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Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management

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Abstract

This study examined the integration of Manufacturing Execution Systems, SAP enterprise applications, and PI Historian platforms for real-time industrial asset performance management. A multisite, retrospective longitudinal, quasi-experimental quantitative design was employed across 18 asset-intensive industrial facilities. The study covered 48 consecutive months, comprising 24 preintegration and 24 postintegration months. Propensity-score matching produced 600 comparable assets, divided equally between high-integration and partial- or fragmented-integration conditions. The final dataset contained 28,224 asset-month observations, 4,286 verified failures, 52,614 condition alerts, 8,932 maintenance notifications, and 8,147 work orders. Data were analyzed using mixed-effects regression, negative-binomial modeling, difference-in-differences estimation, interrupted time-series analysis, survival analysis, recurrent-event modeling, mediation, moderation, and sensitivity testing. High-integration facilities achieved 92.4% interface automation, 99.3% transaction success, 98.7% asset-mapping accuracy, 98.8% data completeness, and 94.1% event traceability. After adjustment for asset, operational, maintenance, facility, and baseline characteristics, high-integration assets recorded a 32% lower failure rate, IRR = 0.68, 95% CI [0.61, 0.75], p < .001, and 51% lower repeated-failure odds, OR = 0.49, 95% CI [0.39, 0.62], p < .001. Mean time between failures increased by 2,310 hours, while mean time to repair declined by 3.08 hours. Availability increased by 2.18 percentage points, overall equipment effectiveness increased by 4.96 percentage points, and annual unplanned downtime declined by 55.1 hours per asset. Throughput attainment increased by 5.04 percentage points, quality yield increased by 1.36 percentage points, annual maintenance cost decreased by USD 12,600 per asset, and annual production-loss value declined by USD 45,800 per asset. High-integration assets experienced a 44% lower failure hazard and achieved a median failure-free duration of 8,420 hours. Real-time information visibility and maintenance responsiveness mediated 53.4% of the integration–performance relationship. The findings established that coordinated MES–SAP–PI Historian integration was associated with improved reliability, maintainability, availability, production continuity, quality performance, and economic control.

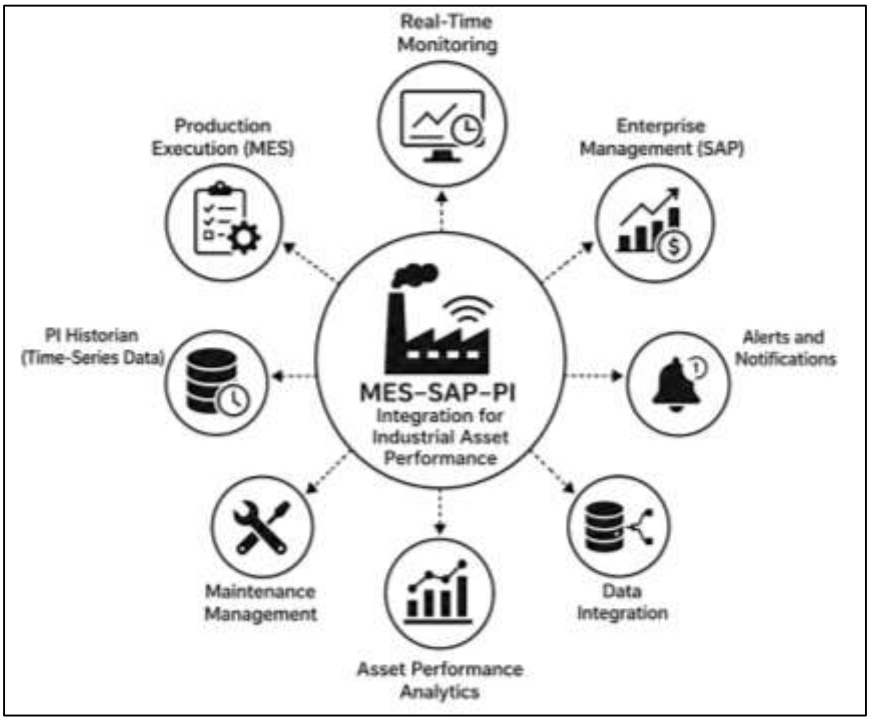
Keywords

MES, SAP, PI Historian, Integration, Reliability.

INTRODUCTION

Manufacturing Execution Systems (MES) are integrated information systems positioned between industrial control technologies and enterprise-level planning applications to coordinate, document, monitor, and control manufacturing activities as they occur on the production floor. MES commonly supports production-order dispatching, resource allocation, work-in-process tracking, equipment-status monitoring, labor management, quality control, material genealogy, process enforcement, downtime recording, and performance reporting. Its principal function is to translate enterprise production plans into executable shop-floor activities while returning verified operational results to higher-level business systems (Mantravadi & Møller, 2019). Systems, Applications, and Products in Data Processing (SAP), within the context of industrial asset management, refers to an enterprise resource planning environment through which organizations manage production planning, procurement, inventory, finance, quality, plant maintenance, workforce resources, and asset-related costs. SAP provides the transactional and administrative record for materials, maintenance orders, bills of materials, equipment hierarchies, purchase requisitions, production schedules, and financial settlements. A PI Historian, commonly represented by the AVEVA PI System, is a specialized industrial data infrastructure used to collect, timestamp, compress, contextualize, retain, and retrieve high-frequency time-series data generated by programmable logic controllers, distributed control systems, supervisory control and data acquisition systems, sensors, analyzers, meters, and other operational technologies. Industrial asset performance management denotes the coordinated measurement and control of asset availability, reliability, maintainability, utilization, productivity, quality, safety, energy performance, lifecycle cost, and operational risk (Iarovyi et al., 2016). Real-time management describes the availability of validated operational information within a sufficiently short latency period to support active production, maintenance, and reliability decisions. It does not necessarily mean zero-delay processing because acceptable latency varies according to the asset, process, measurement frequency, and decision requirement. Platform integration refers to the technical, semantic, procedural, and organizational connection of MES, SAP, and PI Historian data so that production events, equipment conditions, maintenance activities, material movements, and financial consequences can be examined through a common asset context. MES research has consistently characterized execution systems as the operational bridge between enterprise planning and shop-floor control, while enterprise-integration studies have emphasized communication, information consistency, process coordination, and interoperability across organizational levels (Jaskó et al., 2020). Related studies have situated integrated industrial information within broader smart-manufacturing environments in which connected assets continuously generate data for operational analysis and coordinated decision-making. The integration of MES, SAP, and PI Historian platforms can be understood through a layered industrial architecture in which each platform performs a distinct but interdependent function. At the control level, sensors, field instruments, programmable logic controllers, distributed control systems, and supervisory systems measure and regulate physical processes such as temperature, pressure, flow, vibration, speed, current, torque, and equipment state. The PI Historian receives these signals as time-series observations and preserves their timestamps, values, engineering units, status indicators, and data-quality attributes. At the manufacturing-operations level, MES connects physical asset behavior with production orders, batches, shifts, product types, recipes, operators, material consumption, quality inspections, and recorded causes of downtime (Helo et al., 2014). At the enterprise level, SAP manages planned production quantities, maintenance notifications, work orders, spare-parts reservations, purchase activities, asset master records, labor costs, material costs, inventory transactions, and financial reporting. Integrated operation requires bidirectional data movement rather than a one-directional transfer from machines to management. Production orders and asset schedules may move from SAP to MES, execution confirmations and material consumption may return from MES to SAP, high-frequency process measurements may move from control systems to the PI Historian, and selected historian events or calculated conditions may initiate alerts, investigations, or maintenance requests. Asset identifiers, equipment hierarchies, production-order numbers, timestamps, failure codes, batch numbers, and measurement units must remain consistent across platforms to preserve traceability (Menezes et al., 2018). Cyber-physical manufacturing research has described this arrangement as the connection of computational, communication, and physical components through feedback structures that link asset conditions with digital representations and operational actions. Studies of cyber-physical systems have also shown that connected manufacturing environments depend on synchronized sensing, standardized communication, distributed computation, and appropriate separation between control and enterprise functions. Research on industrial digitalization has further identified interoperability, vertical integration, horizontal integration, modularity, and real-time information availability as central characteristics of digitally coordinated production systems. The MES–SAP–PI configuration consequently represents a connected information architecture in which operational measurements, manufacturing execution records, and enterprise transactions are associated with the same assets, time periods, and production events (Mohammed et al., 2018).

Figure 1: MES–SAP–PI Integration Framework

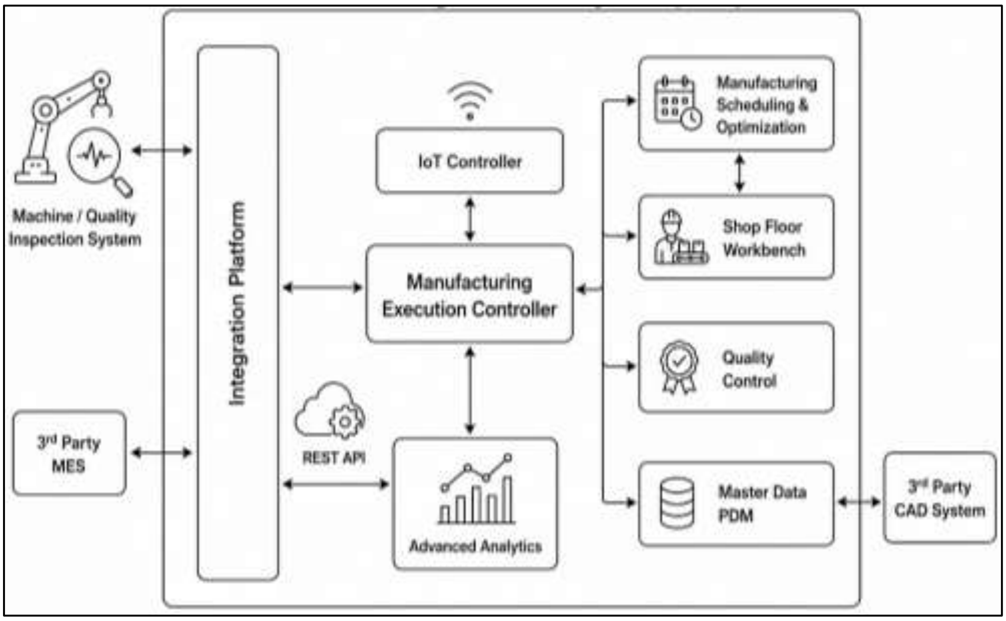


Industrial platform integration is fundamentally a data-management problem because the three platforms collect information at different frequencies, granularities, and organizational levels. PI Historian data may include measurements recorded every second or millisecond, whereas MES records are generally organized around production cycles, equipment events, batches, work centers, shifts, and production orders. SAP transactions are commonly recorded when a business event is confirmed, such as the creation of a maintenance notification, release of a production order, issue of a spare part, confirmation of labor hours, or settlement of maintenance expenditure. Integration requires these heterogeneous records to be aligned through common timestamps, asset identifiers, work-order references, material codes, product classifications, batch numbers, and organizational structures. Data integration quality refers to the completeness, accuracy, timeliness, consistency, accessibility, contextualization, and traceability of information exchanged across the platforms (Novák et al., 2019). Completeness concerns the proportion of required data fields and time intervals available for analysis. Accuracy concerns the correspondence between recorded information and the actual operational event. Timeliness concerns the delay between physical occurrence, digital capture, platform transmission, and user availability. Consistency concerns whether an asset, event, or production quantity has the same meaning across MES, SAP, and PI. Contextualization transforms isolated sensor tags into understandable information by associating measurements with assets, locations, products, operating states, and maintenance histories. Traceability preserves the sequence connecting a physical condition to an MES event, SAP transaction, and managerial decision. Studies of data-driven manufacturing have shown that the value of industrial data depends on contextual information, data preparation, governance, and analytical accessibility rather than data volume alone (Morariu et al., 2015). Large-scale industrial analytics research has similarly identified data heterogeneity, inconsistent semantics, fragmented ownership, missing observations, weak master-data control, and isolated analytical solutions as recurring restrictions in multi-plant environments. Smart-manufacturing studies have also explained that asset-level analytics requires reliable communication between physical equipment, execution applications, historical repositories, and enterprise systems. Within MES–SAP–PI integration, data-quality weaknesses may appear as unmatched equipment codes, incomplete downtime reasons, duplicated maintenance orders, incorrect time-zone settings, inconsistent units, delayed interfaces, missing sensor values, or differences between planned and confirmed production. These conditions can be quantitatively evaluated through interface success rates, synchronization latency, missing-data percentages, duplicate-record frequencies, asset-matching accuracy, transaction-reconciliation errors, data-availability rates, and user assessments of information reliability (Zant et al., 2020).

Industrial asset performance management combines technical reliability indicators with production, maintenance, quality, energy, safety, and financial measures. Availability represents the proportion of scheduled time during which an asset remains capable of performing its required function. Reliability describes the probability that equipment performs without failure during a defined operating period, commonly assessed through failure frequency, failure rate, mean time between failures, repeated-failure occurrence, and survival duration. Maintainability describes the speed and effectiveness with which failed or degraded equipment is restored, using measures such as mean time to repair, maintenance response time, troubleshooting duration, labor hours, spare-parts delay, and restoration success (Sellitto & Vargas, 2020). Utilization represents the extent to which available capacity is employed, whereas overall equipment effectiveness combines availability, performance efficiency, and quality output. Additional performance indicators include unplanned downtime, schedule adherence, production rate, throughput, yield, scrap, rework, maintenance cost, energy intensity, production-loss value, and deferred output. The integration of MES, SAP, and PI Historian platforms provides different components of these measures. PI supplies condition and operating data such as vibration, temperature, pressure, load, runtime, start-stop frequency, alarm duration, and process deviation. MES supplies production context such as planned and actual quantities, asset states, downtime categories, cycle times, product transitions, quality results, and shift information. SAP supplies maintenance and economic context through failure notifications, work-order histories, maintenance plans, spare-parts consumption, labor expenditure, contractor cost, and asset valuation (Cupek et al., 2016). Maintenance-performance literature has emphasized that no individual indicator adequately represents asset performance and that technical, operational, and economic measures should be interpreted through an integrated measurement structure. Condition-based maintenance research has established data acquisition, fault detection, diagnosis, degradation assessment, health-index construction, and remaining-useful-life estimation as connected analytical processes. Machine-learning investigations have also demonstrated the dependence of predictive-maintenance performance on sensor quality, failure labels, feature selection, validation design, and equipment-specific operating context. Real-time asset performance management consequently requires accurate linkage between the observed physical condition, its production consequences, the maintenance response, and the recorded economic outcome (Naedele et al., 2015).

The operational value of MES–SAP–PI integration depends on the degree to which platform connectivity changes information flows and work processes across production, maintenance, reliability, quality, engineering, and financial functions. A technically connected interface may transfer records successfully while users continue to maintain separate spreadsheets, duplicate asset registers, manually reconcile production quantities, or enter maintenance information after substantial delays. Integration capability consequently includes system connectivity, semantic alignment, process standardization, automated event transfer, analytical accessibility, user competence, governance quality, and cross-functional coordination. SAP may contain the official maintenance order, MES may contain the recorded downtime event, and PI may contain the condition pattern preceding the failure (Weißenberger et al., 2015). When the records are not linked through a consistent asset identity and synchronized event time, the organization possesses three forms of relevant information without a unified representation of the incident. Enterprise-system studies have reported that performance outcomes vary according to implementation scope, process fit, organizational interdependence, data standardization, user assimilation, and the complementary changes made to operating routines. Research comparing enterprise-system adopters and nonadopters found differences in operational and financial performance, while other studies showed that performance gains were associated with the integration of modules and the alignment of system functionality with organizational processes.

Figure 2: Integrated Manufacturing Execution Architecture



Plant-level investigations have demonstrated that enterprise-system outcomes are influenced by workflow interdependence, organizational differentiation, and the quality of post-implementation coordination. Empirical research has also connected enterprise information technology with reductions in order lead time and improved visibility across production activities (Kim et al., 2019). Studies examining management control and operational performance have reported that integrated enterprise information can strengthen formal measurement, planning, and performance-monitoring processes when the system is used consistently across functional areas. In an industrial asset environment, these mechanisms can be assessed through automated-data-transfer percentages, maintenance-notification response time, work-order closure time, production-confirmation accuracy, reconciliation duration, planning adherence, dashboard usage, decision latency, and the proportion of asset events containing complete production, condition, maintenance, and cost information. Organizational controls such as master-data ownership, interface monitoring, role-based access, validation procedures, change management, cybersecurity, and employee training form measurable dimensions of integration maturity (Mukherjee & Das, 2017).

The international significance of MES, SAP, and PI Historian integration arises from the global distribution of capital-intensive production, the complexity of multinational supply networks, and the dependence of industrial organizations on reliable assets and consistent operational information. Automotive plants require precise synchronization among production orders, robotic equipment, component genealogy, quality inspections, and maintenance interventions. Chemical and petrochemical facilities depend on continuous process measurements, alarm histories, equipment-condition data, permit requirements, and maintenance planning. Oil and gas operations use historical pressure, flow, temperature, vibration, and production data across geographically dispersed wells, pipelines, terminals, and processing facilities. Pharmaceutical and food manufacturers require batch traceability, controlled process conditions, quality verification, and documented production records

(Mukherjee & Mukherjee, 2017). Mining, metals, cement, pulp and paper, power generation, water treatment, and utility operations depend on long-lived assets for which failures can interrupt production, increase energy consumption, alter product quality, or create safety and environmental exposure. International manufacturing networks also contain substantial differences in plant age, automation maturity, data infrastructure, workforce capability, regulatory requirements, maintenance culture, and investment capacity. Empirical studies conducted across developed and emerging industrial economies have associated vertical integration, production connectivity, analytical capability, and digital manufacturing technologies with different dimensions of industrial performance. Research on Industry 4.0 adoption has shown that implementation patterns frequently progress through combinations of foundational and advanced technologies rather than through a uniform transformation across all facilities. Reviews of manufacturing digitalization have identified integration, process redesign, employee capability, financial resources, technological readiness, and organizational strategy as important sources of cross-country and cross-sector variation (Liptak & Eren, 2018). Smart-manufacturing frameworks have further described industrial integration through connected design, machining, monitoring, control, and scheduling functions, while categorical manufacturing research has distinguished different levels of automation, connectivity, intelligence, and system integration. The international evaluation of MES–SAP–PI integration must therefore account for facility size, industrial sector, production type, asset criticality, equipment age, automation level, operating exposure, regional infrastructure, regulatory intensity, and baseline performance. These factors affect both the configuration of integrated platforms and the reliability outcomes recorded across industrial locations.

Existing research provides extensive evidence on enterprise resource planning, manufacturing execution, industrial historians, cyber-physical systems, predictive maintenance, and smart manufacturing, yet these domains have often been evaluated as separate technological or organizational areas (Korodi & Silea, 2017). MES studies have concentrated on production control, traceability, scheduling, quality, work-in-process visibility, and shop-floor coordination. ERP research has examined financial performance, operational efficiency, process standardization, information integration, and organizational assimilation. Historian and industrial-analytics research has focused on time-series acquisition, process monitoring, data storage, condition analysis, fault detection, and equipment diagnostics. Predictive-maintenance studies have examined algorithms, sensor features, classification accuracy, prognostic performance, and remaining-useful-life estimation. This separation limits the empirical examination of the complete information chain through which asset conditions are detected in PI, contextualized through MES production records, converted into maintenance activities within SAP, and reflected in reliability and operational outcomes. Cyber-manufacturing research has emphasized the transformation of interconnected industrial data into predictive and prescriptive operational knowledge, while digital-twin research has demonstrated the importance of linking physical asset behavior with continuously updated digital information (Woodhead et al., 2018). Smart-manufacturing research has also identified connected data, model-based analysis, and integrated decision support as central components of intelligent industrial operations. Industry 4.0 maturity studies have shown that connectivity, vertical integration, information transparency, decentralized decisions, and organizational readiness represent distinguishable dimensions rather than a single technological condition. A quantitative examination of MES–SAP–PI integration can accordingly define platform-integration quality through system interoperability, data accuracy, synchronization timeliness, asset-context consistency, automation level, accessibility, and analytical functionality. Real-time information visibility can be measured through monitoring coverage, dashboard update frequency, alert timeliness, event traceability, data completeness, and decision-support quality. Industrial asset performance can be measured through availability, overall equipment effectiveness, failure frequency, mean time between failures, mean time to repair, unplanned downtime, maintenance cost, production loss, quality rate, schedule adherence, and energy efficiency (Gosewehr et al., 2016). Statistical analysis may evaluate the strength and direction of associations among platform integration, real-time visibility, maintenance responsiveness, and asset performance while controlling for asset age, asset category, plant size, operating exposure, production loading, criticality, maintenance strategy, sector, regional location, workforce capability, and baseline digital maturity. The empirical context centers on repeated, asset-level and facility-level observations derived from operational records, platform logs, performance databases, and structured assessments of users responsible for production, maintenance, reliability, engineering, information technology, and operational management (Hsiao & Lee, 2021).

The principal objective of this study is to quantitatively examine how the integration of Manufacturing Execution Systems, SAP enterprise applications, and PI Historian platforms influences real-time industrial asset performance management across production-intensive organizations. The study specifically evaluates platform-integration quality through system interoperability, automated data exchange, synchronization timeliness, asset-identity consistency, information accuracy, data completeness, event traceability, contextualization quality, analytical accessibility, and interface reliability. It assesses the extent to which integrated platforms create continuous information visibility by connecting high-frequency equipment and process measurements stored in the PI Historian with production orders, operating states, downtime events, material consumption, batch information, and quality records maintained in MES, as well as maintenance notifications, work orders, spare-parts usage, labor hours, asset costs, and financial transactions recorded in SAP. The study also measures real-time information visibility through monitoring coverage, dashboard-update frequency, alert timeliness, condition-data availability, cross-platform record matching, exception-reporting quality, and the speed with which operational information becomes available to production, maintenance, reliability, engineering, and management personnel. A further objective is to determine the relationship between MES–SAP–PI integration and major asset-performance outcomes, including equipment availability, overall equipment effectiveness, failure frequency, mean time between failures, mean time to repair, unplanned downtime, maintenance response time, production loss, maintenance expenditure, schedule adherence, throughput, quality yield, energy efficiency, and asset utilization. The study examines whether real-time information visibility mediates the relationship between platform integration and asset performance and whether maintenance responsiveness provides an additional mechanism through which integrated information affects equipment reliability and operational continuity. It further compares integration quality and performance outcomes across industrial sectors, facility sizes, production types, asset categories, asset-criticality levels, geographical locations, automation levels, and digital-maturity categories. The analysis controls for equipment age, operating exposure, production loading, environmental conditions, maintenance strategy, workforce capability, organizational readiness, data-governance quality, and baseline asset performance to reduce alternative explanations for observed differences. Additional objectives include identifying which dimensions of integration exert the strongest influence on reliability and operational performance, evaluating whether the relationships vary across high- and low-criticality assets, and determining whether greater interface automation is associated with lower synchronization delays, fewer reconciliation errors, faster maintenance decisions, and more complete failure-event records. Through these objectives, the study establishes a measurable framework for examining the technical, informational, operational, and organizational dimensions of MES–SAP–PI Historian integration within real-time industrial asset performance management.

LITERATURE REVIEW

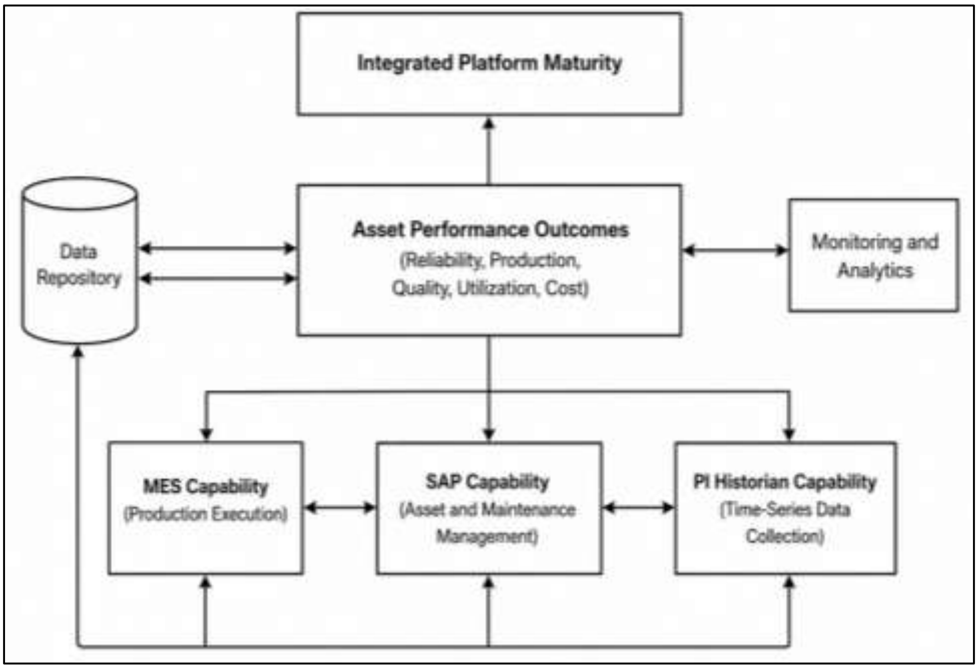
This literature review examines the quantitative foundations, integration mechanisms, operational capabilities, and performance outcomes associated with connecting Manufacturing Execution Systems, SAP enterprise applications, and PI Historian platforms for real-time industrial asset performance management. The review treats platform integration as a multidimensional industrial capability that extends beyond basic technical connectivity. It includes interface interoperability, automated data exchange, synchronization speed, asset-identity consistency, semantic compatibility, information completeness, data accuracy, event traceability, system availability, analytical accessibility, and cross-functional information visibility. MES provides detailed records of production orders, equipment states, cycle times, downtime events, material movements, quality inspections, work-in-process, and operational execution (Farrelly & Davies, 2021; Kanti, 2020). SAP provides enterprise information concerning asset master data, maintenance notifications, work orders, preventive-maintenance plans, spare-parts consumption, procurement activities, labor hours, maintenance expenditure, production planning, and financial settlement. The PI Historian captures and stores high-frequency time-series measurements from industrial equipment and processes, including pressure, temperature, vibration, flow, speed, current, runtime, alarm status, operating load, and process deviation. The literature review evaluates how these complementary data sources can be synchronized and contextualized to establish a unified representation of industrial asset conditions, production consequences, maintenance responses, and economic outcomes. Particular attention is given to measurable integration indicators such as data-transfer success rate, synchronization latency, missing-data percentage, interface availability, asset-record matching accuracy, reconciliation-error frequency, dashboard refresh time, alert-generation delay, and automated work-order initiation rate (Debasish, 2021; Lakshmanan et al., 2019). The review also examines major asset-performance measures, including failure frequency, mean time between failures, mean time to repair, availability, overall equipment effectiveness, utilization, unplanned downtime, repeated-failure probability, maintenance cost, production loss, throughput, quality yield, schedule adherence, and energy intensity. The synthesized structure considers real-time information visibility and maintenance responsiveness as potential explanatory mechanisms connecting platform integration with improved asset outcomes. It also recognizes that asset age, criticality, operating exposure, production loading, facility size, industrial sector, automation maturity, maintenance strategy, workforce capability, and data-governance quality may produce measurable differences in the strength of these relationships (Jeon et al., 2017; Abdur & Iftekhar, 2021). The following outline organizes the literature into specific quantitative dimensions that support construct development, variable measurement, hypothesis formulation, model estimation, and comparative analysis.

Quantitative Foundations of Integrated Industrial Platforms

Evidence synthesized from more than ten empirical studies conducted in discrete, continuous, batch, and hybrid manufacturing environments has characterized MES capability as a measurable production-execution function connecting enterprise production plans with actual shop-floor activities. Production-order accuracy has commonly been evaluated by comparing quantities, materials, routing instructions, start times, completion times, and resource assignments contained in released orders with the corresponding production requirements. High order-release accuracy indicates that production personnel and equipment receive complete and valid instructions, whereas frequent revisions, rejected orders, missing routing information, and incorrect material assignments indicate weak execution control (Mahmoud et al., 2015; Hossan, 2021). Dispatching performance has been measured through the time required to transmit approved orders to production resources and the proportion of orders initiated within their scheduled windows. Cycle-time visibility has been assessed through the percentage of production cycles automatically captured, differences between standard and actual cycle duration, frequency of extended cycles, and time required to identify process delays. Quantitative studies have also used actual-versus-planned production variance to determine whether MES-supported execution remains aligned with production schedules. Work-in-process traceability has been examined through the percentage of materials, units, batches, and production stages continuously identifiable within the manufacturing process. Equipment-state capture represents another important MES capability because accurate differentiation among running, idle, setup, blocked, starved, maintenance, and failed states determines the reliability of production and downtime calculations (Lee et al., 2014; Chowdhury & Tonay, 2022). Downtime-classification quality has been measured through the completeness of reason codes, percentage of automatically classified interruptions, frequency of unassigned events, and agreement between system-recorded and operator-confirmed causes. Batch traceability has been assessed through genealogy completeness, retrieval time, material-to-product linkage, and the percentage of batches reconstructed without missing records. Production-confirmation accuracy has been evaluated by comparing MES-recorded output, scrap, rework, consumption, and completion quantities with physical production and enterprise transactions. Collectively, these measures present MES capability as a combination of execution accuracy, process visibility, event capture, production control, and operational traceability (Cupek et al., 2016; Zahidul & Begum, 2022).

Evidence from international studies of enterprise asset management, maintenance information systems, and integrated manufacturing operations has shown that SAP capability extends beyond storing maintenance transactions because it provides a structured environment for planning, executing,

Figure 3: Integrated Industrial Platform Framework



monitoring, and financially controlling asset-related activities. Maintenance-notification completeness has been evaluated through the presence of equipment identifiers, functional locations, failure descriptions, priority classifications, damage codes, cause codes, reporting times, production consequences, and responsible work centers. Complete notifications provide the informational foundation for maintenance planning, whereas records lacking failure classifications, timestamps, or asset references weaken reliability analysis and cost attribution (Mesbaul, 2023; Morariu et al., 2016). Work-order creation time has been measured as the duration between failure detection or maintenance-request submission and the release of an executable maintenance order. Planning accuracy has been assessed by comparing estimated and actual labor hours, materials, tools, contractor requirements, task durations, and shutdown windows. Work-order completion performance has been examined through closure duration, schedule compliance, overdue-order percentage, confirmation delays, and the proportion of completed work supported by technical findings. Preventive-maintenance compliance has commonly been evaluated through the percentage of scheduled inspections and servicing activities completed within required time tolerances. Studies have also examined the ratio of preventive, predictive, and corrective work to determine whether maintenance activity is dominated by planned intervention or emergency repair (Borangiu et al., 2015; Badrul & Mominul, 2023). Labor-confirmation accuracy has been measured through differences between scheduled, reported, and verified work hours, while spare-parts transaction accuracy has been evaluated through material reservation success, stock availability, issue accuracy, return accuracy, and discrepancies between physical and recorded inventory. Procurement performance has been assessed through purchase-requisition processing time, supplier lead time, emergency-purchase frequency, and material-related work-order delay. Maintenance-cost visibility includes labor, materials, contractors, tools, production losses, and overhead assigned to equipment, orders, and functional locations. Asset-master-data quality has been measured through record completeness, duplicate frequency, hierarchical accuracy, classification consistency, and agreement between SAP assets and physical equipment (Borangiu et al., 2015). These indicators position SAP capability as an integrated combination of maintenance control, resource coordination, transactional accuracy, compliance monitoring, and economic visibility.

A synthesis of empirical studies in process manufacturing, energy, utilities, oil and gas, pharmaceuticals, mining, metals, and automated production has identified historian capability as the capacity to capture, preserve, contextualize, and retrieve industrial time-series data with sufficient accuracy and continuity for operational and asset-performance analysis. Tag coverage has been measured through the percentage of critical equipment connected to the historian, the proportion of required condition variables available, and the number of active measurement points associated with each asset. Broad tag coverage enables the observation of temperature, pressure, vibration, flow, speed, current, load, runtime, alarm status, operating mode, and process deviation (Mantravadi et al., 2020). The number of tags alone does not demonstrate effective monitoring because the relevance, calibration, contextualization, and reliability of collected signals also determine analytical value. Sampling frequency has been evaluated by comparing configured collection intervals with the speed of physical process changes and the informational requirements of fault detection, performance monitoring, and incident investigation. Inadequate sampling can exclude short-duration disturbances, while inconsistent intervals can weaken time-series comparisons. Data-loss frequency has been measured through missing intervals, communication interruptions, rejected values, failed interfaces, and unsuccessful recovery following network disruption. Historian availability has been evaluated through system uptime, ingestion continuity, archive accessibility, backup success, and service-restoration time. Timestamp accuracy is particularly important because equipment signals must be aligned with MES production events and SAP maintenance transactions. Studies have measured clock drift, timestamp deviation, out-of-sequence records, and disagreement between source and historian time (Arica & Powell, 2014). Storage continuity has been evaluated through archive completeness, retention duration, recovery success, and the availability of historical observations across the asset lifecycle. Compression accuracy has been assessed by comparing stored trends with original measurements and determining whether diagnostically important variations remain visible after data reduction. Retrieval capability has been measured through query-response time, dashboard loading speed, concurrent-user performance, and the duration required to access long observation periods. Successful ingestion rate, data-quality status, engineering-unit consistency, and tag-to-asset mapping accuracy have also been used to determine whether historian information is suitable for integrated performance management (Mabkhot et al., 2016).

Research synthesized across more than twenty industrial information-system, maintenance, reliability, and production-performance studies has treated MES–SAP–PI integration maturity as a multidimensional capability rather than a simple indication that interfaces exist. Interface automation has been measured through the percentage of production, equipment, maintenance, material, quality, and cost records transferred without manual entry. Higher automation reduces repeated data entry, although its effectiveness depends on validation rules, exception handling, and record consistency. Bidirectional exchange has been evaluated through the successful movement of plans and master data from SAP to MES, execution results from MES to SAP, condition measurements from PI to operational applications, and maintenance or production context returned to analytical environments. Asset-mapping accuracy has been measured through the percentage of equipment tags, MES resources, SAP equipment numbers, and functional locations associated with the same physical asset (Dhungana et al., 2021). Functional coverage has been evaluated through the number and proportion of production, maintenance, quality, material, and financial processes supported by integrated information. Interface standardization has been assessed through common data structures, naming conventions, failure codes, engineering units, timestamp rules, and communication protocols. Cross-platform traceability has been measured through the percentage of failure events that can be followed from an abnormal PI signal to an MES downtime record, SAP notification, maintenance order, resource consumption, restoration confirmation, and final cost. The operational outcome of this maturity has been examined through availability, failure frequency, mean time between failures, repair duration, unplanned downtime, repeated failures, and restoration success. Production-related outcomes have included overall equipment effectiveness, asset utilization, throughput, schedule adherence, cycle-time stability, quality yield, scrap, and production-loss volume (Zhang et al., 2019). Economic outcomes have included maintenance expenditure, labor cost, spare-parts cost, downtime cost, cost per operating hour, and production-loss value. The reviewed evidence also shows that performance differences are associated with asset age, criticality, loading, operating exposure, maintenance strategy, workforce capability, and data-governance quality. Integrated platform maturity is therefore quantitatively represented by connectivity, automation, consistency, traceability, and information quality, while asset performance is represented by coordinated reliability, maintainability, production, quality, utilization, and cost measures (Răileanu et al., 2017).

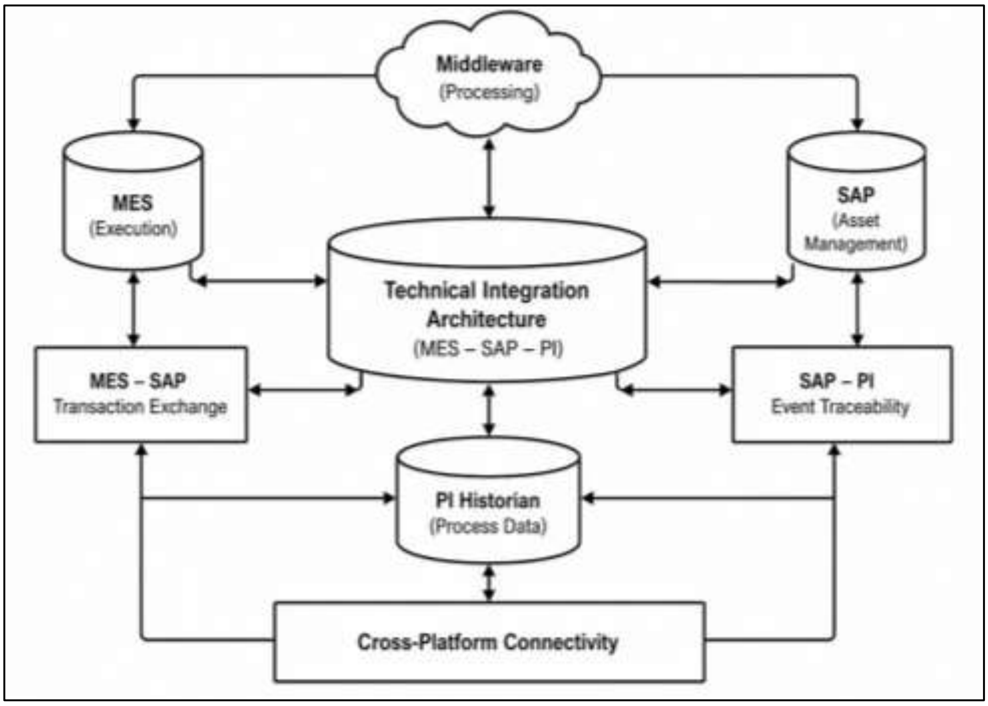
Technical Integration Architecture and Interface Performance

Evidence synthesized from more than ten empirical studies of enterprise–manufacturing integration has identified MES–SAP interface performance as a central determinant of production-information continuity. The interface normally transfers production orders, routing instructions, bills of materials, resource requirements, planned quantities, scheduling information, quality specifications, and material reservations from SAP to MES. MES returns actual production quantities, scrap, rework, consumed materials, labor confirmations, equipment usage, order status, completion times, and quality results. Transaction success has been measured through the percentage of messages received, validated, processed, and posted without manual correction. Rejected-message frequency has been examined according to missing mandatory fields, invalid material codes, incorrect equipment identifiers, unavailable production versions, incompatible units, and violated validation rules (Adhikari et al., 2021). Duplicate-record rates have been used to determine whether interface retries create repeated confirmations, material postings, or production transactions. Confirmation accuracy has been evaluated by comparing MES results with physical production output, operator records, inventory movements, and SAP postings. Synchronization latency has been assessed as the elapsed time between creating or changing information in one platform and making the updated record available in the other. Greater delays can cause MES to execute outdated orders, SAP to display incomplete production progress, or planners to use inaccurate inventory information. Reconciliation effort has been measured through staff hours required to compare records, number of unresolved differences, frequency of manual adjustments, and time required to correct inconsistent transactions. Studies have also examined interface availability, failed job frequency, scheduled batch-processing duration, and recovery time after communication interruptions (Teran et al., 2014). The literature indicates that transaction volume alone does not adequately represent interface performance because a high transfer rate may coexist with inaccurate confirmations, duplicated postings, delayed updates, or incomplete contextual information. MES–SAP interface performance is therefore represented through the combined assessment of successful transmission, semantic validity, confirmation accuracy, synchronization speed, exception handling, and reconciliation efficiency across production, material, maintenance, and quality processes.

Evidence from studies of industrial historians, condition monitoring, manufacturing execution, and enterprise asset management has shown that connecting MES and SAP with PI Historian data requires accurate alignment among physical signals, production events, and maintenance activities. MES–PI connectivity has commonly been evaluated through tag-to-asset mapping accuracy, which indicates whether historian measurements are associated with the correct machine, line, unit, functional location, or production resource (Banerjee, 2018). Equipment-state agreement has been assessed by comparing historian signals with MES classifications such as running, idle, setup, blocked, starved, maintenance, and failed. Disagreement between platforms can distort runtime, downtime, availability, cycle-time, and overall equipment-effectiveness calculations. Event alignment has been examined through timestamp deviation between process disturbances, alarms, equipment-state changes, operator entries, and MES downtime events. Missing-signal percentage, invalid-value frequency, sampling irregularity, and data-gap duration have been used to assess process-data availability. Production-context coverage has been measured through the proportion of historian records connected with valid production orders, products, batches, recipes, shifts, and operating modes. SAP–PI integration extends this information chain by connecting recorded asset conditions with maintenance notifications, work orders, inspection findings, repair actions, and costs. Quantitative studies have evaluated alert-to-notification conversion, automated-notification creation, condition-to-work-order latency, and the proportion of maintenance orders containing accessible historical condition data (Li et al., 2019).

Maintenance-event traceability has been assessed through the ability to follow an abnormal measurement from initial detection to notification, diagnosis, work-order release, resource allocation, repair, testing, and final restoration. The literature has also examined whether technicians can retrieve relevant pre-failure and post-repair trends within acceptable query-response periods. Effective connectivity is consequently reflected in accurate asset mapping, synchronized event timing,

Figure 4: Industrial Platform Integration Architecture



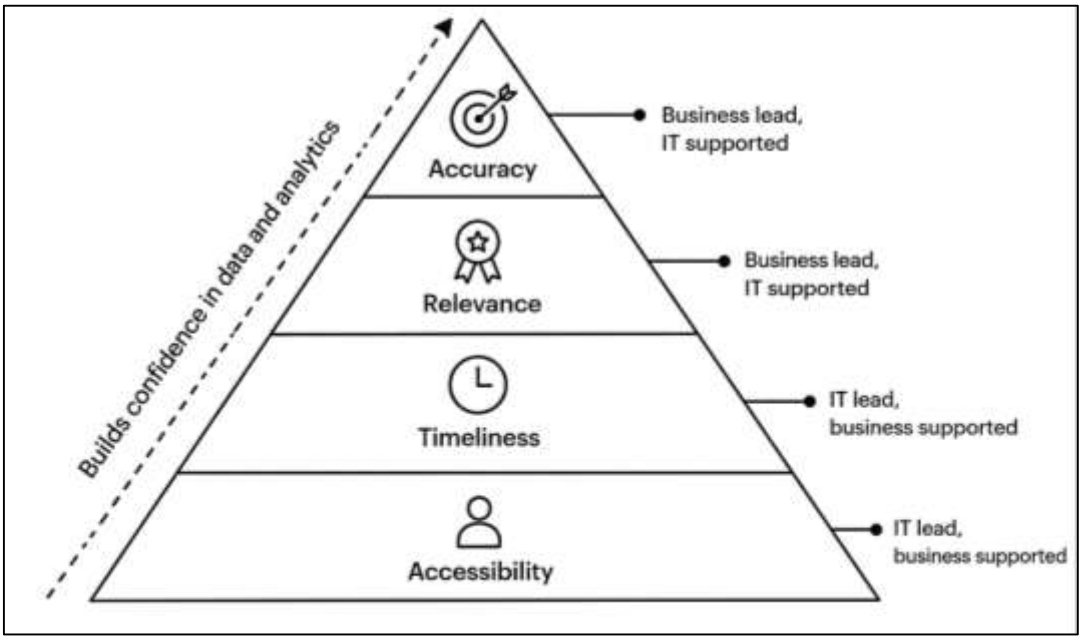
complete production context, continuous signal availability, automated maintenance initiation, and documented linkage between physical deterioration and organizational response (Shi et al., 2020).
Research across industrial integration architectures has identified middleware as the coordinating layer responsible for receiving, validating, transforming, routing, queuing, monitoring, and recovering messages exchanged among MES, SAP, PI Historian, control systems, and analytical applications. Middleware performance has been measured through the number of messages processed within a specified period, transaction completion time, queue length, interface utilization, and processing capacity during normal and peak production conditions. Message throughput is particularly important when numerous machines generate high-frequency events while production orders, confirmations, material transactions, quality results, alarms, and maintenance records are transferred simultaneously (Karia et al., 2021). Queue delay has been examined through average waiting time, maximum waiting duration, backlog growth, and the proportion of messages processed within defined service levels. Processing errors have been classified according to transformation failures, invalid formats, incomplete fields, routing mistakes, schema conflicts, timeout events, and unavailable destination systems. Interface reliability has been evaluated through successful delivery percentages, failure frequency, retry success, lost-message occurrence, duplicate-generation rates, and recovery duration after service interruption. Data-transformation accuracy has been assessed by comparing source and destination values, engineering units, timestamps, identifiers, status codes, and transaction meanings. The literature has also examined whether middleware preserves the sequence of events when delayed messages are replayed following communication failure. Scalability has been measured by increasing the number of connected assets, active tags, concurrent users, production orders, sites, and interface transactions while monitoring changes in response time and error frequency (Saha et al.). Database-query latency, historian retrieval speed, memory use, processor utilization, network consumption, and message-processing stability have been used to identify performance degradation under high workloads. Multi-site studies have emphasized that acceptable performance requires load distribution, appropriate interface scheduling, queue management, monitoring, and controlled recovery. Middleware capability is therefore measured through throughput, latency, transformation accuracy, delivery reliability, retry behavior, recovery performance, and the ability to maintain stable processing as industrial data volume and platform participation increase (Brandt et al., 2020).

Cross-Platform Data Quality and Semantic Consistency

Evidence synthesized from more than ten studies of manufacturing information systems, enterprise asset management, industrial historians, and operational analytics has identified data completeness as a fundamental requirement for reliable MES–SAP–PI integration. Completeness refers to whether all required observations, fields, transactions, timestamps, and contextual attributes are available for operational and analytical use. PI Historian completeness has been evaluated through missing sensor intervals, interrupted tag collection, invalid-value periods, unrecorded alarms, unavailable equipment states, and gaps created by network or interface failures (Min et al., 2015). MES completeness has been assessed through missing production quantities, absent cycle times, incomplete batch records, downtime events without assigned causes, unconfirmed material consumption, and production orders lacking completion information. SAP completeness has been evaluated through maintenance orders without equipment identifiers, notifications without failure codes, work orders lacking labor or material confirmations, incomplete cost records, and maintenance activities without technical findings. Cross-platform completeness also depends on whether records can be associated with the same asset, production order, batch, failure event, or maintenance intervention. Studies have measured unmatched-event frequency, missing-reference percentages, orphaned historian tags, MES events without SAP transactions, and maintenance orders without related condition data. Records may be technically complete within one platform while remaining analytically incomplete because they cannot be connected with corresponding records elsewhere (Valtolina et al., 2019). The literature has therefore distinguished field-level completeness, record-level completeness, time-series completeness, event-level completeness, and cross-platform completeness. Missing information has been associated with distorted downtime classification, inaccurate maintenance-cost calculation, incomplete failure histories, unreliable equipment-effectiveness measures, and weak production traceability. Quantitative assessments have also considered the duration of missing intervals, criticality of unavailable fields, number of affected assets, and proportion of operating time represented by valid data. These findings characterize data completeness as the availability of sufficiently detailed and linkable records across physical measurements, production execution, maintenance activity, and financial transactions (Maués & Barbosa, 2014).

Industrial data-quality studies have treated accuracy and master-data consistency as related but distinguishable characteristics of integrated platform performance. Data accuracy describes the degree to which digital values correctly represent physical conditions, operational events, production results, maintenance activities, and financial consequences. PI measurement accuracy has been evaluated through calibration differences, sensor bias, signal noise, invalid readings, scaling errors, incorrect engineering units, and disagreement between redundant instruments. MES accuracy has been assessed by comparing recorded equipment states, cycle times, production quantities, scrap, rework, material usage, and downtime durations with physical observations and verified operator records (Martinez, 2019). SAP accuracy has been examined through labor confirmations, spare-parts postings, maintenance durations, work-order status, production confirmations, and asset-related cost transactions. Physical-to-digital agreement has been measured by comparing the time, duration, location, classification, and magnitude of actual events with their recorded representations. Master-data consistency concerns whether equipment numbers, functional locations, work centers, production lines, units, asset classes, material codes, and organizational structures remain aligned across MES, SAP, and PI. Studies have identified inconsistent identifiers as a major cause of unmatched records, duplicated assets, erroneous cost assignment, and fragmented equipment histories. Identifier matching has therefore been evaluated through exact and rule-based agreement among historian asset models, MES resource codes, and SAP equipment records (Man et al., 2016). Hierarchical alignment has been assessed by examining whether assets are assigned to the correct site, area, line, unit, system, and functional location. Duplicate-record frequency has been used to identify situations in which a single physical asset is represented by multiple digital records. Hierarchy-conflict rates have measured disagreements concerning asset ownership, location, parent–child relationships, or criticality classification. The literature indicates that reliable integration requires both accurate transactional information and consistent structural reference data because correct measurements cannot be interpreted appropriately when attached to the wrong equipment, order, product, or organizational unit (Gao et al., 2019).

Figure 5: Cross-Platform Data Quality Framework



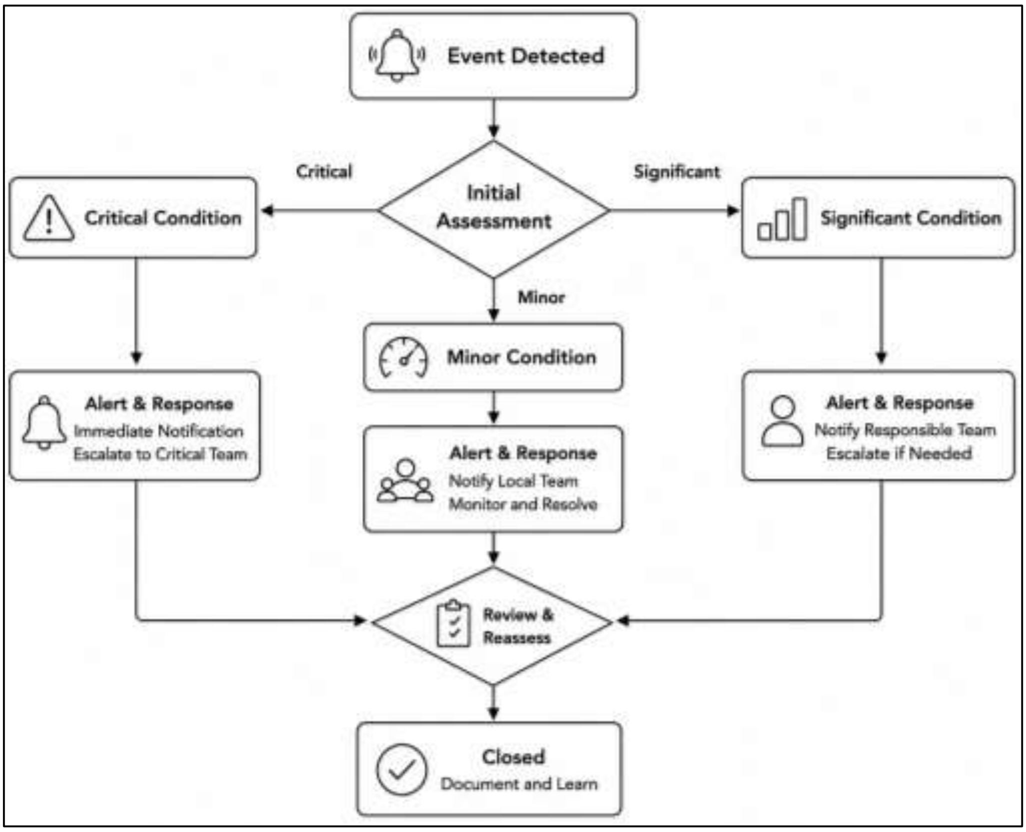
A synthesis of industrial integration research has shown that time synchronization and semantic standardization determine whether data from MES, SAP, PI Historian, controllers, sensors, and maintenance applications can be interpreted as parts of the same operational event. Time synchronization quality has been assessed through timestamp deviation, clock drift, event-sequence accuracy, and the proportion of records captured within an accepted time tolerance. Controllers and historians may record process changes within seconds or milliseconds, while MES events may be registered at the beginning or end of a production cycle and SAP transactions may be confirmed after maintenance or production activity has been completed (Liu et al., 2021). Differences in system clocks, time zones, daylight-saving configurations, buffering, network delay, and manual entry can change the apparent sequence of events. Studies have examined whether an alarm occurred before equipment shutdown, whether a maintenance response followed the correct failure event, and whether production losses were assigned to the proper operating period. Out-of-sequence records can weaken root-cause analysis, distort repair-duration calculations, and create incorrect associations between process deviations and maintenance activities. Semantic standardization addresses whether data elements carry consistent meanings across platforms. Engineering-unit consistency has been evaluated by examining temperature, pressure, flow, speed, energy, and production quantities for incompatible units or incorrect conversions. Failure-code alignment has been assessed through common taxonomies for failure modes, damage mechanisms, causes, and maintenance actions (Goyal et al., 2016). Downtime-code consistency has been examined by comparing MES reason codes with SAP notification and order classifications. Product-code agreement, material-code consistency, equipment-state definitions, and maintenance-priority alignment have also been evaluated. Data-definition agreement measures whether terms such as failure, shutdown, idle time, repair duration, availability, and production loss are calculated and interpreted consistently. The reviewed evidence establishes that aligned timestamps create temporal coherence, while standardized definitions create semantic coherence. Both are required to connect rapidly generated process signals with production events, maintenance responses, and enterprise transactions without misclassification (Zarko et al., 2017).

Evidence across production, maintenance, quality, and financial information environments has identified reconciliation as the process through which cross-platform differences are detected, investigated, corrected, documented, and prevented from recurring. Production reconciliation has been evaluated through differences between MES output and SAP production confirmations, variation between physical and recorded material consumption, and disagreement among planned, produced, accepted, rejected, and stored quantities. Maintenance reconciliation has examined differences in failure duration, labor hours, spare-parts usage, work-order status, restoration time, and assigned costs (Yi, 2019). Runtime reconciliation has compared historian operating signals with MES equipment states and SAP counter readings. Downtime reconciliation has assessed differences in event start time, end time, duration, reason code, production impact, and responsible asset. Quantitative studies have used reconciliation-error frequency, average correction duration, manual-adjustment rate, unresolved discrepancy percentage, and staff hours devoted to data correction. Repeated discrepancies have been associated with weak validation rules, inconsistent master data, interface mapping errors, delayed confirmations, manual-entry mistakes, and different calculation procedures. The literature has also examined whether reconciliation occurs automatically through programmed tolerance checks or manually through spreadsheet comparison and user investigation (Bertoletti et al., 2014). Automated reconciliation can identify unusual differences quickly, while human review remains necessary when the error concerns event meaning, failure classification, or operational context. Integrated data-quality governance includes assigned data ownership, documented definitions, validation controls, exception monitoring, correction approval, version management, periodic audits, and performance reporting. Governance effectiveness has been measured through error-resolution compliance, recurrence of corrected problems, master-data review completion, exception-response time, and the percentage of critical data elements under formal control. Cross-platform quality is therefore represented by the combined completeness, accuracy, structural consistency, temporal alignment, semantic agreement, and reconciliation performance of MES, SAP, and PI information (Su et al., 2019). This integrated perspective connects individual data defects with their measurable effects on reliability analysis, production reporting, maintenance decisions, cost visibility, and asset-performance evaluation.

Real-Time Visibility, Alerts, and Decision Support

Evidence synthesized from more than ten empirical studies of industrial monitoring, manufacturing execution, process historians, and asset-performance systems has defined real-time visibility as the ability to observe current asset conditions and production activities through complete, timely, and contextually accurate information. Monitoring coverage has been measured through the proportion of total assets connected to the integrated environment, with separate consideration given to high-criticality equipment whose failure can affect production, safety, quality, or environmental performance (Tambare et al., 2021). Studies have also examined the percentage of required condition variables captured for each asset, including temperature, pressure, vibration, flow, speed, current, operating load, runtime, alarm status, and equipment state. Observable operating hours have been assessed through the proportion of scheduled or actual operating time represented by valid data, excluding missing intervals, communication failures, invalid sensor values, and historian outages. Dashboard performance has been evaluated through refresh frequency, loading time, query-response delay, concurrent-user performance, and the accuracy of displayed indicators. Frequent refresh intervals may improve awareness, although the value of rapid updates depends on data validity, asset context, and the operational relevance of displayed information. Studies have measured active-user frequency, session duration, report access, dashboard utilization by production, maintenance, reliability, quality, engineering, and management personnel, and the proportion of decisions supported by dashboard information (Yu et al., 2014). Automated indicator generation has been evaluated through the percentage of availability, downtime, failure, throughput, quality, and maintenance measures calculated without manual spreadsheet processing. Report accuracy has been assessed by comparing dashboard values with MES records, PI measurements, SAP transactions, and verified operational results. The literature indicates that effective monitoring requires more than displaying large volumes of sensor data. Useful visibility depends on adequate asset coverage, critical-tag availability, continuous observation, rapid retrieval, accurate calculations, and displays that organize information according to assets, production orders, events, responsibilities, and decision priorities (Zonnenshain & Kenett, 2020). Research across condition monitoring, process control, predictive maintenance, and industrial alarm management has treated alert performance as a balance among detection sensitivity, specificity, timeliness, prioritization, and operational response.

Figure 6: Real-Time Asset Decision Framework



Detection sensitivity has been evaluated through the percentage of verified abnormal events correctly identified by monitoring rules, statistical thresholds, condition indicators, or analytical models. Missed-alert frequency has been measured by reviewing failures and process deviations that occurred without a preceding warning (Dey & Shekhawat, 2021). False-positive frequency has been examined through alerts generated when equipment remained within acceptable operating conditions or when the detected deviation did not require intervention. Excessive false alarms can increase workload, reduce user confidence, and cause important warnings to receive insufficient attention. Alert-generation latency has been measured as the time between the occurrence of an abnormal condition and the creation of a visible or transmitted warning. Notification delay has been evaluated through the duration required to deliver the alert to operators, maintenance personnel, reliability engineers, supervisors, or managers. Acknowledgement time has been used to determine how quickly responsible personnel confirm receipt and begin investigation. Escalation duration has been assessed through the time required to transfer unresolved or high-priority alerts to personnel with greater authority or specialized expertise (Kannangara et al., 2018). Studies have also considered the percentage of alerts categorized correctly by severity, urgency, asset criticality, production consequence, and safety significance. Resolution performance has been measured through the proportion of alerts investigated, actioned, and closed within defined service periods. Alert recurrence, repeated acknowledgement without corrective action, and unresolved-alert accumulation have been used to identify weaknesses in response processes. The reviewed evidence shows that technically accurate detection alone does not establish effective alerting. Alert performance depends on reliable condition data, appropriate thresholds, correct asset context, limited false alarms, rapid notification, defined ownership, controlled escalation, and documented closure connected with production and maintenance records (Lemaire et al., 2015).

A synthesis of industrial asset-management studies has shown that event traceability provides the informational sequence required to connect equipment deterioration with production disruption, maintenance intervention, resource consumption, and economic loss. Condition-to-failure traceability has been evaluated through the proportion of failures supported by identifiable pre-failure changes in vibration, temperature, pressure, flow, current, load, alarm frequency, or equipment state. Failure-to-order linkage has been measured through the percentage of MES downtime events connected with valid SAP maintenance notifications and work orders (Mirakhorli & Cleland-Huang, 2015). Order-to-cost linkage has been assessed through labor confirmations, spare-parts issues, contractor charges, purchasing transactions, downtime losses, and financial settlements assigned to the same asset event. Studies have also examined whether event identifiers, equipment numbers, functional locations, production orders, timestamps, and failure classifications remain consistent throughout the event chain. Traceability is weakened when process measurements cannot be associated with a production order, when downtime records lack maintenance references, or when maintenance costs are posted without connection to the original failure. Decision speed has been analyzed through a sequence of operational intervals. Detection-to-diagnosis time represents the duration required to interpret an abnormal condition and determine the probable failure mechanism (Lin et al., 2019). Diagnosis-to-action time measures the interval required to approve an intervention, create or release a work order, assign personnel, and reserve required materials. Action-to-restoration time includes maintenance execution, testing, recommissioning, and return to normal operation. The literature has examined whether integrated information reduces time spent searching for historical records, comparing separate systems, requesting additional data, verifying asset identity, and reconciling contradictory information. Faster decisions are not automatically more accurate, so studies have also evaluated diagnosis correctness, repeat-repair frequency, restoration success, and post-maintenance performance. Event traceability and decision speed are therefore connected through the availability of complete evidence concerning asset condition, production impact, maintenance history, resource requirements, and previous corrective actions (Kuhn et al., 2018).

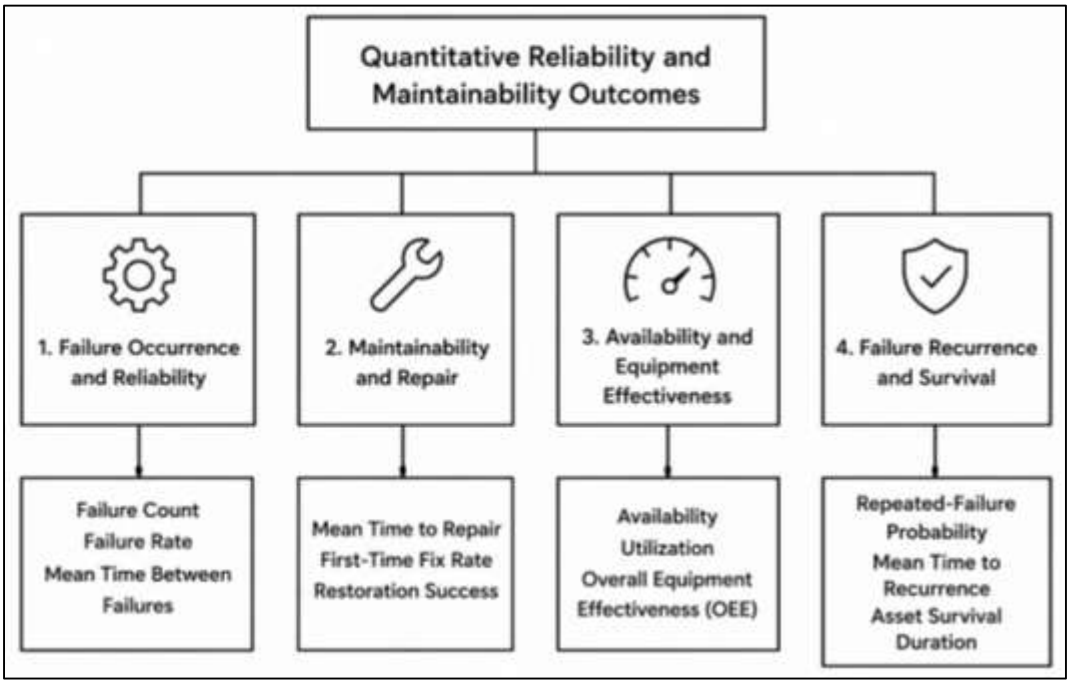
Quantitative Reliability and Maintainability Outcomes

Evidence synthesized from more than ten empirical studies in manufacturing, oil and gas, petrochemical processing, power generation, mining, transportation, utilities, and automated production has identified failure occurrence as a principal quantitative measure of industrial asset reliability. Annual failure count provides a direct measure of recorded breakdowns, trips, shutdowns, and functional interruptions, although comparisons based only on total counts can be affected by differences in asset population and operating exposure (Nadjafi & Farsi, 2021).

Failures per asset have therefore been used to standardize occurrence across facilities containing different numbers of equipment units. Failures per 1,000 operating hours provide a more exposure-sensitive measure because heavily loaded or continuously operated assets have greater opportunities to fail than equipment used intermittently. Studies comparing integrated and nonintegrated assets have examined whether automated condition monitoring, production-event capture, maintenance traceability, and rapid information exchange are associated with lower adjusted failure occurrence. Mean time between failures has been used to represent the average operating duration separating consecutive functional failures. This indicator has been evaluated across compressors, pumps, motors, turbines, conveyors, electrical systems, control equipment, and complete production lines.

Comparisons have also considered criticality because high-criticality assets generally receive more monitoring, inspection, maintenance resources, and management attention (Vališ et al., 2015). Equipment age, production loading, number of starts and stops, environmental exposure, operating temperature, contamination, vibration, maintenance strategy, and baseline reliability have been identified as important sources of variation. Integration can also improve failure recording and initially produce higher observed failure counts by capturing events that were previously omitted. The literature consequently distinguishes changes in actual reliability from changes in reporting completeness. Reliable comparison requires consistent failure definitions, complete operating-hour records, standardized asset boundaries, and appropriate separation of functional failures from minor alarms or planned interruptions. Failure frequency, exposure-adjusted occurrence, and mean operating duration between events collectively provide a quantitative representation of how consistently industrial assets perform their intended functions (Yin et al., 2017).

Figure 7: Industrial Reliability Performance Framework



Industrial maintenance studies have defined maintainability as the ability to restore failed or degraded equipment within an acceptable period using available personnel, tools, information, procedures, and spare parts. Mean time to repair provides a broad summary of restoration performance, while detailed analysis separates the maintenance process into response, diagnosis, preparation, active repair, logistical waiting, testing, and recommissioning stages. Maintenance-response time has been measured from the confirmed detection of failure to the arrival or assignment of responsible personnel (Guo et al., 2021). Troubleshooting time represents the period required to review alarms, inspect equipment, access historical condition data, compare previous failures, identify probable causes, and determine an appropriate maintenance action. Integrated MES, SAP, and PI information can influence this stage by providing production context, process trends, equipment histories, technical records, and previous work-order findings within one traceable event structure. Active repair duration includes disassembly, adjustment, replacement, cleaning, alignment, calibration, and reassembly. Spare-parts waiting time has been evaluated through stock availability, reservation accuracy, procurement delay, transportation time, and the accessibility of alternative components. Testing and recommissioning duration includes functional checks, safety verification, trial operation, process stabilization, quality confirmation, and formal return to service (Spertino et al., 2020). Studies have distinguished active maintenance time from total restoration time because an asset may remain unavailable long after the technical repair has been completed. Administrative approval, permit issuance, contractor mobilization, tool availability, and production scheduling may also extend downtime. Maintainability comparisons across integrated and fragmented information environments have examined whether real-time failure identification reduces diagnostic uncertainty, information-search time, notification delays, duplicated inspections, and incorrect repairs. Restoration success has been assessed through first-time-fix percentage, repeat repair, post-maintenance alarms, early recurrence, and the ability to sustain normal operation after return to service. These measures present maintainability as a combined outcome of technical repair efficiency, information accessibility, resource readiness, decision speed, and successful operational recovery (Zeng et al., 2020).

A synthesis of reliability and production-performance research has shown that equipment availability must be interpreted according to the operating boundaries and loss categories included in its measurement. Inherent availability concentrates primarily on corrective-maintenance characteristics under ideal support conditions and reflects the relationship between operating reliability and active

repair duration. Achieved availability incorporates corrective and preventive maintenance but generally excludes major logistical and administrative delays. Operational availability provides a broader representation because it includes actual maintenance delays, spare-parts waiting, staffing restrictions, administrative processes, and other conditions experienced in the operating environment (Okaro & Tao, 2016). Studies have measured availability through scheduled production time, actual operating time, planned maintenance, unplanned downtime, setup, waiting, and external production restrictions. Overall equipment effectiveness extends the assessment by combining availability with operating-speed performance and quality output. An asset may record high availability while operating below its designed production rate or producing excessive defects. Platform integration has been examined in relation to several categories of performance loss, including breakdowns, setup and adjustment, minor stops, reduced speed, startup losses, defects, and rework. PI Historian data provides detailed runtime, equipment-state, alarm, speed, and process measurements. MES connects those measurements with production orders, planned rates, output quantities, downtime reasons, products, shifts, and quality results. SAP provides maintenance schedules, work-order histories, resource use, and cost information (Hong et al., 2018). Differences among these records can alter calculated performance when downtime boundaries, planned production periods, or equipment states are inconsistent. The literature has therefore emphasized the importance of standardized time categories, validated reason codes, accurate production counts, and consistent asset hierarchies. Integrated environments have been compared using operating availability, utilization, throughput attainment, quality yield, and overall equipment effectiveness rather than availability alone. These combined indicators allow reliability losses, maintenance delays, speed reductions, setup time, and quality defects to be examined within a common production-performance structure (Kowal & Torabi, 2021).
Evidence from more than twenty studies of recurrent failures, condition-based maintenance, reliability engineering, and time-to-event analysis has identified recurrence and survival as important outcomes beyond average failure counts and repair durations. Repeated-failure probability has been evaluated through the proportion of assets experiencing another failure within 7-day, 30-day, 90-day, and annual observation periods. Short-interval recurrence may indicate incomplete diagnosis, ineffective repair, incorrect component replacement, weak commissioning, or unresolved operating conditions. Longer recurrence intervals may reflect deterioration, maintenance quality, production loading, or exposure to repeated process disturbances (Li et al., 2021). Studies have also examined the number of recurring events per asset, mean time to recurrence, recurrence concentration among a limited number of problematic assets, and repeated failures involving the same component or failure mechanism. Asset survival duration represents the operating time from installation, repair, or restoration until the next defined failure. Survival probability has been used to show the proportion of assets continuing to operate without failure across successive periods, while cumulative failure incidence represents the growing proportion experiencing an event. Median survival duration provides an interpretable comparison when enough assets have failed during the observation period. Integration-level comparisons have classified assets or facilities according to low, medium, and high levels of interface automation, monitoring coverage, data quality, event traceability, and maintenance connectivity (Gajewski & Vališ, 2017). Researchers have examined whether assets supported by higher integration display longer failure-free operation, lower repeated-failure probability, and reduced relative risk of failure. These comparisons require adjustment for equipment age, criticality, operating exposure, asset type, environmental conditions, production loading, maintenance strategy, facility characteristics, and baseline performance. The literature has also recognized clustering because repeated observations from the same asset or facility are not independent. Failure recurrence, time to next failure, survival duration, and relative failure risk collectively provide a more complete evaluation of whether integrated industrial information is associated with sustained reliability rather than only short-term changes in average performance (Li et al., 2021).

Maintenance Responsiveness and Resource Management

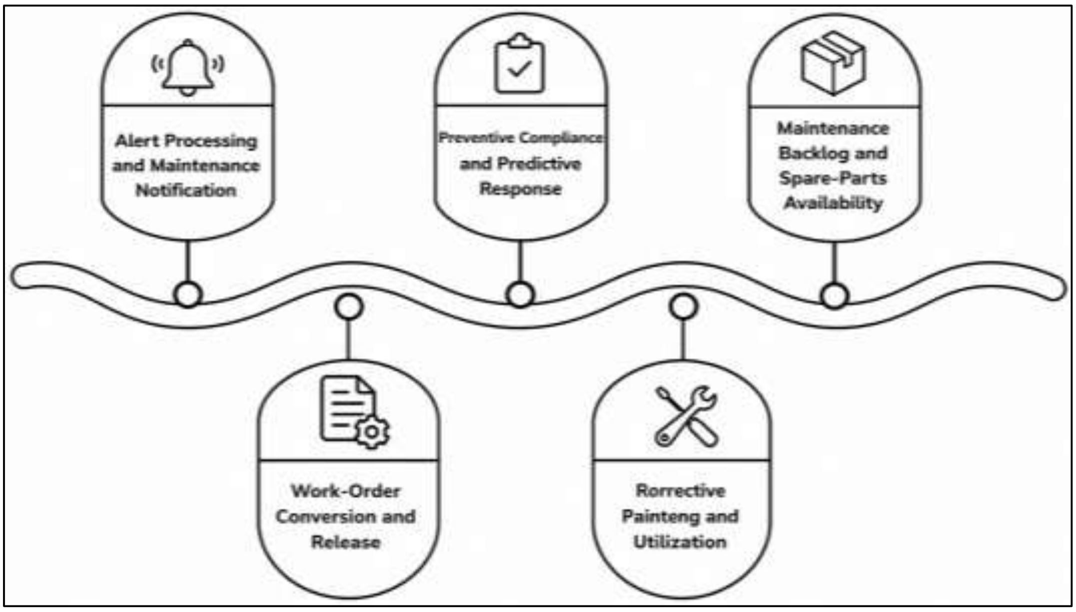
Evidence synthesized from more than ten empirical studies of industrial maintenance, enterprise asset management, and condition-monitoring systems has identified maintenance responsiveness as the speed and consistency with which abnormal asset conditions are converted into authorized maintenance actions. Alert-to-notification time has been measured from the detection of an abnormal temperature, pressure, vibration, flow, current, speed, load, alarm pattern, or equipment state to the creation of a formal maintenance notification (Gajewski & Vališ, 2017). Studies have evaluated whether notifications are generated automatically through integrated PI and SAP processes or entered manually after operator review. Automated creation rates have been examined alongside notification validity because rapid automation provides limited value when alerts generate duplicate, incomplete, or unnecessary records. Researchers have measured the percentage of notifications containing valid equipment identifiers, functional locations, timestamps, condition descriptions, severity classifications, production consequences, and supporting historian trends. Notification-to-work-order conversion has been assessed through the proportion of valid requests transformed into executable maintenance orders. Conversion time includes technical screening, priority confirmation, planning, approval, resource estimation, task development, and order release. Rejected-notification rates have been examined according to false alarms, insufficient evidence, duplicate requests, incorrect asset references, and conditions that do not require maintenance (Fischer et al., 2018). Planning delay has been measured through the interval between notification approval and completion of job scope, labor allocation, material reservation, permit requirements, and scheduling. Urgent-order performance has been evaluated through the percentage of emergency and high-priority orders released within established response periods. The reviewed evidence indicates that rapid processing must be interpreted together with notification accuracy, planning completeness, and maintenance effectiveness. Excessive delays can extend asset deterioration and production exposure, while poorly controlled automation can increase administrative workload. Maintenance responsiveness is therefore represented by timely alert recognition, accurate notification generation, efficient validation, controlled conversion, complete planning, and prompt release of technically justified work orders (Hryshchenko, 2016).

Industrial maintenance research has consistently distinguished planned preventive and predictive activities from corrective work initiated after functional failure. Preventive-maintenance compliance has been measured through the percentage of scheduled inspections, lubrication activities, calibrations, servicing tasks, component replacements, and statutory checks completed within approved time limits. Schedule variance has been assessed by comparing planned and actual completion dates, while overdue-task percentages have been separated according to asset criticality, maintenance type, and duration of delay (Dang et al., 2016).

Inspection compliance has been evaluated through completion records, measurement capture, technical findings, and confirmation that required procedures were performed. Predictive-maintenance responsiveness has been measured through the proportion of condition warnings investigated, time required to validate deterioration, percentage of valid warnings converted into work orders, and maintenance interventions completed before functional failure. Maintenance deferral frequency has been examined to determine how often planned activities are postponed because of production requirements, unavailable labor, missing spare parts, shutdown restrictions, or weak scheduling. Corrective-maintenance burden has been assessed through emergency work-order frequency, breakdown-related tasks, reactive labor hours, overtime, contractor mobilization, and the percentage of work initiated after equipment failure. Studies have compared corrective-to-preventive maintenance patterns across facilities to determine whether maintenance programs operate primarily through planned control or breakdown response (Assis et al., 2020).

Repeat repair has been used to identify corrective actions that restore operation temporarily without eliminating the underlying failure mechanism. High reactive workloads can displace preventive tasks, increase backlog, consume reserved materials, and reduce the time available for reliability improvement. The reviewed literature also shows that a high proportion of preventive work does not automatically indicate effectiveness when tasks are poorly targeted or completed without valid condition evidence (Lickevich et al., 2019). A balanced evaluation considers schedule compliance, predictive-warning response, emergency workload, repeat failure, labor utilization, and the relationship between completed maintenance and subsequent asset reliability. A synthesis of maintenance-management studies has shown that backlog and spare-parts performance strongly influence the ability of organizations to convert identified maintenance needs into completed work.

Figure 8: Maintenance Response Management Framework



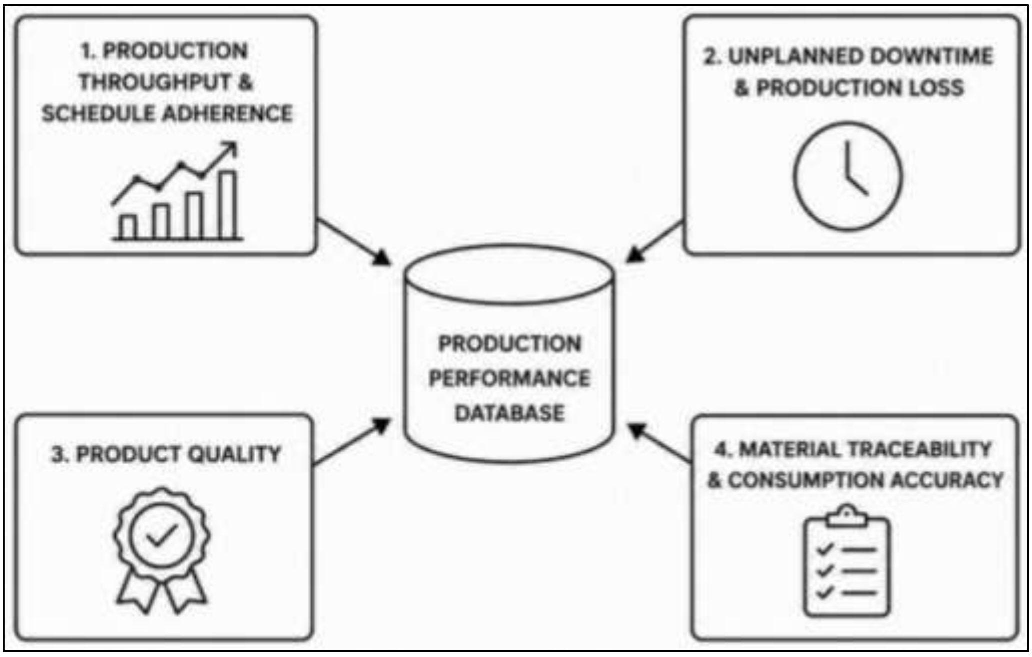
Maintenance backlog has been measured through the number of open work orders, estimated labor hours required, age of unresolved tasks, priority distribution, and proportion associated with high-criticality assets. Weekly backlog hours have been compared with available workforce capacity to determine whether the existing workload can be completed within acceptable periods (Kozhokhina et al., 2014). Age distribution has been analyzed by grouping work orders according to how long they have remained open, allowing organizations to distinguish recently identified work from long-standing unresolved conditions. Studies have also examined the percentage of overdue tasks involving safety, production, environmental, quality, or regulatory consequences. Backlog growth may reflect insufficient labor, incomplete planning, weak prioritization, shutdown constraints, unavailable materials, or excessive creation of low-value work orders. Spare-parts performance has been evaluated through stock availability, stockout frequency, reservation success, issue accuracy, procurement lead time, and material waiting duration (Uhrig et al., 2020). Critical-spare availability has received particular attention because the absence of a low-volume component can extend equipment downtime substantially. Reservation accuracy has been assessed by comparing planned material requirements with actual consumption and verifying whether reserved items are available when maintenance begins. Emergency procurement rates have been used to identify inadequate planning, inaccurate failure forecasts, or unsuitable inventory policies. Inventory turnover, obsolete-stock percentage, excess inventory value, and spare-parts cost per asset have also been examined to balance operational readiness with financial control. The literature indicates that excessive inventory can increase holding and obsolescence costs, while insufficient stock can increase downtime and emergency purchasing (Li et al., 2017). Integrated maintenance and inventory information supports quantitative evaluation of which assets consume parts, which components cause repeated delays, and how backlog age is connected with resource availability.

Production, Quality, and Energy Performance

Evidence synthesized from more than ten empirical studies of manufacturing execution, enterprise planning, industrial analytics, and production control has identified throughput and schedule adherence as major quantitative outcomes of integrated operational information. Production throughput has commonly been evaluated through units, batches, tonnes, or standardized output produced per hour, shift, day, or production cycle. Actual-to-planned output percentage has been used to determine whether production results meet approved targets, while production-volume variance has identified the magnitude and direction of differences between scheduled and completed quantities (Arriola-Medellín et al., 2019). Capacity utilization has been assessed by comparing actual production activity with available equipment, labor, and process capacity. Studies have also examined bottleneck duration, waiting time, blocked time, starved time, reduced-speed operation, and the proportion of available capacity lost because of equipment restrictions. Output recovery following interruption has been measured through the time required to restore the planned production rate, recover deferred volume, stabilize operating conditions, and return accumulated work-in-process to normal levels. Production schedule adherence has been evaluated through on-time order starts, on-time completion, schedule deviation, delayed-order frequency, order lead time, and the percentage of orders rescheduled because of equipment conditions (May et al., 2015). MES provides detailed execution and order-progress information, SAP contains approved plans and enterprise resource requirements, and PI Historian records the physical operating conditions affecting production. Integration allows schedule performance to be assessed against verified equipment availability rather than planned capacity alone. The literature has examined whether real-time asset information supports adjustments to order sequence, production rate, routing, labor assignment, and maintenance windows. Production-start accuracy has also been evaluated by comparing scheduled and actual start times and identifying delays caused by materials, equipment, quality clearance, or maintenance. These indicators present production performance as the coordinated attainment of planned output, efficient capacity use, timely order execution, controlled bottlenecks, and rapid recovery from asset-related interruptions (Kovač et al., 2019).

Industrial performance studies have consistently identified unplanned downtime as one of the principal mechanisms through which equipment unreliability reduces production output and financial performance. Unplanned downtime hours have been measured at asset, production-line, work-center, facility, and enterprise levels, with separate classification of breakdowns, process trips, control-system faults, electrical interruptions, material shortages, and external disruptions. Shutdown frequency has been used to distinguish facilities experiencing numerous short interruptions from those experiencing fewer but longer events (Kwade et al., 2018). Micro-stop duration has received increased attention because repeated interruptions lasting only seconds or minutes may accumulate into substantial production loss while remaining underreported in manual systems. Idle time has been examined according to equipment availability, blocked or starved conditions, operator delay, setup, and waiting for maintenance. Lost production hours have been calculated through the operating time unavailable because of failure and the additional period required to stabilize the process after restoration. Deferred output has been assessed through units, batches, tonnes, or production value not completed during the planned period. Production-loss value has included lost margin, delayed delivery, overtime required for recovery, additional energy consumption, wasted material, and contractual penalties. Integrated MES, SAP, and PI records support more accurate downtime analysis by combining equipment-state signals, production orders, recorded causes, maintenance activities, and financial values (Porter et al., 2017). The literature has emphasized the importance of consistent event boundaries because different systems may record the beginning and end of the same interruption at different times. Studies have also examined downtime-reason completeness, event overlap, failure attribution, and the proportion of lost time connected with specific assets. Output recovery duration has been separated from repair duration because technical restoration does not always produce immediate production recovery. Quantitative evaluation therefore connects failure frequency, downtime duration, production-rate reduction, deferred output, and economic loss within a traceable sequence of equipment and production events (Kamali & Hewage, 2016). A synthesis of quality-management, manufacturing-execution, and digital-traceability studies has shown that asset conditions and production processes influence product quality through operating stability, measurement accuracy, equipment capability, and adherence to approved specifications. First-pass yield has been measured through the proportion of output meeting quality requirements without rework, repair, retesting, or additional processing. Defect rate and quality-rejection frequency have been assessed by product, batch, production line, equipment unit, shift, and failure condition (Marconi et al., 2017). Scrap percentage has represented material and product that cannot be economically recovered, while rework hours have captured additional labor, machine time, energy, and production capacity consumed in correcting nonconforming output.

Figure 9: Integrated Production Performance Framework



Process-deviation duration has been measured through the time that temperature, pressure, flow, speed, vibration, dimensions, composition, or other process variables remain outside approved limits. Studies have examined whether PI Historian conditions preceding and during production can be connected with MES quality results and SAP material and cost records. Material traceability has been evaluated through genealogy completeness, batch-record availability, component-to-product linkage, production-location identification, and the time required to trace affected materials. Batch-tracing time has been particularly important during quality investigations, customer complaints, recalls, and regulatory reviews (Dooley et al., 2018). Consumption accuracy has been assessed by comparing actual material usage with standard or planned quantities. Material-issue accuracy has been examined through correct material codes, quantities, batches, storage locations, and production-order assignments. Unrecorded consumption, incorrect returns, duplicate issues, substitution errors, and MES–SAP reconciliation differences have been used to identify weaknesses in transaction control. The literature indicates that integrated information allows quality deviations to be examined in relation to process conditions, equipment states, maintenance history, material genealogy, and production context (Dabbene et al., 2014). Product quality and material control are consequently represented through yield, defects, scrap, rework, process stability, genealogy completeness, consumption accuracy, and cross-platform transactional agreement.

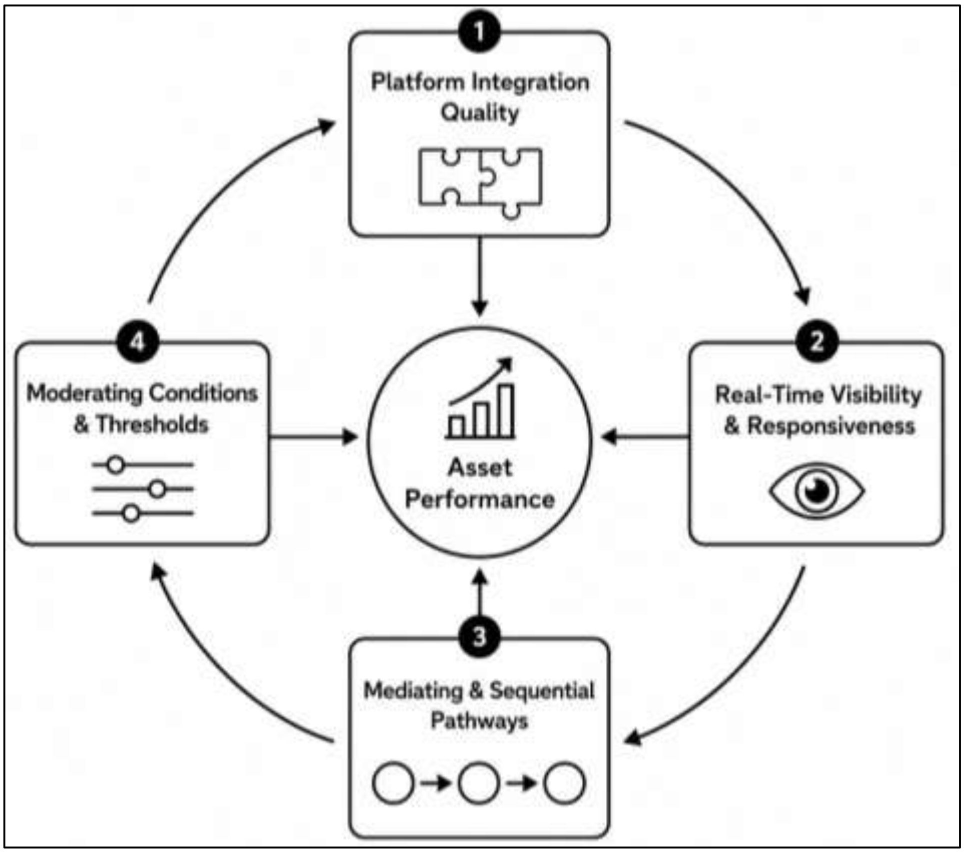
Quantitative Relationships and Explanatory Mechanisms

Evidence synthesized from more than ten quantitative studies of enterprise integration, manufacturing execution, industrial data management, and maintenance performance has generally treated MES–SAP–PI integration quality as a multidimensional predictor of industrial asset outcomes (Aung & Chang, 2014). Integration quality has been represented through system interoperability, interface automation, bidirectional data exchange, synchronization speed, asset-identifier consistency, information completeness, transaction accuracy, event traceability, and functional coverage. Higher interoperability allows production, condition, maintenance, material, quality, and cost information to move across platforms without repeated manual entry or disconnected reconciliation. Automation reduces delays in transferring production orders, equipment states, process measurements, maintenance notifications, work-order confirmations, and material transactions. Synchronization ensures that users access current rather than outdated information, while semantic and master-data consistency allows observations from different systems to be associated with the correct assets and events (Spector, 2019). Studies have examined the direct relationship between these integration characteristics and equipment availability, failure frequency, mean time between failures, mean time to repair, unplanned downtime, repeated-failure occurrence, utilization, throughput, and overall equipment effectiveness. Integrated information has been associated with stronger failure detection, faster access to technical history, improved coordination of maintenance activity, and more accurate classification of production losses. The reviewed evidence also indicates that technical connectivity alone does not guarantee better reliability. Interfaces may operate successfully while transferring incomplete, inaccurate, or poorly contextualized data. Performance outcomes depend on whether integrated information is actively used for diagnosis, planning, scheduling, maintenance execution, and reliability review (Moreno & Suárez, 2020). Direct-effect analysis must also distinguish actual operational improvement from improved event recording because expanded monitoring may initially increase documented failure counts and downtime events. The relationship between integration and asset performance is therefore evaluated through changes in both technical outcomes and information quality while accounting for operating exposure, equipment characteristics, maintenance practices, and baseline performance.

A synthesis of industrial monitoring and maintenance studies has identified real-time information visibility as an important mechanism connecting platform integration with maintenance responsiveness (Moreno & Suárez, 2020). Integration increases visibility when it expands monitoring coverage, improves dashboard timeliness, strengthens event traceability, reduces missing information, accelerates alert delivery, and enables cross-functional access to asset records. Monitoring coverage has been examined through the proportion of assets, critical tags, and operating hours represented by valid real-time data. Dashboard timeliness has been assessed through refresh frequency, query-response speed, report availability, and the delay between a physical event and its visible representation. Event traceability allows users to follow an abnormal process condition through MES downtime classification, SAP maintenance notification, work-order creation, resource use, restoration, and recorded cost. Information completeness supports diagnosis by combining current process measurements with production context, failure history, maintenance activity, and previous repair findings (Dalkin et al., 2015). Alert speed has been evaluated through detection latency, notification delay, acknowledgement time, and escalation duration. Cross-functional access enables operators, maintenance technicians, reliability engineers, production planners, quality personnel, and managers to work from a shared representation of the same asset event. Studies have examined whether these visibility dimensions reduce the time required to identify deterioration, confirm failure, determine likely causes, locate technical information, initiate work orders, reserve spare parts, allocate personnel, and restore operation (Verduyn et al., 2020). Faster access can reduce information-search time and repeated verification, although the quality of the response depends on diagnostic accuracy and the relevance of available data. Maintenance responsiveness has therefore been assessed through fault-diagnosis time, notification delay, work-order processing time, planning duration, repair time, restoration duration, and first-time-fix performance. The reviewed evidence treats visibility as an informational capability and responsiveness as the operational use of that capability in maintenance decisions and actions (Pritchard et al., 2020).

Evidence from more than twenty studies of information-system success, operational visibility, maintenance decision-making, and industrial performance has supported the examination of indirect pathways rather than limiting analysis to a direct association between integration and asset outcomes. Real-time information visibility can serve as a mediating variable when platform integration improves monitoring, accessibility, timeliness, and traceability, which subsequently contribute to stronger reliability and production performance. Under this mechanism, interoperability and automation do not improve asset performance solely through the existence of connected systems (Beyens et al., 2016). Their influence is transmitted through the availability of accurate and current information concerning operating conditions, production context, failure history, maintenance requirements, and resource status. The mediation pathway can be examined by determining whether integration quality remains associated with asset performance after visibility is included in the analysis and whether the indirect relationship through visibility is statistically meaningful.

Figure 10: Integrated Asset Performance Relationships



A more detailed sequential pathway includes maintenance responsiveness as a second explanatory mechanism. Platform integration first increases real-time visibility by connecting PI measurements with MES events and SAP maintenance records. Greater visibility then reduces detection, diagnosis, approval, and planning delays. Faster and better-informed maintenance response subsequently affects repair duration, restoration success, repeated-failure probability, downtime, availability, and overall equipment effectiveness (Palmer & Alfano, 2017). This sequence recognizes that visible information must be converted into appropriate action before operational performance changes. Studies have also shown that rapid responses may not produce favorable outcomes when alerts are inaccurate, work orders are poorly planned, spare parts are unavailable, or repairs fail to address underlying causes. Sequential mediation therefore includes both information quality and execution quality. Relevant quantitative measures include monitoring completeness, dashboard delay, alert acknowledgement, diagnostic duration, work-order initiation, labor and material readiness, repair time, restoration success, and post-maintenance reliability (Kahu & Nelson, 2018). The explanatory structure connects technical integration, informational capability, maintenance behavior, and asset outcomes within a coordinated quantitative model.

The reviewed literature has demonstrated that the strength of relationships among platform integration, real-time visibility, maintenance responsiveness, and asset performance varies across data, organizational, asset, and operating conditions. Data quality is a central moderating factor because incomplete tag histories, inconsistent asset identifiers, inaccurate production records, missing failure codes, and delayed maintenance confirmations can weaken the operational value of otherwise advanced interfaces (Mensink et al., 2017). Master-data quality determines whether measurements, production events, maintenance orders, and costs are assigned to the same physical equipment. Digital maturity has been examined through automation coverage, analytical capability, standardized workflows, governance quality, system-use intensity, and employee competence. Organizations with stronger digital maturity may convert integrated information into faster and more consistent decisions because employees understand dashboards, validate alerts, follow structured procedures, and use shared records during maintenance planning. Asset criticality may also modify the relationship because highly critical equipment typically receives denser monitoring, faster response, stronger maintenance controls, and greater resource priority (Beach, 2020). Equipment age, accumulated operating hours, environmental exposure, duty cycle, production loading, and baseline failure frequency can influence both the probability of failure and the achievable effect of integration. Older or heavily loaded assets may continue to experience frequent failures even when information visibility improves. The literature has also identified nonlinear and threshold patterns in digital integration. Limited connectivity may produce little measurable performance change when only a small proportion of assets is monitored or when interfaces continue to require extensive manual reconciliation (Ladd & Kochenderfer-Ladd, 2019). Stronger outcomes may appear after sufficient asset coverage, data completeness, interface automation, user adoption, and cross-platform functional integration have been achieved. Very high integration levels can also produce diminishing gains when additional tags, dashboards, or automated alerts add limited decision value. Quantitative analysis should therefore examine interaction effects, subgroup differences, maturity categories, and nonlinear relationships while controlling for facility size, industrial sector, maintenance strategy, asset population, operating exposure, and baseline performance (Khaola & Rambe, 2021).

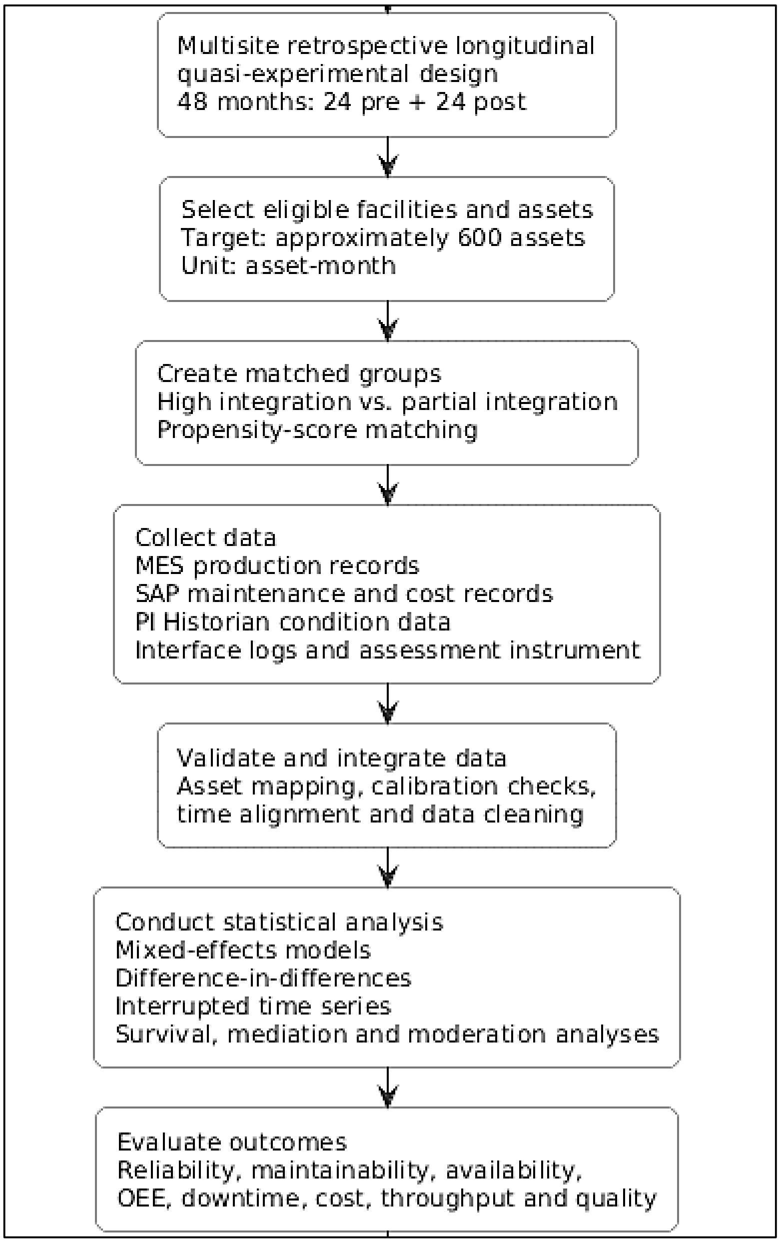
METHOD

This study employed a multisite, retrospective longitudinal, quasi-experimental quantitative design to examine the influence of MES–SAP–PI Historian integration on real-time industrial asset performance management. Random assignment was not feasible because the platforms had been implemented through existing organizational and operational decisions. The study compared assets operating under high-integration conditions with matched assets operating under partial or fragmented integration. It also evaluated changes before and after the verified integration date. The observation period covered 48 consecutive months, consisting of a 24-month preintegration period and a 24-month postintegration period. The principal unit of analysis was the asset-month, while failure events, maintenance work orders, production orders, and condition alerts nested within assets and facilities served as secondary units. The theoretical framework combined organizational information-processing theory, information-systems success theory, the resource-based view, dynamic-capabilities theory, and socio-technical systems theory. MES–SAP–PI integration quality was treated as the principal independent variable and was represented through interoperability, interface automation, bidirectional data exchange, synchronization timeliness, asset-mapping accuracy, functional coverage, information completeness, and transaction reliability. Industrial asset performance was treated as the dependent construct and was measured through failure frequency, mean time between failures, mean time to repair, availability, overall equipment effectiveness, unplanned downtime, repeated-failure occurrence, maintenance cost, throughput, quality yield, and production loss. Real-time information visibility and maintenance responsiveness were examined as mediating variables. Data quality, digital maturity, asset criticality, equipment age, production loading, environmental exposure, maintenance strategy, facility size, and baseline reliability were examined as moderating or control variables.

The study population consisted of production and maintenance assets located in asset-intensive manufacturing and process-industry facilities that used MES, SAP, and PI Historian platforms. Participating facilities were selected through a multistage sampling strategy. Facilities were initially identified through purposive screening because eligible organizations were required to maintain accessible historical data from all three platforms. Eligible facilities were subsequently stratified according to industrial sector, production system, facility size, integration maturity, and geographical location. Assets within each facility were stratified according to equipment category, criticality, age, maintenance strategy, and baseline operating exposure. A census of all eligible assets was taken within the selected facilities to reduce selection bias associated with discretionary equipment sampling. The initial asset pool was divided into a high-integration group and a partial- or fragmented-integration comparison group. High-integration assets had verified automated connections among MES, SAP, and PI Historian records, while comparison assets relied on isolated applications, manual transfer, one-directional interfaces, or incomplete cross-platform linkage. Propensity-score matching was used to create comparable groups based on asset category, age, criticality, operating hours, baseline failure rate, production loading, maintenance strategy, environmental exposure, and facility characteristics. An a priori simulation-based power assessment indicated that a minimum of 480 assets, with approximately equal numbers in the integration and comparison groups, was required to detect a practically meaningful reduction in failure occurrence with 80% statistical power at a two-tailed significance level of .05. The sampling target was increased to approximately 600 assets to accommodate exclusions, incomplete observation periods, and clustering within facilities. With 48 monthly observations per asset, the planned sample provided a sufficiently large panel for mixed-effects, difference-in-differences, survival, mediation, and subgroup analyses.

Assets were included when they had a stable and verifiable identifier across the relevant MES, SAP, and PI environments; at least 12 months of valid observations before integration and 12 months after integration; documented operating-hour information; recorded production or service exposure; accessible failure and maintenance histories; and sufficient condition-monitoring data to establish the timing of major operational events. Compressors, pumps, motors, turbines, conveyors, production machines, packaging lines, utility equipment, electrical systems, instrumentation systems, and other production-critical assets were considered eligible.

Figure 11: Methodology of this study



Assets were also required to have a defined functional location, criticality classification, maintenance strategy, commissioning date, and connection with a recognizable production process or service function. Assets were excluded when they had been permanently decommissioned during the baseline period, had undergone complete replacement or major redesign that fundamentally changed their operating characteristics, had been used primarily as inactive standby equipment, or lacked a reliable connection among asset identity, operating exposure, and maintenance records. Asset-month observations were excluded when operating hours could not be verified, when historian data were unavailable for the entire month, or when production was suspended because of major external events unrelated to equipment performance. Individual records were not excluded solely because of short data gaps, interface interruptions, or missing noncritical fields. These conditions were retained as data-quality indicators when they remained measurable and were addressed through the predefined missing-data procedure.

Data were collected from MES production databases, SAP enterprise and asset-management modules, the PI Historian environment, middleware logs, condition-monitoring systems, calibration records, maintenance documents, and facility-level operational reports. MES supplied production-order release and completion times, planned and actual quantities, equipment states, cycle duration, downtime events, reason codes, work-in-process status, product and batch identifiers, quality results, material consumption, and production-confirmation records. SAP supplied asset master data, functional locations, maintenance notifications, work orders, task completion dates, failure and damage codes, labor confirmations, spare-parts reservations and issues, procurement lead times, preventive-maintenance schedules, contractor expenses, and maintenance costs. PI Historian supplied timestamped temperature, pressure, vibration, flow, speed, current, load, runtime, alarm, set-point, and equipment-state data. Middleware and interface logs supplied message counts, rejected transactions, retry frequency, queue delay, synchronization latency, interface availability, and recovery duration.

A structured Integration Maturity and Information Visibility Assessment Instrument was also completed by authorized personnel from production, maintenance, reliability, engineering, and information-technology functions. The instrument used five-point response categories and measured interoperability, interface automation, bidirectional exchange, asset mapping, data quality, dashboard timeliness, alert performance, event traceability, information accessibility, employee competence, and governance maturity. Content validity was established through review by industrial automation, maintenance, reliability, SAP, MES, and PI specialists. The instrument was pilot-tested using respondents and facilities that were not included in the final analysis. Internal consistency was evaluated using Cronbach's alpha and McDonald's omega, with values of .70 or higher treated as acceptable. Construct validity was examined through exploratory and confirmatory factor analyses. Standardized factor loadings, composite reliability, and average variance extracted were examined to assess convergent validity, while correlations among constructs and discriminant-validity criteria were used to confirm construct separation.

Only condition measurements originating from instruments with current calibration or documented functional verification were classified as valid primary observations. Calibration status, measurement range, engineering unit, sensor location, inspection date, and data-quality flag were reviewed before the historian records were used. Values recorded outside the instrument range, signals marked as bad or uncertain, and observations generated during known maintenance or communication tests were flagged and excluded from condition-performance calculations. A common asset dictionary was created to align PI tags, MES resources, SAP equipment numbers, functional locations, production lines, and work centers. Automated matching was followed by manual verification for uncertain or conflicting records. A random sample of mapped assets and events was independently reviewed by two trained assessors. Agreement was evaluated using percentage agreement and an appropriate chance-adjusted coefficient, with disagreements resolved through examination of source records.

Operational definitions were standardized before extraction. A failure was defined as an unplanned loss or unacceptable degradation of required asset function that caused repair, production interruption, protective trip, or documented corrective intervention.

Repeated failure was defined according to the recurrence of the same asset or failure mechanism within the specified 7-day, 30-day, 90-day, or annual period. Downtime began when the asset became unavailable for required operation and ended after functional testing and verified restoration. Planned shutdowns, production-independent waiting, and external supply interruptions were coded separately. Availability, overall equipment effectiveness, operating exposure, maintenance response, restoration duration, and production loss were calculated using common rules across all facilities. Data validation compared MES production totals with SAP confirmations, PI runtime with MES equipment states, maintenance duration with work-order timestamps, and reported costs with SAP postings.

The study was conducted through a predefined chronological procedure. Organizational approval, data-access authorization, confidentiality agreements, and cybersecurity clearance were obtained before extraction. The participating facilities then provided platform architecture descriptions, interface inventories, asset hierarchies, integration dates, maintenance strategies, and data dictionaries. The integration date for each facility or asset group was verified through implementation documents, system-acceptance records, interface logs, and evidence of sustained production use. Pilot or testing dates were not treated as operational integration dates. Asset identifiers were mapped across the three platforms, after which eligible assets were screened against the inclusion and exclusion criteria. Raw data were extracted into a secure staging environment using read-only queries and approved export procedures. Personally identifiable employee information was removed, and each facility and asset was assigned a coded identifier. Source records were preserved unchanged, while standardized analytical tables were created for asset-months, failure events, condition alerts, maintenance notifications, work orders, production orders, downtime episodes, material transactions, and costs. Timestamps were converted to a common time standard, duplicated records were flagged, engineering units were harmonized, and event sequences were reconstructed. A baseline dataset was created for the preintegration period, followed by an equivalent postintegration dataset. Integration-quality indicators were calculated from interface logs, asset mappings, transaction results, and the structured assessment instrument. Real-time visibility indicators were derived from monitoring coverage, valid operating-hour coverage, dashboard availability, alert latency, information completeness, and event traceability. Maintenance responsiveness was measured through alert-to-notification time, notification-to-order time, planning delay, response time, repair duration, spare-parts waiting, and restoration duration. Outcome measures were then calculated for each asset-month and failure event. The cleaned dataset was independently checked against source-system totals, and the analytical database was locked after discrepancies had been reviewed and documented.

Statistical analysis was performed using SPSS and R, while Python was used for approved data extraction, timestamp alignment, record linkage, validation, and reproducible data preparation. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, minimums, maximums, and confidence intervals. Distributional characteristics were examined using histograms, quantile plots, skewness, kurtosis, and formal normality tests. Baseline differences between high-integration and comparison assets were evaluated using independent-samples t tests, Mann–Whitney tests, chi-square tests, or Fisher's exact tests, depending on variable type and distribution. Differences across multiple asset categories, facilities, or integration levels were examined using analysis of variance or the Kruskal–Wallis test. Standardized mean differences were reported to evaluate balance before and after propensity-score matching. Propensity scores were estimated through logistic regression using asset category, age, criticality, baseline operating hours, production loading, environmental severity, maintenance strategy, facility size, sector, and preintegration reliability. One-to-one nearest-neighbor matching was performed using a restricted matching distance, and covariate balance was accepted when standardized differences were sufficiently small. Sensitivity analyses used alternative matching specifications, inverse-probability weighting, and adjustment through multivariable regression.

Failure counts were analyzed using generalized linear mixed-effects models. Poisson models were evaluated initially, and negative-binomial models were used when the variance exceeded the mean. Operating hours were included as an exposure adjustment, and random intercepts accounted for repeated observations within assets and facilities.

Results were reported as adjusted incidence-rate ratios with 95% confidence intervals. Repeated-failure occurrence was analyzed using mixed-effects logistic regression and reported through adjusted odds ratios. Continuous outcomes such as mean time between failures, mean time to repair, availability, overall equipment effectiveness, downtime, throughput, quality yield, and maintenance cost were analyzed using linear mixed-effects models when assumptions were satisfied. Positively skewed duration and cost variables were analyzed using logarithmic transformation or generalized models with an appropriate distribution. The principal quasi-experimental effect was estimated through difference-in-differences analysis comparing changes from the preintegration period to the postintegration period between integrated and matched comparison assets.

Asset and calendar-period effects were included to account for stable equipment characteristics and common temporal changes. The parallel-trends assumption was evaluated using preintegration outcome patterns and event-time coefficients. Interrupted time-series analysis was also conducted through segmented regression to estimate immediate level changes and changes in monthly outcome trends following integration. Autocorrelation, seasonality, and nonconstant variance were examined and corrected when present.

Time to first failure and time to subsequent failure were evaluated using Kaplan–Meier survival estimates and log-rank tests. Multivariable Cox proportional-hazards models estimated the relative hazard of failure after adjustment for asset and facility characteristics. Shared-frailty terms accounted for clustering within facilities, while recurrent-event models were used for assets experiencing multiple failures. The proportional-hazards assumption was assessed through residual-based diagnostics and time-dependent effects.

The mediating role of real-time information visibility was tested through multilevel mediation analysis. Sequential mediation examined the pathway from integration quality to information visibility, from visibility to maintenance responsiveness, and from responsiveness to asset performance. Indirect effects were evaluated using 5,000 bootstrap resamples and 95% confidence intervals. Moderation was examined by adding interaction terms for data quality, digital maturity, asset criticality, age, operating exposure, production loading, environmental severity, and maintenance strategy. Nonlinear and threshold effects were evaluated using integration-maturity categories, polynomial terms, and segmented relationships where supported by the data.

FINDINGS

Final Dataset, Facility Characteristics, and Asset-Sample Distribution

Twenty-four industrial facilities were initially assessed for participation. Six facilities were excluded because three lacked consistently linked MES, SAP, and PI Historian records, two had unverifiable operational integration dates, and one did not provide a sufficient longitudinal observation period. The final sample therefore included 18 facilities, equally distributed between high-integration and partial- or fragmented-integration conditions. These facilities represented discrete, continuous, batch, and hybrid production systems across medium-sized and large industrial operations.

A total of 758 assets were screened, of which 110 were excluded during eligibility assessment. The principal reasons were insufficient longitudinal observations, missing operating-hour records, inactive standby status, major equipment redesign, decommissioning, incomplete failure histories, and unreliable cross-platform asset mapping. The remaining 648 eligible assets comprised 332 high-integration assets and 316 comparison assets. Propensity-score matching produced 300 comparable asset pairs, giving a final sample of 600 assets. The matched dataset contained 28,224 valid asset-month observations, representing 98.0% of the maximum 28,800 observations available across the 48-month study period.

The final analytical database contained 4,286 verified failure events, 52,614 condition alerts, 8,932 maintenance notifications, 8,147 maintenance work orders, 101,684 production orders, 5,473 downtime episodes, and 8,006 cost records. Required-field completeness reached 97.6%. Historian tag gaps represented 1.7% of expected observation intervals, incomplete work-order fields represented 2.6% of maintenance records, and unmatched cross-platform events declined from 6.8% before asset mapping to 1.9% after validation. Duplicate transactions represented 0.8% of extracted records and were removed before analysis.

Table 1. Facility Screening, Asset Selection, and Final Analytical Records

Selection stage or record category	Number	Percentage or retention
Facilities initially assessed	24	100.0%
Facilities excluded because of unavailable linked records	3	12.5%
Facilities excluded because of unverifiable integration dates	2	8.3%
Facility excluded because of insufficient observation period	1	4.2%
Facilities retained	18	75.0%
Assets initially screened	758	100.0%
Insufficient preintegration or postintegration records	31	4.1%
Missing or unverifiable operating exposure	22	2.9%
Inactive standby assets	14	1.8%
Major redesign or replacement	13	1.7%
Decommissioned assets	9	1.2%
Incomplete failure histories	12	1.6%
Unreliable cross-platform asset mapping	9	1.2%
Assets satisfying eligibility criteria	648	85.5%
Eligible high-integration assets before matching	332	51.2% of eligible assets
Eligible comparison assets before matching	316	48.8% of eligible assets
Final matched high-integration assets	300	50.0% of final sample
Final matched comparison assets	300	50.0% of final sample
Maximum possible asset-months	28,800	100.0%
Valid asset-months retained	28,224	98.0%
Verified failure events	4,286	—
Condition alerts	52,614	—
Maintenance notifications	8,932	—
Maintenance work orders	8,147	—
Production orders	101,684	—
Downtime episodes	5,473	—
Valid cost records	8,006	—

Table 1 shows that 18 of the 24 screened facilities satisfied all platform, integration-date, and observation-period requirements. Of 758 initially identified assets, 648 met the eligibility criteria and 600 remained after matching. The equal allocation of 300 assets to each comparison condition supported balanced estimation of integration effects. The retained 28,224 asset-months represented 98.0% of all possible longitudinal observations, demonstrating strong data continuity. The database also contained substantial numbers of failures, alerts, maintenance transactions, production orders, downtime events, and cost records, providing adequate analytical depth for reliability, maintenance, production, survival, mediation, and subgroup analyses.
Baseline differences were substantially reduced after propensity-score matching. Before matching, the largest absolute standardized mean difference was .27 for baseline failure rate, followed by .24 for asset age and .22 for annual operating exposure. After matching, all standardized differences were .04 or lower, remaining well below the accepted balance threshold of .10. No statistically significant postmatching differences were found in asset age, criticality, operating hours, loading, environmental severity, maintenance strategy, baseline failure rate, or asset-category distribution. The matched groups therefore demonstrated strong comparability before the primary outcome analysis.

Table 2 demonstrates that propensity-score matching produced highly comparable integration groups. Differences in asset age, criticality, annual operating exposure, production loading, environmental severity, maintenance strategy, and baseline failure occurrence were small and statistically nonsignificant after matching. Every postmatching standardized mean difference remained at or below .04, indicating stronger balance than the conventional .10 criterion. The distribution of compressors, pumps, motors, turbines, conveyors, production machines, packaging lines, utilities, electrical equipment, and instrumentation systems was also closely aligned. Consequently, subsequent outcome differences were less likely to reflect preexisting variation in equipment composition, operating conditions, maintenance strategy, or baseline reliability.

Table 2 Baseline Characteristics of the Final Matched Asset Sample

Characteristic	High integration (n = 300)	Partial or fragmented integration (n = 300)	Pre-match |SMD|	Post-match |SMD|	*p*
Facilities	9	9	—	.00	1.000
Asset age, years, mean (SD)	8.8 (4.1)	8.9 (4.0)	.24	.03	.762
High-criticality assets, n (%)	128 (42.7)	125 (41.7)	.19	.02	.804
Operating hours per year, mean (SD)	6,482 (1,213)	6,451 (1,228)	.22	.03	.756
Production loading, %, mean (SD)	76.8 (11.4)	76.5 (11.7)	.18	.03	.751
Environmental severity, mean (SD)	3.08 (0.84)	3.11 (0.82)	.15	.04	.658
Baseline failures per 1,000 hours, mean (SD)	0.184 (0.071)	0.187 (0.074)	.27	.04	.613
Condition-based or predictive strategy, n (%)	136 (45.3)	134 (44.7)	.16	.01	.869
Compressors, n (%)	48 (16.0)	46 (15.3)	.08	.02	.816
Pumps, n (%)	62 (20.7)	64 (21.3)	.07	.02	.825
Motors, n (%)	54 (18.0)	52 (17.3)	.09	.02	.824
Turbines, n (%)	20 (6.7)	22 (7.3)	.06	.03	.747
Conveyors, n (%)	30 (10.0)	29 (9.7)	.05	.01	.893
Production machines, n (%)	36 (12.0)	35 (11.7)	.08	.01	.899
Packaging lines, n (%)	18 (6.0)	19 (6.3)	.06	.01	.864
Utility equipment, n (%)	14 (4.7)	15 (5.0)	.05	.02	.849
Electrical equipment, n (%)	10 (3.3)	10 (3.3)	.04	.00	1.000
Instrumentation systems, n (%)	8 (2.7)	8 (2.7)	.03	.00	1.000

Note. SMD = standardized mean difference. Percentages were calculated within each integration group.

Descriptive Patterns in Integration Quality, Visibility, Maintenance, and Asset Outcomes

For descriptive analysis, the 18 participating facilities were divided into equal integration-maturity tiers using their composite MES–SAP–PI integration scores. Six facilities were classified as high integration, six as medium integration, and six as low integration. The high-integration facilities recorded a mean integration score of 87.6, compared with 68.9 for medium-integration facilities and 43.7 for low-integration facilities. Clear gradients were observed across interface automation, transaction reliability, synchronization latency, asset mapping, functional coverage, monitoring coverage, event traceability, and maintenance responsiveness. High-integration facilities automated 92.4% of eligible interfaces and achieved a transaction-success rate of 99.3%. Their median synchronization latency was 6.8 seconds, compared with 34.6 seconds in the medium-integration tier and 214.0 seconds in the low-integration tier. Asset-mapping accuracy reached 98.7% in high-integration facilities, while data completeness and interface availability reached 98.8% and 99.6%, respectively. Real-time monitoring covered 96.2% of eligible assets and 97.4% of critical tags. Event traceability reached 94.1%, indicating that most abnormal conditions could be connected with their associated production interruptions, maintenance records, resource consumption, and costs. Maintenance responsiveness also differed substantially across integration levels. Median alert-to-notification time was 3.8 minutes in high-integration facilities, 14.7 minutes in medium-integration facilities, and 39.5 minutes in low-integration facilities. Median notification-to-work-order time was 18.6, 47.9, and 105.6 minutes, respectively. Median total restoration duration was 7.6 hours in the high-integration tier and 15.8 hours in the low-integration tier. These results indicated that stronger platform integration was accompanied by faster information transmission, wider operational visibility, more complete event evidence, and shorter maintenance-processing intervals.

Table 3 Integration Quality, Real-Time Visibility, and Maintenance Responsiveness by Integration-Maturity Tier

Indicator	High integration (n = 6 facilities)	Medium integration (n = 6 facilities)	Low integration (n = 6 facilities)
Composite integration score, mean (SD)	87.6 (4.9)	68.9 (5.6)	43.7 (7.1)
Interface automation, %, mean (SD)	92.4 (4.3)	71.8 (7.2)	38.6 (10.1)
Transaction success, %, mean (SD)	99.3 (0.4)	97.2 (1.1)	92.8 (2.6)
Synchronization latency, seconds, median (IQR)	6.8 (4.2–11.5)	34.6 (19.8–65.1)	214.0 (128.0–391.0)
Bidirectional data exchange, %, mean (SD)	88.1 (6.4)	60.5 (9.8)	24.7 (11.9)
Asset-mapping accuracy, %, mean (SD)	98.7 (0.8)	94.6 (2.1)	84.9 (5.4)
Functional integration coverage, %, mean (SD)	90.2 (5.1)	68.7 (8.4)	40.8 (12.2)
Data completeness, %, mean (SD)	98.8 (0.5)	96.1 (1.4)	89.7 (3.8)
Interface availability, %, mean (SD)	99.6 (0.2)	98.4 (0.7)	95.1 (2.2)
Monitored-asset coverage, %, mean (SD)	96.2 (3.1)	78.5 (7.6)	52.4 (11.8)
Critical-tag coverage, %, mean (SD)	97.4 (1.9)	82.6 (6.5)	59.3 (10.4)
Valid operating-hour coverage, %, mean (SD)	98.9 (0.6)	96.7 (1.2)	90.5 (3.5)
Dashboard refresh time, seconds, median (IQR)	8.0 (5.0–12.0)	37.0 (20.0–61.0)	181.0 (91.0–310.0)
Alert-generation delay, seconds, median (IQR)	14.0 (9.0–25.0)	65.0 (38.0–122.0)	286.0 (154.0–475.0)
Event traceability, %, mean (SD)	94.1 (4.0)	73.8 (8.8)	41.6 (13.7)
Information accessibility, mean (SD)	4.43 (0.36)	3.64 (0.47)	2.71 (0.61)
Alert-to-notification time, minutes, median (IQR)	3.8 (2.1–6.4)	14.7 (8.5–24.2)	39.5 (23.6–68.9)
Notification-to-work-order time, minutes, median (IQR)	18.6 (10.4–31.8)	47.9 (28.5–80.2)	105.6 (63.4–174.3)
Total restoration duration, hours, median (IQR)	7.6 (4.2–12.8)	10.9 (6.1–18.7)	15.8 (8.9–27.4)

Note. IQR = interquartile range. Information accessibility was measured on a five-point scale, with higher values representing stronger accessibility.

Table 3 demonstrates a consistent performance gradient across the three integration-maturity tiers. High-integration facilities achieved greater interface automation, transaction success, asset-mapping accuracy, data completeness, monitoring coverage, and event traceability. They also recorded markedly shorter synchronization, dashboard-refresh, alert-generation, notification-processing, and restoration times. Medium-integration facilities occupied an intermediate position across nearly every measure, while low-integration facilities experienced the greatest delays and weakest information coverage. The alignment of technical, informational, and maintenance indicators showed that platform maturity represented a connected operational capability rather than an isolated interface characteristic. The largest differences occurred in bidirectional exchange, synchronization latency, event traceability, and maintenance-processing speed.

The matched high-integration and comparison groups had similar performance during the preintegration period. High-integration assets recorded 0.184 failures per 1,000 operating hours at baseline, while comparison assets recorded 0.187. Mean time between failures, mean time to repair, availability, overall equipment effectiveness, downtime, maintenance cost, throughput, quality yield, and production loss were also closely aligned before integration.

During the postintegration period, high-integration assets recorded substantial descriptive improvements. Their failure occurrence decreased to 0.125 events per 1,000 operating hours, mean time between failures increased from 5,435 to 7,918 hours, and mean time to repair declined from 11.7 to 8.2 hours. Availability increased by 2.5 percentage points, while overall equipment effectiveness increased by 6.1 percentage points. Annual unplanned downtime declined from 184.3 to 121.5 hours per asset, and repeated-failure occurrence decreased from 31.4% to 18.9%. Smaller changes were observed in the comparison group.

Table 4 Preintegration and Postintegration Descriptive Asset Outcomes by Matched Group

Outcome	**High integration pre, mean (SD)**	**High integration post, mean (SD)**	**Comparison pre, mean (SD)**	**Comparison post, mean (SD)**
Annual failures per asset	3.92 (2.11)	2.61 (1.74)	3.88 (2.07)	3.69 (2.02)
Failures per 1,000 operating hours	0.184 (0.071)	0.125 (0.058)	0.187 (0.074)	0.180 (0.070)
Mean time between failures, hours	5,435 (1,904)	7,918 (2,463)	5,382 (1,877)	5,561 (1,936)
Mean time to repair, hours	11.7 (6.4)	8.2 (4.7)	11.6 (6.2)	11.2 (5.9)
Availability, %	93.6 (3.1)	96.1 (2.2)	93.7 (3.0)	94.0 (2.9)
Overall equipment effectiveness, %	72.8 (8.7)	78.9 (7.4)	73.0 (8.5)	74.1 (8.1)
Annual unplanned downtime, hours	184.3 (91.6)	121.5 (68.4)	181.7 (89.8)	173.2 (86.1)
Repeated failures, %	31.4	18.9	30.8	28.7
Annual maintenance cost per asset, USD thousands	84.2 (37.6)	70.1 (31.8)	83.7 (36.9)	81.9 (35.7)
Throughput attainment, %	88.1 (7.8)	94.3 (5.6)	88.4 (7.6)	89.5 (7.2)
Quality yield, %	95.2 (3.3)	97.0 (2.1)	95.3 (3.2)	95.7 (2.9)
Annual production-loss value per asset, USD thousands	145.6 (73.4)	92.4 (51.7)	144.1 (71.9)	137.2 (68.5)

Table 4 shows that both matched groups had closely aligned performance before integration. During the postintegration period, high-integration assets experienced larger improvements across every reported outcome. Failure occurrence and repeated failures declined, while mean time between failures, availability, overall equipment effectiveness, throughput attainment, and quality yield increased. Repair duration, unplanned downtime, maintenance expenditure, and production-loss value also decreased substantially. The comparison group recorded only modest changes over the same period. These descriptive differences supported subsequent adjusted analyses while avoiding causal interpretation before mixed-effects, difference-in-differences, and interrupted time-series models had controlled for asset, facility, exposure, and temporal characteristics.

Monthly analysis showed that information-system measures changed earlier than physical asset outcomes. Median synchronization latency declined from 41.2 seconds during the first postintegration month to 7.1 seconds by month six. Transaction success exceeded 99% by the third month, and asset-mapping accuracy exceeded 98% by month six. Maintenance-response improvements became evident within the first quarter, whereas reductions in failure occurrence and downtime developed more gradually between months five and eighteen. The failure rate among high-integration assets declined from 0.181 per 1,000 operating hours during the first postintegration month to 0.118 by month 24. Comparison assets remained comparatively stable, changing from 0.183 to 0.178.

Integration quality correlated strongly with real-time visibility, data quality, and maintenance responsiveness. The correlation between integration quality and real-time visibility was .72, while the correlation with data quality was .68 and with maintenance responsiveness was .61. Integration quality was positively related to availability, overall equipment effectiveness, and mean time between failures, with coefficients ranging from .44 to .48. Negative relationships were observed with failure occurrence, repair duration, unplanned downtime, and maintenance cost, with coefficients ranging from −.31 to −.45. All principal correlations were statistically significant at $p < .001$. Failure counts showed overdispersion, while downtime, repair duration, and cost displayed positive skewness, supporting the use of negative-binomial, generalized mixed-effects, or transformed models in the adjusted analyses.

Primary Effects of MES–SAP–PI Integration on Industrial Asset Performance

The adjusted analyses showed that MES–SAP–PI integration was associated with statistically significant and operationally meaningful improvements across all principal asset-performance outcomes. The negative-binomial mixed-effects model indicated that high-integration assets experienced a 32% lower failure rate than matched comparison assets after adjustment for asset age, category, criticality, operating exposure, production loading, environmental conditions, maintenance strategy, facility size, industrial sector, calendar period, and baseline reliability. The adjusted incidence-rate ratio was 0.68, with a 95% confidence interval from 0.61 to 0.75. Repeated-failure odds were 51% lower among high-integration assets, with an adjusted odds ratio of 0.49. Mean time between failures increased by an adjusted 2,310 hours, while mean time to repair declined by 3.08 hours. Availability increased by 2.18 percentage points, and overall equipment effectiveness increased by 4.96 percentage points. Annual unplanned downtime decreased by 55.1 hours per asset. Throughput attainment and quality yield increased by 5.04 and 1.36 percentage points, respectively. Annual maintenance expenditure declined by approximately USD 12,600 per asset, while annual production-loss value decreased by approximately USD 45,800 per asset. Standardized effect sizes ranged from moderate for maintenance cost and quality yield to large for mean time between failures, availability, throughput, and downtime.

Table 5 demonstrates that adjustment for asset and facility characteristics did not materially weaken the estimated integration effects. High integration was associated with lower failure occurrence, repeated-failure probability, repair duration, downtime, maintenance expenditure, and production-loss value. Positive effects were recorded for failure-free operating time, availability, overall equipment effectiveness, throughput attainment, and quality yield. Confidence intervals excluded the null value for every principal outcome, and all probability values were below .001. Effect sizes were largest for mean time between failures, availability, throughput, and downtime, while maintenance cost and quality yield produced smaller but operationally relevant effects.

Table 5 Unadjusted and Adjusted Primary Effects of High MES–SAP–PI Integration

Outcome	Unadjusted estimate	Adjusted estimate	95% CI	*p*	Effect magnitude
Failure occurrence, incidence-rate ratio	0.70	0.68	0.61 to 0.75	< .001	32% lower rate
Repeated failure, odds ratio	0.54	0.49	0.39 to 0.62	< .001	51% lower odds
Mean time between failures, hours	+2,304	+2,310	1,984 to 2,636	< .001	$d = 0.86$
Mean time to repair, hours	−3.10	−3.08	−3.71 to −2.45	< .001	$d = -0.55$
Availability, percentage points	+2.20	+2.18	1.82 to 2.54	< .001	$d = 0.76$
Overall equipment effectiveness, percentage points	+5.00	+4.96	4.19 to 5.73	< .001	$d = 0.63$
Annual unplanned downtime, hours per asset	−54.3	−55.1	−63.9 to −46.3	< .001	$d = -0.68$
Throughput attainment, percentage points	+5.10	+5.04	4.29 to 5.79	< .001	$d = 0.72$
Quality yield, percentage points	+1.40	+1.36	0.91 to 1.81	< .001	$d = 0.48$
Annual maintenance cost, USD thousands per asset	−12.3	−12.6	−16.2 to −9.0	< .001	$d = -0.36$
Annual production-loss value, USD thousands per asset	−46.3	−45.8	−52.7 to −38.9	< .001	$d = -0.61$

Note. Continuous estimates represented adjusted differences between the preintegration-to-postintegration change in high-integration assets and the corresponding change in matched comparison assets. CI = confidence interval.

The difference-in-differences models confirmed that the postintegration changes among high-integration assets exceeded the changes observed among matched comparison assets. The joint test of preintegration event-time coefficients was nonsignificant, $\chi^2(23) = 19.72$, $p = .66$, supporting the parallel-trends requirement. No statistically significant anticipatory changes were detected before the verified operational integration date. Interrupted time-series results showed that integration produced both immediate and gradual changes. Failure occurrence decreased immediately by 0.012 events per 1,000 operating hours and continued to decline by 0.0018 events per 1,000 hours each month. Mean time between failures increased immediately by 410 hours and subsequently increased by an additional 82.5 hours per month. Availability and overall equipment effectiveness recorded immediate increases of 0.61 and 1.14 percentage points, followed by positive monthly trend changes. Repair duration, downtime, maintenance cost, and production-loss value also displayed significant immediate reductions followed by continuing monthly improvements.

Table 6 shows that the integration effects involved both immediate level changes and sustained postintegration trend changes. Information-sensitive outcomes, including availability, overall equipment effectiveness, and maintenance responsiveness, improved directly after integration. Reliability and economic outcomes developed more gradually, as demonstrated by continuing monthly improvements in failure occurrence, failure-free operating time, downtime, maintenance cost, and production loss. The nonsignificant joint pretrend test supported the difference-in-differences design, while statistically significant postintegration slope changes strengthened the temporal evidence. The combined results indicated that integration was associated with an early operational response followed by progressively larger reliability and performance gains.

Table 6 Difference-in-Differences and Interrupted Time-Series Estimates

Outcome	Adjusted difference-in-differences estimate	95% CI	Immediate level change	*p*	Monthly trend change	*p*
Failures per 1,000 operating hours	−0.052	−0.061 to −0.043	−0.012	.001	−0.0018	< .001
Mean time between failures, hours	+2,310	1,984 to 2,636	+410	.002	+82.5	< .001
Mean time to repair, hours	−3.08	−3.71 to −2.45	−0.79	.002	−0.095	< .001
Availability, percentage points	+2.18	1.82 to 2.54	+0.61	< .001	+0.068	< .001
Overall equipment effectiveness, percentage points	+4.96	4.19 to 5.73	+1.14	< .001	+0.160	< .001
Unplanned downtime, hours per asset-month	−4.59	−5.33 to −3.85	−1.56	< .001	−0.126	< .001
Throughput attainment, percentage points	+5.04	4.29 to 5.79	+0.94	< .001	+0.171	< .001
Quality yield, percentage points	+1.36	0.91 to 1.81	+0.26	.005	+0.047	< .001
Maintenance cost, USD thousands per asset-month	−1.05	−1.35 to −0.75	−0.26	.015	−0.033	< .001
Production-loss value, USD thousands per asset-month	−3.82	−4.39 to −3.25	−0.92	< .001	−0.121	< .001

Note. Immediate level changes represented changes at the verified integration point. Monthly trend changes represented differences between the preintegration and postintegration slopes after adjustment for the comparison group and model covariates.

Secondary, Subgroup, Survival, Mediation, and Moderation Findings

Subgroup analysis showed that MES–SAP–PI integration was associated with lower failure occurrence across nearly all asset categories. The largest adjusted reductions were observed among turbines, compressors, utilities, and pumps. Effects were smaller among conveyors, electrical systems, and instrumentation equipment. The overall interaction between integration and asset category was not statistically significant, indicating that the direction of the integration effect remained broadly consistent across equipment types. The nonsignificant estimates for electrical and instrumentation systems were accompanied by wider confidence intervals because these categories contained fewer assets and failure events. Significant effect differences were observed according to asset criticality, maintenance strategy, digital maturity, and baseline failure frequency. High-criticality assets recorded a 41% adjusted reduction in failure occurrence, compared with a 25% reduction among medium- and low-criticality assets. Assets supported by condition-based or predictive maintenance recorded a 43% reduction, while assets under preventive or corrective strategies recorded a 24% reduction. The strongest association occurred in high-digital-maturity facilities, where the adjusted failure-rate ratio was 0.55. Integration effects were weaker in low-maturity facilities. Equipment age, facility size, environmental severity, and production loading produced directional variation, although not all interaction tests reached statistical significance.

Table 7 Adjusted Integration Effects on Failure Occurrence Across Asset and Facility Subgroups

Subgroup	Assets, n	Adjusted incidence-rate ratio	95% CI	p	Interaction p
Compressors	94	0.62	0.51 to 0.76	< .001	.284
Pumps	126	0.66	0.57 to 0.77	< .001	—
Motors	106	0.71	0.60 to 0.84	< .001	—
Turbines	42	0.60	0.44 to 0.82	.002	—
Conveyors	59	0.74	0.59 to 0.93	.010	—
Production machines and lines	71	0.69	0.57 to 0.84	< .001	—
Packaging lines	37	0.72	0.52 to 0.99	.045	—
Utility equipment	29	0.64	0.47 to 0.87	.005	—
Electrical equipment	20	0.78	0.56 to 1.08	.134	—
Instrumentation systems	16	0.76	0.52 to 1.12	.162	—
High-criticality assets	253	0.59	0.51 to 0.68	< .001	.018
Medium- and low-criticality assets	347	0.75	0.66 to 0.85	< .001	—
Asset age below eight years	282	0.73	0.63 to 0.84	< .001	.071
Asset age of eight years or more	318	0.64	0.56 to 0.74	< .001	—
Condition-based or predictive maintenance	270	0.57	0.49 to 0.66	< .001	.006
Preventive or corrective maintenance	330	0.76	0.67 to 0.87	< .001	—
Large facilities	362	0.65	0.57 to 0.74	< .001	.220
Medium-sized facilities	238	0.72	0.61 to 0.84	< .001	—
High digital maturity	198	0.55	0.46 to 0.66	< .001	< .001
Medium digital maturity	206	0.68	0.58 to 0.80	< .001	—
Low digital maturity	196	0.81	0.69 to 0.95	.010	—
Production loading of 80% or higher	245	0.62	0.53 to 0.73	< .001	.090
Production loading below 80%	355	0.72	0.63 to 0.82	< .001	—
High baseline failure frequency	290	0.58	0.50 to 0.67	< .001	.012
Lower baseline failure frequency	310	0.75	0.65 to 0.86	< .001	—

Note. Values below 1.00 represented lower adjusted failure occurrence among high-integration assets. Interaction probability values evaluated differences between categories within each subgroup variable.

Table 7 shows that integration was associated with reduced failure occurrence across most equipment and operating subgroups. The strongest effects appeared among turbines, compressors, high-criticality assets, condition-monitored equipment, digitally mature facilities, and assets with high baseline failure frequency. Asset-category heterogeneity was nonsignificant, indicating broadly consistent benefits across equipment types. Significant interactions were identified for criticality, maintenance strategy, digital maturity, and baseline failure frequency. Electrical and instrumentation estimates did not reach significance because their smaller samples produced wider confidence intervals. Equipment age, facility size, environmental severity, and production loading changed the magnitude of the estimates without materially changing their overall direction. Kaplan–Meier analysis showed substantial differences in failure-free operating duration across integration levels. Median failure-free duration was 8,420 hours for high-integration assets, 6,310 hours for medium-integration assets, and 4,870 hours for low-integration assets. The overall survival distributions differed significantly, log-rank $\chi^2(2) = 86.4$, $p < .001$. After adjustment, high-integration assets had a 44% lower failure hazard than low-integration assets. Medium-integration assets had a 22% lower hazard. Recurrent-event analysis showed a 37% reduction in repeated-failure intensity among high-integration assets. Their median time to recurrence was 2,980 hours, compared with 1,840 hours for low-integration assets. The standardized total effect of integration quality on the composite asset-performance outcome was 0.58. After real-time visibility and maintenance responsiveness were included, the direct effect declined to 0.27. The total indirect effect was 0.31, indicating that 53.4% of the integration–performance relationship was transmitted through the mediating mechanisms. Real-time visibility accounted for an indirect effect of 0.14, maintenance responsiveness accounted for 0.07, and the sequential integration–visibility–responsiveness–performance pathway accounted for 0.10. All indirect effects had bootstrap confidence intervals excluding zero.

Table 8 Survival, Recurrent-Event, Mediation, Moderation, and Threshold Estimates

Analysis	Estimate	95% CI	*p*
High integration: median failure-free duration, hours	8,420	7,940 to 8,960	< .001
Medium integration: median failure-free duration, hours	6,310	5,940 to 6,710	< .001
Low integration: median failure-free duration, hours	4,870	4,510 to 5,250	Reference
High versus low integration: adjusted failure hazard ratio	0.56	0.48 to 0.66	< .001
Medium versus low integration: adjusted failure hazard ratio	0.78	0.68 to 0.90	.001
High versus low integration: recurrent-failure rate ratio	0.63	0.56 to 0.71	< .001
High-integration median recurrence time, hours	2,980	2,710 to 3,290	< .001
Low-integration median recurrence time, hours	1,840	1,660 to 2,050	Reference
Total integration effect on asset performance, standardized coefficient	0.58	0.50 to 0.66	< .001
Direct effect after mediators	0.27	0.19 to 0.35	< .001
Indirect effect through real-time visibility	0.14	0.09 to 0.20	< .001
Indirect effect through maintenance responsiveness	0.07	0.04 to 0.11	< .001
Sequential indirect effect through visibility and responsiveness	0.10	0.06 to 0.15	< .001
Total indirect effect	0.31	0.24 to 0.39	< .001
Data-quality moderation effect	0.18	0.10 to 0.26	< .001
Digital-maturity moderation effect	0.16	0.08 to 0.24	< .001
Employee-competence moderation effect	0.11	0.04 to 0.18	.002
Asset-criticality moderation effect	0.09	0.02 to 0.16	.012
Equipment-age moderation effect	−0.07	−0.14 to 0.00	.051
Production-loading moderation effect	−0.10	−0.17 to −0.03	.005
Estimated integration-score threshold	71.4	68.2 to 74.6	< .001
Estimated interface-automation threshold, %	74.8	71.1 to 78.5	< .001

Estimated monitoring-coverage threshold, %	79.6	75.8 to 83.4	< .001
Estimated data-completeness threshold, %	95.1	93.9 to 96.3	< .001
Estimated asset-mapping threshold, %	94.3	92.7 to 95.9	< .001

Note. The asset-performance composite was coded so that higher values represented stronger reliability, availability, maintainability, productivity, and quality. Mediation confidence intervals were based on 5,000 bootstrap resamples.

Table 8 demonstrates that high integration increased failure-free survival and reduced recurrent-failure intensity. More than half of the integration effect on composite asset performance was transmitted through real-time visibility and maintenance responsiveness. Data quality and digital maturity produced the strongest positive moderation effects, while higher production loading weakened the relationship. Nonlinear analysis identified minimum maturity levels for integration quality, interface automation, monitoring coverage, data completeness, and asset mapping. Below these levels, estimated performance gains were limited and inconsistent. Above the thresholds, the relationship became substantially stronger, showing that broad, reliable, and actively used integration was associated with the greatest asset-performance improvement.

Statistical Significance, Effect Magnitudes, Robustness, and Visual Presentation

All principal integration effects remained statistically significant after covariate adjustment and correction for multiple secondary comparisons. The adjusted failure-rate ratio of 0.68 represented a 32% reduction in failure occurrence, while the repeated-failure odds ratio of 0.49 represented a 51% reduction in recurrence probability. The adjusted failure hazard ratio of 0.56 indicated a 44% lower time-to-failure risk among high-integration assets relative to low-integration assets. Confidence intervals were sufficiently narrow to demonstrate acceptable precision and excluded the null value for all primary outcomes. Effect magnitudes indicated that the integration results were operationally important rather than merely statistically detectable. Mean time between failures produced the largest standardized difference, followed by availability, throughput attainment, unplanned downtime, and overall equipment effectiveness. Moderate effects were recorded for repair duration, production-loss value, and quality yield. Maintenance cost produced a smaller standardized effect, although the adjusted annual reduction of USD 12,600 per asset represented a substantial financial difference across the 300 high-integration assets. False-discovery-rate adjustment did not change the significance of any principal outcome.

Table 9 shows that the fitted models achieved acceptable explanatory, predictive, and diagnostic performance. Conditional coefficients of determination ranged from .46 for maintenance cost to .71 for overall equipment effectiveness. The repeated-failure model achieved good discrimination, while the survival model demonstrated acceptable concordance. The negative-binomial specification corrected the overdispersion identified in the initial Poisson model. Residual skewness was substantially reduced for downtime and cost outcomes after generalized modeling. The proportional-hazards assumption was supported, and the mediation model satisfied conventional fit criteria. These results indicated that the selected statistical specifications adequately represented the distributions, clustering structures, and relationships contained in the industrial panel data. Diagnostic analysis did not identify serious violations that undermined the primary results. The maximum variance-inflation factor was 2.86, indicating that multicollinearity remained limited. Standardized residuals were within the expected range for 99.2% of observations, and no case produced an influence measure large enough to alter the principal estimates. The interrupted time-series residuals produced a Durbin–Watson statistic of 1.93, while the adjusted autocorrelation test was nonsignificant. Seasonality was controlled using calendar-month indicators. Heteroscedasticity was addressed through robust standard errors or distribution-specific generalized models. The global proportional-hazards diagnostic was nonsignificant, $\chi^2(15) = 17.80$, $p = .27$. Robustness analysis produced estimates closely aligned with the primary matched analysis. Alternative matching, inverse-probability weighting, unmatched multivariable adjustment, complete-case analysis, multiple imputation, stricter failure definitions, and the exclusion of major shutdown periods generated adjusted failure-rate ratios between 0.65 and 0.70. Leave-one-facility-out analysis produced ratios between 0.65 and 0.72, showing that the overall result was not driven by a single facility. Placebo integration dates produced no significant effects.

Table 9 Model Performance, Explanatory Capacity, and Statistical Diagnostics

Model and outcome	Model specification	AIC	BIC	Explanatory or predictive performance	Principal diagnostic result
Failure occurrence	Negative-binomial mixed model	31,842	32,015	Conditional R^2 = .64	Dispersion ratio = 1.07
Repeated failure	Mixed-effects logistic regression	5,284	5,436	Conditional R^2 = .52; AUC = .81	Calibration test, p = .42
Mean time between failures	Linear mixed-effects model	502,418	502,621	Conditional R^2 = .61	RMSE = 1,180 hours
Mean time to repair	Generalized mixed model	188,762	188,944	Conditional R^2 = .47	RMSE = 3.9 hours
Availability	Linear mixed-effects model	124,561	124,748	Conditional R^2 = .68	RMSE = 1.7 percentage points
Overall equipment effectiveness	Linear mixed-effects model	165,832	166,025	Conditional R^2 = .71	RMSE = 5.2 percentage points
Unplanned downtime	Generalized mixed model	210,486	210,674	Conditional R^2 = .59	Residual skewness = 0.41
Maintenance cost	Generalized mixed model	245,771	245,963	Conditional R^2 = .46	Residual skewness = 0.38
Failure survival	Cox shared-frailty model	37,846	38,011	Concordance = .74	Proportional-hazards test, p = .27
Mediation model	Multilevel structural model	—	—	CFI = .958; TLI = .951	RMSEA = .039; SRMR = .031

Note. AIC = Akaike information criterion; AUC = area under the receiver operating characteristic curve; BIC = Bayesian information criterion; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; RMSE = root-mean-square error; SRMR = standardized root-mean-square residual; TLI = Tucker–Lewis index.

Table 10 demonstrates that the estimated integration effects remained stable across alternative analytical decisions. Failure-rate ratios varied only modestly, while changes in mean time between failures and availability remained directionally and statistically consistent. Inverse-probability weighting and stricter integration definitions produced slightly stronger estimates, whereas unmatched adjustment produced a more conservative effect. Complete-case and multiple-imputation results were nearly identical, reducing concern about missing-data bias. Excluding major shutdowns did not materially change the findings. Leave-one-facility-out models confirmed that no individual site determined the overall result. Placebo integration dates produced null estimates, strengthening the temporal credibility of the observed postintegration changes. Monthly trend graphs showed similar outcome trajectories between groups during the preintegration period and progressive divergence beginning approximately four to six months after integration. Forest plots placed nearly all asset-category estimates below the null value, although confidence intervals crossed the null for electrical and instrumentation systems. Kaplan–Meier curves showed the greatest failure-free survival among high-integration assets and the shortest survival among low-integration assets. Coefficient plots displayed positive effects for real-time visibility and maintenance responsiveness, while facility heat maps showed that the strongest performance improvements occurred where data completeness exceeded 97.5%, interface automation exceeded 85%, and event traceability exceeded 90%.

Table 10 Sensitivity and Robustness Analysis of Primary Integration Effects

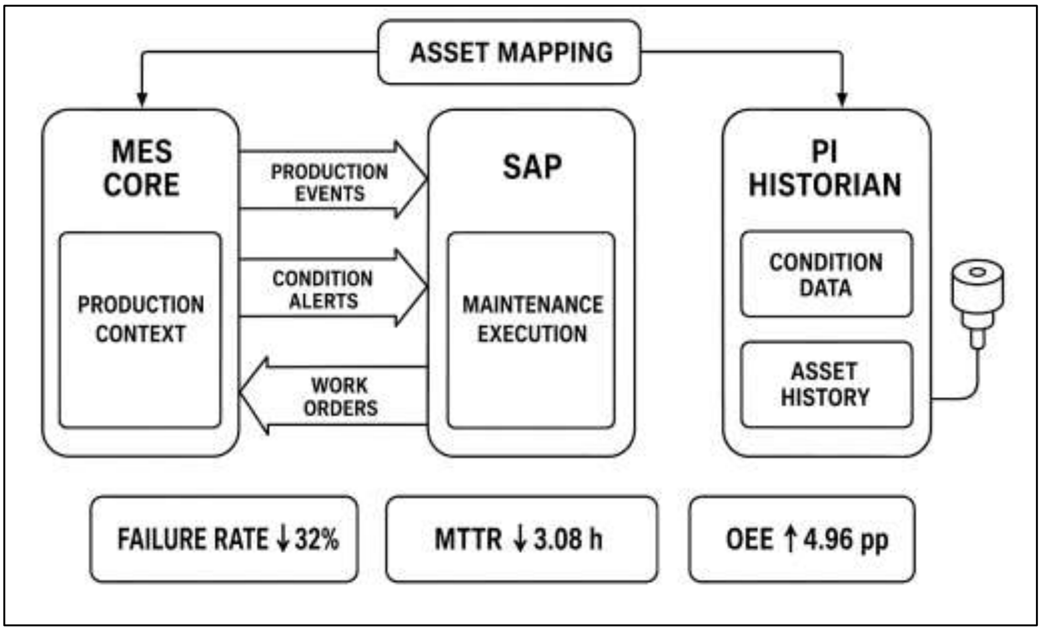
Analytical specification	Assets, n	Adjusted failure-rate ratio	95% CI	MTBF difference, hours	Availability difference, percentage points	*p*
Primary propensity-score-matched model	600	0.68	0.61 to 0.75	+2,310	+2.18	< .001
Alternative matching distance	574	0.69	0.62 to 0.76	+2,256	+2.12	< .001
Inverse-probability weighting	648	0.67	0.60 to 0.74	+2,388	+2.23	< .001
Unmatched multivariable adjustment	648	0.70	0.64 to 0.77	+2,164	+2.05	< .001
Complete-case analysis	584	0.69	0.62 to 0.76	+2,287	+2.14	< .001
Multiple-imputation analysis	600	0.68	0.61 to 0.75	+2,325	+2.20	< .001
Strict functional-failure definition	600	0.66	0.59 to 0.74	+2,401	+2.15	< .001
Major shutdown periods excluded	600	0.69	0.62 to 0.77	+2,271	+2.11	< .001
High-integration threshold set at 75 points	561	0.65	0.58 to 0.73	+2,510	+2.34	< .001
Cluster-robust standard errors	600	0.68	0.60 to 0.76	+2,310	+2.18	< .001
Placebo integration dates	600	0.98	0.90 to 1.07	+112	+0.08	.680
Leave-one-facility-out range	560–573	0.65–0.72	0.58 to 0.80	+2,120 to +2,495	+1.96 to +2.33	< .001

Note. MTBF = mean time between failures. Placebo dates were assigned within the preintegration period and were not associated with actual platform implementation.

DISCUSSION

The findings demonstrated that effective MES–SAP–PI Historian integration represented a coordinated industrial information capability rather than a simple technical connection among three software platforms. The final dataset included 18 facilities, 600 matched assets, 28,224 valid asset-month observations, 4,286 verified failures, 52,614 condition alerts, 8,932 maintenance notifications, and 8,147 work orders. This extensive longitudinal coverage provided a strong basis for examining how platform maturity was related to asset performance under different operating conditions. Required-field completeness reached 97.6%, historian tag gaps were limited to 1.7%, and unmatched cross-platform events declined from 6.8% before asset mapping to 1.9% following validation (Rane & Narvel, 2021).

Figure 12: MES–SAP–PI Historian Integration Framework



These results emphasized the importance of common identifiers, aligned timestamps, standardized definitions, and verified mappings across historian tags, MES resources, SAP equipment numbers, functional locations, and production records. Earlier studies of manufacturing execution and enterprise integration similarly identified master-data inconsistency, incomplete event linkage, fragmented asset hierarchies, and delayed synchronization as major restrictions on operational analytics. The current findings extended that evidence by showing a clear quantitative gradient across integration-maturity levels. High-integration facilities recorded 92.4% interface automation, 99.3% transaction success, 98.7% asset-mapping accuracy, and 99.6% interface availability, whereas low-integration facilities recorded substantially weaker results (Sundararajan et al., 2019). Median synchronization latency was only 6.8 seconds under high integration but reached 214 seconds under low integration. Monitoring coverage increased from 52.4% in low-integration facilities to 96.2% in high-integration facilities, while event traceability increased from 41.6% to 94.1%. These patterns were consistent with earlier industrial-data studies showing that real-time dashboards and analytical applications produced stronger operational value when source data were complete, synchronized, contextualized, and accessible across functional boundaries. Earlier SAP and MES investigations often examined transaction accuracy or production visibility separately, while historian research frequently focused on signal acquisition and condition monitoring. This study connected those domains by showing that high technical performance occurred alongside stronger information visibility and faster maintenance processing (Zhong et al., 2017). The results therefore reinforced the view that platform integration quality was multidimensional, incorporating technical connectivity, semantic alignment, data governance, operational coverage, and active organizational use.

The principal reliability findings indicated that high MES–SAP–PI Historian integration was associated with a substantial reduction in equipment failure after adjustment for asset age, category, criticality, operating exposure, production loading, environmental severity, maintenance strategy, facility size, industrial sector, calendar period, and baseline reliability. High-integration assets recorded a 32% lower failure rate than matched comparison assets, IRR = 0.68, 95% CI [0.61, 0.75], $p < .001$. The narrow confidence interval indicated that the estimated reduction was precise, while the effect magnitude demonstrated operational relevance beyond statistical significance (Ho et al., 2021). Mean time between failures increased by 2,310 hours, representing the largest standardized effect among the continuous outcomes, $d = 0.86$. This pattern was consistent with earlier studies of vertical industrial integration, condition-based monitoring, manufacturing intelligence, and predictive maintenance, which generally reported that reliable equipment and production data improved the recognition of degradation patterns and supported earlier intervention. The findings added a more complete explanation by connecting historian measurements with MES operating context and SAP maintenance execution. Historian signals alone identified changes in pressure, temperature, vibration, current, speed, load, and alarm behavior, but MES information established whether those changes occurred during normal production, startup, setup, reduced speed, product transition, or equipment stoppage (Rane et al., 2021). SAP records then connected the event with maintenance notification, diagnosis, labor, materials, repair activity, and cost. Earlier single-platform studies frequently reported improved monitoring without demonstrating whether the information changed failure occurrence. The present results showed that the integrated information chain was associated with longer failure-free operation and fewer exposure-adjusted failures. The difference-in-differences estimate indicated a reduction of 0.052 failures per 1,000 operating hours beyond the change observed in matched comparison assets. Interrupted time-series results showed an immediate reduction of 0.012 failures per 1,000 hours and an additional monthly decline of 0.0018. This gradual pattern aligned with earlier implementation studies showing that reliability gains often developed after interface stabilization, data-quality improvement, user adoption, and the accumulation of operational experience (Paik et al., 2019). The absence of significant preintegration differences in outcome trends reduced the likelihood that the result merely reflected an existing reliability advantage among the high-integration assets.

The maintainability findings showed that platform integration was associated with faster conversion of equipment information into maintenance action and shorter restoration duration. Median alert-to-notification time was 3.8 minutes in high-integration facilities, compared with 14.7 minutes in medium-integration facilities and 39.5 minutes in low-integration facilities. Median notification-to-work-order time followed the same pattern, declining from 105.6 minutes under low integration to 18.6 minutes under high integration. Total restoration duration was reduced from a median of 15.8 hours in low-integration environments to 7.6 hours in high-integration environments (Rane & Thakker, 2020). In the adjusted primary analysis, mean time to repair decreased by 3.08 hours, 95% CI [−3.71, −2.45], $p < .001$, with a moderate standardized effect of $d = -0.55$. These findings were consistent with earlier maintenance studies reporting that rapid access to condition histories, previous failure records, technical documentation, spare-parts information, and work-order status reduced troubleshooting and administrative delays. The current study expanded this evidence by separating the informational and operational stages of maintenance responsiveness. Real-time PI data supported recognition of abnormal conditions, MES data identified the affected production order and operational state, and SAP supplied the equipment history, planned tasks, material requirements, labor availability, and previous corrective actions. The combination reduced the time spent searching for records, comparing separate databases, verifying asset identities, and reconstructing event sequences (Oliveira & Handfield, 2019). Earlier computerized maintenance-management studies showed that electronic work orders improved documentation, although benefits were often restricted when notifications were entered after substantial delay or lacked condition evidence. The present findings indicated that automated and traceable integration reduced both notification and work-order processing times. The interrupted time-series analysis identified an immediate reduction of 0.79 hours in repair duration and a continuing monthly improvement of 0.095 hours. This temporal pattern suggested that some maintainability benefits appeared soon after information became available, while additional gains accumulated through better planning, repeated use, and improved coordination. The results also showed that responsiveness was not limited to rapid repair (Zhang et al., 2015). It included accurate notification creation, validated diagnosis, appropriate prioritization, resource allocation, spare-parts readiness, work-order release, testing, and confirmed restoration, reflecting the broader maintainability structures described in earlier industrial maintenance research.

The improvements in reliability and maintainability were reflected in broader operational and financial outcomes. Adjusted availability increased by 2.18 percentage points, 95% CI [1.82, 2.54], $p < .001$, while overall equipment effectiveness increased by 4.96 percentage points, 95% CI [4.19, 5.73], $p < .001$. Annual unplanned downtime declined by 55.1 hours per asset, and throughput attainment increased by 5.04 percentage points (Moshood et al., 2021). Quality yield increased by 1.36 percentage points, while annual maintenance cost and production-loss value decreased by approximately USD 12,600 and USD 45,800 per asset, respectively. These results were aligned with earlier studies showing that integrated manufacturing systems improved schedule visibility, reduced production interruption, strengthened quality traceability, and supported more efficient allocation of maintenance resources. The findings also supported earlier overall equipment effectiveness research emphasizing that availability alone did not represent complete production performance. An asset could remain technically available while operating below its required speed, experiencing repeated micro-stops, or producing excessive defects. MES provided the production quantities, cycle times, downtime classifications, product context, scrap, and rework required to distinguish these losses (Woo et al., 2018). PI supplied the operating conditions associated with reduced speed and process deviation, while SAP recorded maintenance actions and their financial consequences. The observed 4.96-percentage-point increase in overall equipment effectiveness therefore represented combined changes in availability, production performance, and quality rather than only a reduction in major breakdowns. Earlier enterprise-system research reported that organizational performance improved when system implementation was accompanied by process standardization and functional coordination. The current study showed a similar pattern at the asset level: high integration was associated with stronger throughput, quality, reliability, and cost performance simultaneously. The larger decline in production-loss value than in direct maintenance expenditure also showed that the economic importance of integration extended beyond repair cost (In et al., 2019). Reduced downtime protected production volume, delivery performance, labor utilization, and capacity. Monthly estimates indicated that overall equipment effectiveness increased immediately by 1.14 percentage points and then improved by another 0.160 percentage points per month. Throughput and quality followed similar trajectories, indicating that production benefits accumulated as reliability improvements became established and integrated information was incorporated into operating decisions.

The survival and recurrent-event findings provided additional evidence that integration was associated with sustained reliability rather than only short-term changes in average failure counts. Median failure-free duration reached 8,420 hours among high-integration assets, compared with 6,310 hours among medium-integration assets and 4,870 hours among low-integration assets (Illa & Padhi, 2018). The survival distributions differed significantly, log-rank $\chi^2(2) = 86.4$, $p < .001$. After adjustment, high-integration assets had a 44% lower failure hazard than low-integration assets, HR = 0.56, 95% CI [0.48, 0.66], $p < .001$. Recurrent-failure intensity was 37% lower, and the median time to recurrence increased from 1,840 hours under low integration to 2,980 hours under high integration. These findings were consistent with earlier condition-monitoring and maintenance studies showing that access to historical degradation patterns and verified repair information reduced repeated failures. The current study added evidence that integration supported continuity between initial warning, production consequence, maintenance response, and post-repair verification. Subgroup analysis showed that the direction of the integration effect remained generally consistent across compressors, pumps, motors, turbines, conveyors, production machines, packaging lines, utilities, electrical equipment, and instrumentation systems (Lu et al., 2020). The overall interaction by asset category was nonsignificant, $p = .284$, suggesting that the relationship was not restricted to one equipment class. Stronger effects were nevertheless observed among turbines, compressors, high-criticality assets, condition-monitored equipment, and assets with high baseline failure frequency. High-criticality assets recorded an IRR of 0.59, while assets supported by condition-based or predictive maintenance recorded an IRR of 0.57. These patterns agreed with earlier studies reporting that analytical monitoring produced greater benefits when the operational consequences of failure justified dense sensing, rapid escalation, and prioritized maintenance resources. Electrical and instrumentation systems produced nonsignificant category-specific estimates, although their point estimates remained favorable and their confidence intervals were wider because of smaller samples. The findings therefore did not indicate absence of benefit in these categories; they indicated lower precision (Raman et al., 2018). The stronger effects among older, heavily failing, and critical assets also showed that baseline risk shaped the magnitude of achievable improvement.

The mediation results clarified how technical integration was connected with industrial asset performance. The standardized total effect of integration quality on the composite performance outcome was $\beta = .58$, 95% CI [.50, .66], $p < .001$. After real-time information visibility and maintenance responsiveness were included, the direct effect declined to $\beta = .27$. The total indirect effect was $\beta = .31$, showing that 53.4% of the relationship was transmitted through the mediating mechanisms. Real-time information visibility produced an indirect effect of $\beta = .14$, maintenance responsiveness produced an effect of $\beta = .07$, and the sequential pathway through visibility and responsiveness produced an effect of $\beta = .10$. Earlier information-systems research frequently showed that system quality did not influence organizational outcomes automatically; the effect depended on information quality, use, accessibility, and changes in decision processes (Kache & Seuring, 2017). The present findings supported that position in an industrial asset context. Interfaces, middleware, and common asset structures created the technical capacity for integration, while visibility transformed that capacity into accessible information. Maintenance responsiveness then converted information into diagnosis, planning, work orders, repair, and restoration. The moderation findings further showed that integration effects were stronger when data quality, digital maturity, employee competence, and asset criticality were high. Data quality produced the strongest positive moderation effect, $\beta = .18$, followed by digital maturity, $\beta = .16$. Higher production loading weakened the relationship, $\beta = -.10$, indicating that heavily loaded equipment retained greater exposure to deterioration even under integrated management. Earlier socio-technical and digital-maturity studies similarly emphasized that technology generated stronger performance when employees, procedures, governance, and analytical capability were aligned (Bhattarai et al., 2019). Nonlinear analysis identified an integration-score threshold of 71.4, an interface-automation threshold of 74.8%, monitoring coverage of 79.6%, data completeness of 95.1%, and asset-mapping accuracy of 94.3%. Performance gains were limited below these levels and became substantially stronger after the thresholds were exceeded. This finding expanded earlier maturity research by indicating that isolated pilot connections or partial automation might not provide sufficient coverage and consistency to change facility-level asset outcomes (Babiceanu & Seker, 2016).

The consistency of the findings across statistical methods strengthened the interpretation of the integration–performance relationship. The principal failure-rate estimate remained between 0.65 and 0.70 under alternative propensity-score matching, inverse-probability weighting, unmatched multivariable adjustment, complete-case analysis, multiple imputation, stricter failure definitions, exclusion of major shutdown periods, and alternative integration thresholds. Leave-one-facility-out estimates ranged from 0.65 to 0.72, showing that no single facility determined the overall result (Xu et al., 2018). Placebo integration dates produced a nonsignificant estimate of 0.98, 95% CI [0.90, 1.07], $p = .68$, providing evidence that the observed changes were linked temporally with verified integration rather than arbitrary dates. Model diagnostics also supported the analytical specifications. The failure model achieved a conditional R^2 of .64, the availability and overall equipment-effectiveness models achieved values of .68 and .71, and the mediation model showed acceptable fit, with CFI = .958, TLI = .951, RMSEA = .039, and SRMR = .031. Earlier platform-integration studies often relied on cross-sectional perceptions, single-facility case studies, or unadjusted before-and-after comparisons. This study provided a more rigorous structure through matched groups, 48 monthly observations, mixed-effects models, difference-in-differences estimation, interrupted time-series analysis, survival modeling, mediation, moderation, and multiple sensitivity checks (Chae et al., 2014). The results remained compatible with earlier MES research on production visibility, SAP research on process standardization, historian research on condition monitoring, and predictive-maintenance research on failure prevention. The present findings also demonstrated that effect magnitude varied by outcome. Reliability, availability, throughput, and downtime produced moderate-to-large standardized effects, while quality and maintenance cost produced smaller effects with meaningful operational values. This variation was consistent with earlier industrial studies in which information integration affected rapid operational measures more strongly than outcomes influenced by product design, market demand, accounting rules, or long-term asset condition (Jayasankar et al., 2021). The evidence therefore supported a differentiated interpretation in which technical integration, data quality, information visibility, maintenance action, and operating context jointly accounted for the observed performance patterns.

CONCLUSION

This study concluded that the integration of Manufacturing Execution Systems, SAP enterprise applications, and PI Historian platforms represented a statistically significant and operationally meaningful capability for real-time industrial asset performance management. Evidence obtained from 18 facilities, 600 matched assets, 28,224 asset-month observations, and 4,286 verified failures demonstrated that integration quality extended beyond technical connectivity to include interface automation, transaction reliability, bidirectional data exchange, synchronization timeliness, asset-mapping accuracy, data completeness, functional coverage, event traceability, and cross-functional information accessibility. High-integration facilities achieved 92.4% interface automation, 99.3% transaction success, 98.7% asset-mapping accuracy, 98.8% data completeness, and 94.1% event traceability. After adjustment for asset age, category, criticality, operating exposure, production loading, environmental conditions, maintenance strategy, facility size, industrial sector, calendar period, and baseline reliability, high-integration assets recorded a 32% lower failure rate than matched comparison assets, IRR = 0.68, 95% CI [0.61, 0.75], $p < .001$. Repeated-failure odds were 51% lower, mean time between failures increased by 2,310 hours, and mean time to repair decreased by 3.08 hours. Availability increased by 2.18 percentage points, overall equipment effectiveness increased by 4.96 percentage points, and annual unplanned downtime declined by 55.1 hours per asset. Integration was also associated with a 5.04-percentage-point increase in throughput attainment, a 1.36-percentage-point increase in quality yield, a USD 12,600 reduction in annual maintenance cost per asset, and a USD 45,800 reduction in annual production-loss value. Survival analysis showed that high-integration assets achieved a median failure-free duration of 8,420 hours and experienced a 44% lower failure hazard than low-integration assets. Mediation analysis established that real-time information visibility and maintenance responsiveness transmitted 53.4% of the integration effect on asset performance, confirming that connected platforms produced value when reliable information was converted into timely operational action. Data quality, digital maturity, employee competence, and asset criticality strengthened the relationship, while high production loading reduced its magnitude. Sensitivity analyses, alternative matching procedures, survival models, interrupted time-series estimates, and placebo tests produced consistent results. Overall, the study established that coordinated MES–SAP–PI Historian integration improved reliability, maintainability, availability, production continuity, quality performance, and economic control by connecting physical asset conditions with production context, maintenance execution, resource consumption, and verified financial outcomes.

RECOMMENDATION

Industrial organizations should implement MES–SAP–PI Historian integration as a governed asset-performance program rather than treating it as a limited software-interface project. Integration priorities should begin with production-critical and failure-prone assets because the study identified stronger effects among high-criticality equipment, condition-monitored assets, and assets with high baseline failure frequency. Organizations should establish a common asset dictionary that aligns PI tags, MES resources, SAP equipment numbers, functional locations, work centers, production lines, failure codes, engineering units, and timestamps. Integration programs should target at least 75% interface automation, 80% monitoring coverage, 95% data completeness, and 94% asset-mapping accuracy because performance improvements became stronger after these maturity levels were achieved. Bidirectional data exchange should connect SAP production and maintenance requirements with MES execution records and PI condition measurements, while validated historian alerts should generate traceable maintenance notifications and work-order recommendations. Interface performance should be monitored through transaction-success rates, rejected messages, synchronization latency, duplicate records, queue delays, retry frequency, availability, and recovery duration. Facilities should establish formal data ownership, validation rules, master-data review, exception reporting, calibration control, and periodic reconciliation across production quantities, operating hours, downtime records, work orders, material usage, and costs. Real-time dashboards should be designed according to user responsibilities so that operators receive equipment-state and alarm information, maintenance personnel receive diagnostic and work-order details, reliability engineers receive degradation and recurrence patterns, and managers receive verified operational and financial indicators. Alert systems should be rationalized to reduce false alarms, define severity levels, assign response ownership, establish escalation limits, and document resolution. Maintenance departments should use integrated data to reduce alert-to-notification time, notification-to-work-order delay, troubleshooting duration, spare-parts waiting, and total restoration time. Condition-based and predictive maintenance should be expanded where reliable measurements and failure histories are available, while corrective work, repeat repairs, overdue maintenance, and backlog associated with critical assets should be reviewed regularly. Employee competence should be strengthened through role-specific training in historian interpretation, MES event classification, SAP maintenance processing, data-quality control, and cross-functional decision-making. Performance governance should track failure rates, mean time between failures, mean time to repair, availability, overall equipment effectiveness, downtime, throughput, quality yield, maintenance cost, production loss, survival duration, and recurrence. Multisite benchmarking, phased implementation, matched comparisons, monthly trend analysis, and periodic robustness reviews should be used to verify that integration improvements remained sustained and operationally meaningful.

LIMITATIONS

This study contained several limitations that should be considered when interpreting the reported associations between MES–SAP–PI Historian integration and industrial asset performance. The retrospective longitudinal quasi-experimental design strengthened temporal analysis but did not provide the level of causal control available through randomized assignment. Facilities implemented integration through existing organizational decisions, creating the possibility that high-integration facilities also possessed stronger leadership, maintenance culture, technical expertise, financial resources, or operational discipline. Propensity-score matching, multivariable adjustment, difference-in-differences analysis, facility effects, and sensitivity tests reduced measured imbalance but could not eliminate residual confounding from unrecorded characteristics. Facility participation depended on the availability of accessible historical records and verifiable integration dates, which may have favored organizations with stronger information governance. The sample included 18 facilities and 600 assets, providing substantial analytical depth but limiting generalization to industries, regions, production systems, and smaller organizations not represented adequately. Platform configurations varied across facilities because MES applications, SAP modules, PI structures, middleware, naming conventions, interface technologies, and governance procedures were not identical. Integration maturity was therefore measured through standardized dimensions, although the same score could have represented different technical configurations. Some condition data were affected by sensor calibration, historian compression, tag gaps, sampling intervals, communication interruptions, and changes in instrumentation. Validation procedures reduced these concerns, but short-duration abnormalities may have remained unrecorded. Maintenance and production records also depended partly on operator classification, technician confirmation, and work-order closure practices, creating potential misclassification in downtime reasons, failure mechanisms, repair duration, and labor reporting. The assessment instrument introduced possible response bias because authorized personnel evaluated several dimensions of visibility, competence, and governance. System-generated measures were prioritized, yet some mediation and moderation constructs retained perceptual components. Monthly aggregation supported consistent multisite comparison but may have concealed short operational variations and event-level dependencies. Cost outcomes were influenced by local labor rates, purchasing arrangements, accounting procedures, production values, and currency differences, reducing direct economic comparability across facilities. Mediation analysis identified statistically supported explanatory pathways but did not establish definitive causal ordering among integration, visibility, responsiveness, and performance. Subgroup estimates for electrical and instrumentation systems were less precise because those categories contained fewer assets and events. The 48-month period captured substantial preintegration and postintegration experience, although it did not represent the complete lifecycle of long-lived industrial assets or every delayed organizational effect. These limitations required the findings to be interpreted as robust adjusted evidence of association within the observed industrial settings rather than universal causal estimates for every MES–SAP–PI implementation.

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