarily adding equipment. Quality improvement reduces material waste, rework and instability. Deep-loss analysis makes these outcomes more actionable by identifying whether the constraint is mechanical reliability, setup design, operating discipline, tooling, process capability, material variability, upstream flow or data quality. In a localization context, such detail matters because local production cannot become globally competitive merely by moving production geographically; it must achieve stable cost, quality and delivery performance. The framework is particularly relevant to Saudi plants undergoing rapid automation. Digital investment can create a temporary gap between technical capability and organizational capability. New sensors, connected machines and analytical platforms may increase available information faster than teams develop standardized definitions, reason codes and improvement routines. Human-performance research shows that ramp-up and learning effects influence OEE during technology adoption [7]. A maturity-based approach therefore prioritizes data governance, operator involvement and engineering ownership alongside automation.

Deep-loss management also supports sustainability objectives without turning OEE into an environmental metric. Energy, material and scrap consequences can be attached to loss events as secondary impact measures. Thiede demonstrates that energy data can support OEE prediction, while cost- and resource-oriented extensions show how equipment inefficiency can be translated into economic consequences [18,19]. This allows a Saudi factory to prioritize a chronic speed loss not only because it reduces throughput, but because it may also increase energy per good unit and operating cost.

At the ecosystem level, consistent performance management can strengthen benchmarking and capability transfer across industrial sites. Standard loss taxonomies, common OEE definitions and reusable countermeasure libraries make it easier to compare factories without oversimplifying local conditions. The strategic value is therefore cumulative: better machines create more reliable lines; reliable lines support stronger plants; and stronger plants contribute to a more competitive, localized and technologically capable manufacturing base. under Vision 2030.

Table 2. Maturity-oriented implementation framework for Saudi manufacturing plants.

Stage	Primary focus	Minimum management controls	Analytical capability	Core performance evidence	Strategic contribution
1. Trusted foundation	Consistent equipment-state data and OEE rules	Time-state dictionary, ideal-cycle master, reason-code ownership	Descriptive OEE and data-quality checks	Data completeness, OEE by A/P/Q, unclassified loss	Reliable baseline and workforce discipline
2. Loss visibility	Granular decomposition and accountable daily management	Loss hierarchy, owner assignment, recurrence review	Pareto, frequency-duration, segmentation	Top losses, recurring events, recoverable capacity	Productivity and quality improvement
3. Predictive control	Anticipation of failure, speed and quality degradation	Model governance, alert ownership, validation rules	Condition monitoring, ML, predictive quality, scenario analysis	Lead time to intervention, avoided downtime, stable cycle/quality	Resilience and advanced-manufacturing capability

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Stage	Primary focus	Minimum management controls	Analytical capability	Core performance evidence	Strategic contribution
4. Competitive orchestration	Portfolio optimization across assets and sites	Value weighting, cross-site standards, knowledge reuse	Constraint analysis, digital twins, cost/energy integration	Capacity value, cost per good unit, energy per good unit	Localization, sustainability and global competitiveness

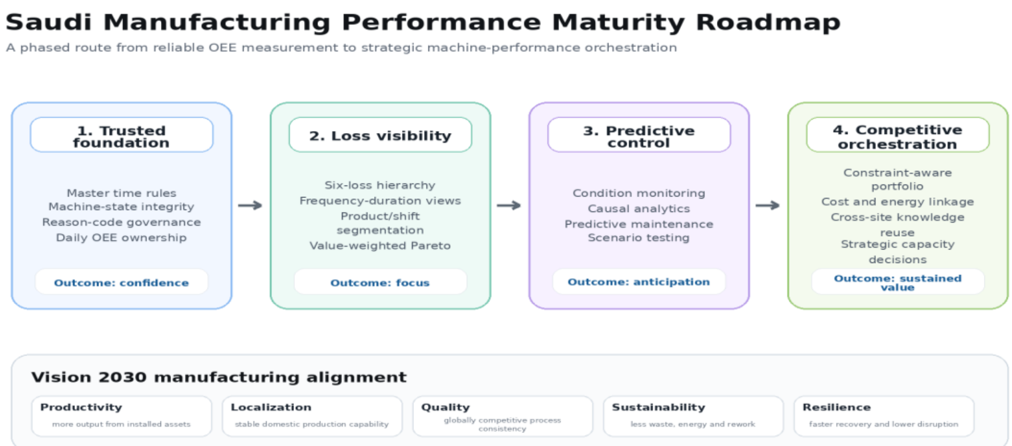

Figure 2. Maturity roadmap linking machine performance management to Saudi manufacturing competitiveness.

IX. DISCUSSION AND MANAGERIAL IMPLICATIONS

The reviewed evidence suggests that the problem in machine performance management is not a shortage of metrics but a shortage of causal resolution. OEE is effective at compressing complex production behavior into three interpretable dimensions, yet compression inevitably removes detail. The managerial task is therefore to use aggregation for control and disaggregation for action. Plants that stop at the headline percentage risk creating target-driven behavior in which teams optimize reporting boundaries, chase small losses that are easy to fix, or invest in technology without addressing basic equipment conditions.

A second implication concerns the relationship between lean practices and digital technologies. The literature does not support a simple substitution logic in which analytics replaces TPM, SMED, standard work or structured problem solving. Instead, Lean 4.0 research indicates a synergistic relationship between lean principles and Industry 4.0 technologies [24]. Data-driven TPM studies reach a similar conclusion: advanced analytics can improve prioritization and reveal hidden interactions, but the realized gain still depends on maintenance standards, kaizen actions and organizational follow-through [27]. For managers, the sequence is “stabilize, digitize, diagnose, optimize,” with iteration where necessary.

Third, deep-loss analysis requires decision rights. A maintenance team cannot eliminate every OEE loss because some losses originate in planning, product design, tooling, quality, procurement or operator methods. Loss ownership should therefore follow causal ownership rather than the department that records the event. Cross-functional daily management can use the same loss tree while assigning actions to the function able to change the mechanism. Fourth, performance improvement should be portfolio-based. The largest loss by minutes is not always the best project. Management should compare recoverable capacity, constraint position, financial impact, implementation cost, recurrence, safety implications and strategic relevance. A portfolio approach also balances quick wins with structural changes. Short setup reductions can release capacity, while redesigning a recurrent failure mode may require engineering investment but protect reliability.

Finally, maturity matters. Plants with unreliable event data should not begin with predictive models. Plants with stable measurement but weak causal routines should strengthen loss stratification and problem solving. Plants with mature data and governance can exploit machine learning and digital twins for anticipation and scenario testing. This staged logic reduces technology waste and makes digital transformation accountable to operational outcomes.

X. LIMITATIONS AND FUTURE RESEARCH

This review has three limitations. First, the evidence base is restricted to 2020–2025, which improves relevance but excludes earlier studies that established TPM and OEE theory. Second, the reviewed research spans different sectors, production modes and OEE conventions. Direct numerical comparison of reported OEE values or improvement percentages would therefore be inappropriate without harmonized definitions. The framework focuses on transferable mechanisms rather than pooled effect estimates. Third, Saudi-specific peer-reviewed evidence on OEE and deep machine-loss structures remains limited; national policy sources establish strategic context but do not provide plant-level validation.

Future research should test the framework longitudinally in Saudi factories across discrete, batch and process manufacturing. Studies should compare conventional six-loss prioritization with event-level deep-loss analysis and examine whether the latter produces faster, more persistent or more economically valuable improvement. Research should also evaluate causal inference methods for machine-event data, digital-twin-supported counterfactual testing, and approaches for integrating cost, energy, carbon and service impact without destroying the simplicity of OEE. A further priority is workforce research: digital loss systems should be assessed for operator usability, reason-code accuracy, problem-solving participation and trust. Finally, cross-factory benchmarking requires shared semantic definitions so that performance comparisons reflect operational differences rather than inconsistent measurement rules.

XI. CONCLUSION

OEE remains a foundation for machine performance management because it connects time, speed and quality losses in a compact operational measure. The literature reviewed here nevertheless shows that the headline percentage is insufficient for manufacturing environments where losses are distributed across equipment, people, materials, software, utilities and organizational decisions. The proposed deep-loss approach preserves OEE while extending it into event granularity, temporal pattern, contextual segmentation, causal diagnosis and value weighting.

The framework is a closed-loop management architecture. Trusted data establish a measurement contract; OEE identifies the performance gap; loss trees locate the dominant patterns; engineering and analytical methods test mechanisms; intervention portfolios allocate resources; and sustained control verifies whether gains persist. Digital technologies create value when they strengthen this loop through real-time monitoring, prediction, simulation and knowledge reuse. They are most effective when combined with TPM, lean methods and cross-functional problem solving rather than treated as substitutes for operational fundamentals.

For Saudi manufacturing, the framework provides a connection between factory performance and Vision 2030. Recovering hidden capacity, stabilizing output, improving first-pass quality, reducing resource loss and developing technical problem-solving capability can strengthen competitiveness without relying on new equipment. A maturity-based implementation path also helps factories sequence digital investment around operational readiness. The central proposition is straightforward: sustainable competitiveness is created not by measuring OEE more frequently, but by understanding losses more deeply and converting that understanding into repeatable operating improvements.

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