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A Multi-Criteria Decision-Support Framework For ERP-Based Business Process Optimization in Mid-Sized Manufacturing Enterprises

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Abstract

Enterprise resource planning systems provide integrated information for manufacturing operations, but their organizational value depends on selecting process improvements through reliable and transparent decision procedures. This study developed and evaluated a multi-criteria decision-support framework for ERP-based business process optimization in mid-sized manufacturing enterprises. A multisite longitudinal quasi-experimental design compared 20 intervention enterprises with 20 matched comparison enterprises across a 12-month pre-implementation period and a 12-month post-implementation period. The final dataset included 480 ERP users, 7,512 process-month observations, and 2,592,180 transaction records covering order processing, procurement, production planning, inventory, quality, maintenance, invoicing, and financial reconciliation. The framework combined the analytical hierarchy process with TOPSIS to weight optimization criteria and rank process alternatives. Data were analyzed using descriptive statistics, mixed-effects models, difference-in-differences estimation, interrupted time-series analysis, moderation, bootstrapped mediation, and structural equation modeling. ERP integration quality averaged 4.08, data quality averaged 4.12, and decision-support effectiveness averaged 4.04. Compared with matched enterprises, intervention enterprises achieved adjusted reductions of 6.50 hours in order-processing time, 1.33 days in procurement cycle time, 3.90 hours in production-release time, and $2.90 in administrative cost per transaction. Schedule adherence increased by 6.90 percentage points, forecast error declined by 3.90 percentage points, and inventory turnover increased by 0.74 annual turns. Transaction errors declined by 31%, stockouts by 27%, emergency purchases by 30%, late supplier deliveries by 24%, production defects by 20%, rework events by 23%, and compliance violations by 34%. Data quality significantly strengthened the integration–optimization relationship, while decision-support effectiveness mediated 48.6% of the total integration effect. The structural model explained 71% of the variance in business process optimization. AHP–TOPSIS priorities strongly corresponded with observed improvements, ρ = .93. The findings demonstrated that ERP-based optimization was most effective when integrated technology, reliable data, structured prioritization, organizational readiness, technological capability, and sustained process adoption operated as a coordinated manufacturing capability.

Keywords
ERP, Optimization, Manufacturing, Integration, Decision-Support.

INTRODUCTION

Enterprise resource planning refers to an integrated information-system architecture that coordinates organizational data, transactions, resources, and operational activities through a common digital platform. In manufacturing enterprises, an ERP system typically connects production planning, materials management, procurement, inventory control, sales, finance, human resources, quality management, maintenance, and customer-order processing. This integration allows information generated in one functional area to become accessible to other authorized areas without repeated manual entry or isolated departmental databases (Katuu, 2020). Business process optimization refers to the systematic assessment and redesign of organizational activities to improve their efficiency, accuracy, consistency, speed, quality, flexibility, and resource utilization. It extends beyond the automation of existing procedures because it examines whether tasks, decision points, approvals, information flows, control mechanisms, and performance measures are appropriately structured. Multi-criteria decision support refers to the use of formal analytical procedures for evaluating alternatives according to several quantitative and qualitative criteria that may differ in importance, measurement scale, and direction. A multi-criteria framework can combine operational, financial, technological, organizational, and strategic considerations when determining which business processes require optimization and which improvement alternatives provide the most balanced organizational value (Langenwalter, 2020). Mid-sized manufacturing enterprises are organizations whose employment, revenue, asset base, production capacity, or market coverage falls between those of small firms and large industrial corporations. Their exact classification varies across countries and industries, yet they commonly possess formal production systems, specialized functional departments, established supplier networks, and significant information requirements while operating with more limited financial and technical resources than large multinational manufacturers. ERP-based business process optimization therefore represents the coordinated use of integrated enterprise data, process analysis, performance measurement, and decision-support techniques to identify inefficiencies and select appropriate improvement priorities. More than thirty empirical, comparative, and analytical studies have examined different components of this relationship, including ERP integration, process standardization, operational performance, decision quality, manufacturing flexibility, user competence, data quality, implementation maturity, and organizational readiness (Ali & Miller, 2017). The combined literature treats ERP not merely as administrative software but as an organizational infrastructure through which process relationships can be measured, compared, and controlled. The central concepts of integration, optimization, and multi-criteria evaluation are closely connected because manufacturing processes usually involve competing objectives. A reduction in inventory may increase stockout exposure, greater production speed may affect quality, extensive customization may reduce system maintainability, and tighter control may lengthen approval time. A structured decision-support framework is therefore required to evaluate optimization alternatives across multiple dimensions rather than relying on a single financial or operational indicator (Seethamraju, 2015).

ERP-based process optimization has substantial international significance because manufacturing enterprises participate in production networks that frequently cross national, regulatory, technological, and cultural boundaries. Mid-sized manufacturers supply components, intermediate goods, finished products, maintenance services, and specialized engineering solutions to domestic and multinational customers. Their operational performance affects delivery reliability, production continuity, product quality, cost stability, and supply-chain resilience across interconnected markets (Aldossari & Mukhtar, 2018). Studies conducted in North America have emphasized the role of ERP integration in coordinating production schedules, customer orders, procurement requirements, and financial reporting across geographically dispersed facilities. European investigations have frequently examined process standardization, regulatory traceability, energy efficiency, quality certification, and integration between ERP platforms and advanced manufacturing technologies. Research from East and Southeast Asia has placed considerable attention on supplier coordination, high-volume production control, export responsiveness, lean manufacturing, inventory visibility, and the alignment of ERP functions with rapidly changing customer requirements (Alaskari et al., 2019). Studies from South Asia, the Middle East, Africa, and Latin America have commonly investigated infrastructure limitations, implementation costs, employee competence, vendor dependence, data inconsistency, and the adaptation of standardized ERP packages to local manufacturing practices. Collectively, these international studies show that the organizational value of ERP systems depends on the quality of process integration and managerial use rather than software acquisition alone. Global supply-chain participation also requires mid-sized manufacturers to provide accurate information concerning order status, material availability, production progress, quality inspection, batch genealogy, delivery schedules, and financial transactions.

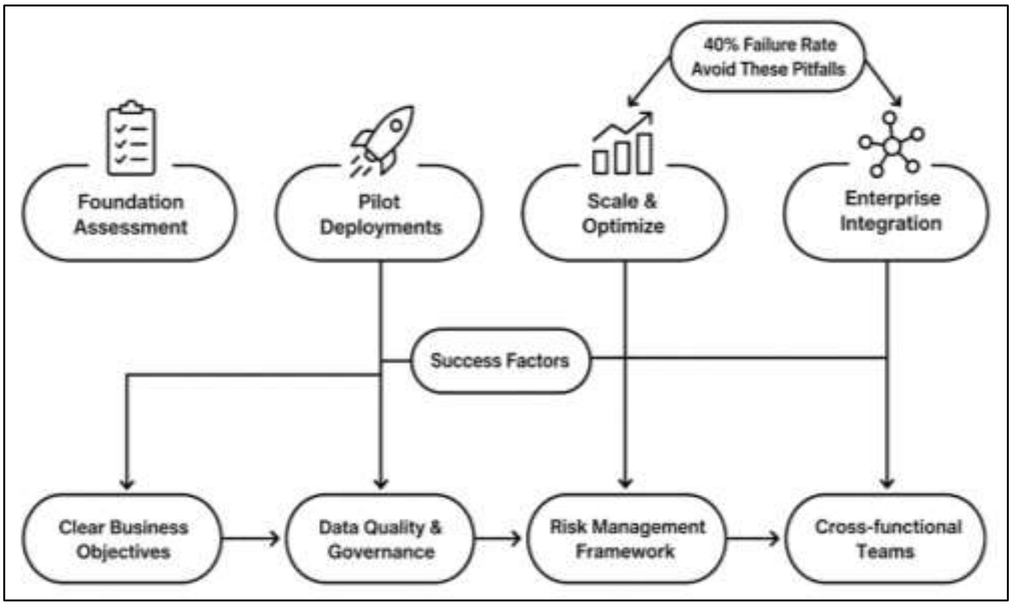
Figure 1: ERP-Based Process Optimization Benefits

Fragmented information can delay responses to customers and suppliers, while integrated process data support more consistent coordination across organizational and national boundaries (Awa et al., 2016). International competition further increases the importance of cost control, delivery performance, product customization, regulatory compliance, and production flexibility. Mid-sized manufacturers often encounter these pressures while operating with smaller information-technology departments, more concentrated customer portfolios, and fewer financial reserves than large corporations. A poorly prioritized optimization program can therefore consume scarce resources without correcting the processes that exert the greatest influence on performance. Cross-national evidence has also shown that the relative importance of optimization criteria varies by industrial context. Manufacturers in high-labor-cost economies may assign greater weight to automation and productivity, whereas firms facing unreliable logistics may emphasize inventory availability and supplier coordination (Almajali et al., 2016). Regulated manufacturers may prioritize traceability, documentation, and quality compliance, while make-to-order producers may emphasize scheduling flexibility, engineering-change control, and lead-time reduction. These variations establish the international relevance of a framework that accommodates multiple criteria and permits decision-makers to adjust their weights according to organizational conditions.

ERP systems establish the transactional and informational infrastructure through which manufacturing processes can be observed and coordinated. Earlier studies of manufacturing information systems reported that disconnected applications created repeated data entry, inconsistent product codes, delayed inventory updates, conflicting production records, and limited visibility across departments (Appelbaum et al., 2017). Subsequent ERP studies found that centralized master data and standardized transaction procedures improved the consistency of bills of materials, routing information, supplier records, inventory balances, purchase orders, work orders, customer orders, and financial accounts. Several investigations also demonstrated that ERP integration strengthened coordination between production planning and materials management by allowing demand forecasts, confirmed orders, available inventory, scheduled receipts, and capacity requirements to be evaluated within a connected environment. Other studies reported improvements in order-processing accuracy, procurement control, production scheduling, cost calculation, and financial reporting after organizations established reliable system use. These improvements were not uniform across organizations. Research repeatedly identified inaccurate master data, incomplete transaction entry, excessive customization, poorly defined process ownership, weak user training, and limited managerial support as conditions associated with reduced ERP performance (Léger et al., 2014). Manufacturing enterprises may possess technically functional ERP systems while continuing to use spreadsheets, paper records, informal approvals, and isolated departmental databases. Such parallel practices weaken integration and make it difficult to determine whether recorded data accurately represent operational conditions. ERP maturity therefore involves more than system availability. It includes data completeness, module integration, workflow standardization, timely transaction processing, role clarity, user competence, reporting accessibility, governance, and the routine use of system information in operational decisions. Process optimization depends on this maturity because reliable measurement requires consistent records of activities, durations, quantities, errors, costs, resources, and outcomes. An integrated ERP environment can reveal where production orders remain open, where approvals accumulate, where inventory discrepancies occur, where purchase orders require repeated changes, and where quality failures generate rework or returns (Chauhan & Jaiswal, 2016). Process-mining and workflow-analysis studies have extended this capability by using transaction logs to reconstruct actual activity sequences and compare them with prescribed procedures. These studies identified process variants, unnecessary repetitions, delayed handoffs, unauthorized deviations, and bottlenecks that were not always visible through interviews or conventional process maps. Other quantitative studies connected ERP records with key performance indicators such as cycle time, schedule adherence, inventory turnover, order accuracy, capacity utilization, overall equipment effectiveness, rejection rates, and operating cost. The accumulated evidence positions ERP data as a measurable representation of business-process execution, while also showing that the usefulness of such data depends on system integration, information quality, and disciplined organizational use (Romero & Vernadat, 2016).

Manufacturing business process optimization is multidimensional because a process can perform strongly according to one criterion while remaining weak according to others. Efficiency refers to the relationship between outputs and the labor, time, materials, energy, equipment, and financial resources required to produce them. Effectiveness represents the extent to which a process achieves its intended objectives, including customer requirements, production targets, quality standards, and delivery commitments. Cycle time measures the duration between the initiation and completion of an activity or process, while cost reflects direct and indirect expenditures associated with labor, materials, machine use, inventory, rework, administration, and information processing. Quality includes product conformity, transaction accuracy, process stability, defect prevention, and adherence to documented standards (Lee et al., 2015). Flexibility represents the ability to accommodate changes in volume, product mix, routing, material availability, customer specifications, and production schedules. Reliability concerns the consistency with which a process produces expected results without disruption, error, or unplanned variation. Several empirical studies evaluated ERP performance primarily through financial indicators such as operating cost, inventory cost, return on assets, and profit margin. Other studies concentrated on operational measures including production lead time, order-fulfillment time, inventory turnover, schedule adherence, capacity utilization, and delivery reliability. A further group examined information-related outcomes such as data accuracy, reporting speed, visibility, traceability, and decision timeliness. Organizational studies assessed user satisfaction, cross-functional coordination, managerial control, employee acceptance, knowledge sharing, and process ownership (Stadtler et al., 2015). These different research streams demonstrate why optimization decisions cannot be based on a single performance measure. For example, reducing safety stock can improve inventory turnover while increasing the probability of production interruption. Automating approval activities can reduce processing time while requiring investment, training, access controls, and system maintenance. Standardizing a process across departments may improve consistency while limiting the flexibility required for specialized products or customers. The selection of optimization priorities must therefore consider performance benefits, resource requirements, implementation complexity, operational risk, employee readiness, strategic alignment, and technological feasibility. In mid-sized enterprises, these criteria are particularly interdependent because a limited number of employees may hold several operational responsibilities, and changes within one process can immediately affect other functions (Bi et al., 2014).

Figure 2: ERP Process Optimization Framework



Procurement changes influence material availability, production scheduling influences inventory and delivery, quality controls influence throughput and cost, and maintenance planning influences equipment capacity. ERP-based optimization requires a comprehensive measurement structure capable of representing these relationships through observable variables and comparable criteria. Such a structure also needs to distinguish between process symptoms, such as delayed orders, and underlying conditions, such as inaccurate lead times, incomplete master data, approval congestion, or poor coordination between functions (Barreto et al., 2017).

Multi-criteria decision-support methods provide formal procedures for organizing complex optimization decisions involving numerous alternatives and competing evaluation criteria. The analytical hierarchy process is commonly used to decompose a decision into objectives, criteria, subcriteria, and alternatives. Decision-makers perform pairwise comparisons to express the relative importance of criteria, after which numerical weights are calculated and examined for logical consistency. The analytic network process extends this structure by allowing interdependence and feedback among decision elements. The technique for order preference by similarity to an ideal solution ranks alternatives according to their distance from an ideal condition and a least desirable condition (Ozkeser, 2019). VIKOR evaluates compromise solutions when decision-makers seek an alternative that balances overall group benefit and the largest individual criterion disadvantage. ELECTRE and PROMETHEE use outranking relationships to compare alternatives when complete compensation between strong and weak performance is not appropriate. Data envelopment analysis evaluates the relative efficiency of comparable units using multiple inputs and outputs, while goal programming identifies solutions that minimize deviations from predefined targets. Fuzzy multi-criteria methods represent linguistic judgments and uncertainty when precise numerical assessments are difficult to obtain (Obrenovic et al., 2020). Manufacturing studies have applied these methods to ERP package selection, vendor evaluation, production scheduling, facility location, technology adoption, maintenance prioritization, supplier selection, inventory classification, quality improvement, and process redesign. Several studies found that weighted decision models improved transparency by making evaluation criteria and managerial preferences explicit. Other investigations reported that sensitivity analysis was necessary because small changes in criterion weights could alter the ranking of alternatives. Comparative studies also showed that different multi-criteria techniques sometimes produced different rankings because they used distinct assumptions concerning normalization, compensation, preference thresholds, and distance measurement. These findings support the use of clearly defined criteria, validated weights, consistent data, and robustness checks (Temur & Bolat, 2018). Within ERP-based process optimization, alternatives may include workflow automation, master-data cleansing, module integration, approval simplification, user training, reporting redesign, process standardization, system reconfiguration, or the elimination of redundant activities. Each alternative can be evaluated according to expected cost reduction, cycle-time improvement, quality enhancement, implementation expense, operational risk, strategic alignment, data requirements, technical feasibility, employee readiness, and implementation duration. ERP data can provide objective values for several of these criteria, while expert judgments can represent qualitative considerations that are not fully captured by transactional records. Combining objective performance data with structured managerial assessment creates a more comprehensive decision basis than either source provides independently (Kilic et al., 2014). The methodological challenge is to integrate these measures without allowing subjective weighting, scale differences, missing information, or criterion overlap to distort the final prioritization.

The performance of ERP-based optimization frameworks is influenced by organizational, technological, and data-related conditions. Organizational readiness includes senior-management support, process ownership, employee participation, change-management capacity, cross-functional cooperation, and the availability of personnel with both operational and analytical knowledge. Studies examining ERP implementation and post-implementation performance have consistently reported that leadership involvement strengthens resource allocation, conflict resolution, policy enforcement, and the alignment of system activities with organizational priorities (Ariya & Puritat, 2020). User competence has also emerged as a central factor because employees determine whether transactions are entered correctly, workflows are followed, exceptions are documented, and reports are interpreted appropriately. Process ownership provides accountability for performance across departmental boundaries, while cross-functional participation helps ensure that optimization does not transfer costs or delays from one department to another. Technological conditions include module integration, system reliability, customization, compatibility, interface quality, cybersecurity, reporting functionality, and integration with manufacturing execution systems, warehouse systems, product lifecycle management, customer relationship management, and supplier platforms. Excessive customization has been associated in several studies with higher maintenance costs, difficult upgrades, inconsistent procedures, and dependence on external consultants (Bhatt et al., 2021). Limited customization can also create process-system misalignment when standardized software workflows do not reflect legitimate manufacturing requirements. Data quality provides the informational foundation for performance measurement and alternative evaluation. Completeness ensures that required fields and transactions are available; accuracy indicates that recorded values correspond with actual conditions; consistency means that definitions and codes remain aligned across modules; timeliness concerns the speed at which operational events are recorded; uniqueness prevents duplicate records; and validity reflects conformity with established formats and business rules. Studies of manufacturing data management found that inaccurate bills of materials, inventory balances, lead times, routing data, supplier records, and equipment information produced distorted planning results and unreliable performance reports (Bokovec et al., 2015). Decision support based on such information may assign high priority to the wrong process or overestimate the value of an improvement alternative. Environmental conditions also shape optimization priorities, including customer concentration, demand variability, supply uncertainty, regulatory requirements, competitive intensity, and production strategy. Make-to-stock, make-to-order, engineer-to-order, batch, and continuous-process manufacturers differ in their process structures and performance priorities. A valid quantitative framework therefore requires contextual control variables alongside measures of ERP integration, data quality, optimization criteria, and decision outcomes. The literature synthesized across more than thirty studies has examined many of these factors separately, but fewer investigations have incorporated organizational readiness, technological capability, information quality, process performance, and multi-criteria prioritization within a unified empirical model focused specifically on mid-sized manufacturing enterprises (Farshidi et al., 2018).

The central research problem concerns the absence of a sufficiently integrated and empirically testable framework for prioritizing ERP-based business process optimization initiatives in mid-sized manufacturing enterprises. Existing studies have produced extensive evidence regarding ERP success factors, operational performance, business process management, data quality, organizational readiness, and multi-criteria decision methods. Much of this evidence remains distributed across separate research streams. ERP studies often measure system use, user satisfaction, information quality, and organizational performance without ranking specific process-improvement alternatives. Business process studies frequently examine workflow efficiency, lean practices, process mining, or reengineering without fully incorporating ERP maturity and integrated transactional data (Podvesovskii et al., 2021). Multi-criteria studies commonly focus on software selection, supplier evaluation, technology adoption, or maintenance decisions rather than the prioritization of cross-functional ERP-enabled processes. Research focused on large enterprises may also provide limited representation of the financial constraints, personnel structures, technical dependence, and process informality found in mid-sized manufacturing organizations. The present quantitative study addresses this problem by examining ERP integration quality, data quality, organizational readiness, technological capability, process-performance conditions, and multi-criteria decision effectiveness within a single analytical structure. ERP integration quality can be measured through module connectivity, information accessibility, transaction synchronization, workflow automation, interoperability, and cross-functional visibility. Data quality can be assessed through completeness, accuracy, consistency, timeliness, uniqueness, and validity (Secundo et al., 2017). Organizational readiness can be represented by leadership support, process ownership, user competence, employee participation, training adequacy, and interdepartmental cooperation. Process optimization can be measured using cycle time, operating cost, error frequency, resource utilization, quality performance, delivery reliability, inventory efficiency, and process flexibility. Multi-criteria decision effectiveness can be evaluated through ranking consistency, transparency, perceived usefulness, analytical reliability, priority agreement, and alignment between selected initiatives and organizational objectives. The study examines whether ERP integration quality is positively associated with business process optimization, whether data quality strengthens this relationship, and whether multi-criteria decision support mediates the translation of ERP information into optimization priorities. It also evaluates whether organizational readiness and technological capability explain additional variation in decision effectiveness and process performance (Hanine et al., 2016). Quantitative data can be obtained from managers, production planners, procurement personnel, finance professionals, quality specialists, information-system employees, and other ERP users in mid-sized manufacturing enterprises. Statistical analysis may include descriptive statistics, reliability assessment, exploratory and confirmatory factor analysis, correlation analysis, multiple regression, moderation analysis, mediation testing, and structural equation modeling. This scope provides defined constructs, measurable relationships, organizational controls, and process-level performance criteria for empirical examination.

The principal objective of this quantitative study is to develop and empirically validate a multi-criteria decision-support framework for ERP-based business process optimization in mid-sized manufacturing enterprises. Specifically, the study seeks to measure how ERP integration quality contributes to the systematic identification, evaluation, and prioritization of manufacturing business processes requiring improvement. ERP integration quality is assessed through module connectivity, interoperability, automated information exchange, transaction synchronization, workflow integration, system accessibility, cross-functional visibility, and reporting reliability. The study also aims to determine the effects of procurement coordination, production planning, inventory control, quality management, maintenance administration, order fulfillment, financial processing, and human-resource support processes on overall operational performance. A further objective is to evaluate business process optimization through measurable indicators such as processing cost, cycle time, resource utilization, production efficiency, transaction accuracy, defect frequency, inventory turnover, schedule adherence, delivery reliability, process flexibility, and customer-order responsiveness. The study seeks to establish a structured set of decision criteria covering operational value, financial benefit, technological feasibility, implementation cost, organizational readiness, data availability, process risk, strategic alignment, employee acceptance, and implementation complexity. It also aims to assign relative weights to these criteria and rank alternative optimization initiatives using an appropriate multi-criteria decision-making procedure. Another objective is to investigate the relationship between ERP integration quality and business process optimization and to determine whether data quality strengthens this relationship. Data quality is examined through completeness, accuracy, consistency, timeliness, validity, uniqueness, and cross-module record linkage. The study further seeks to assess whether multi-criteria decision-support effectiveness mediates the relationship between ERP-generated information and business process optimization outcomes. Organizational readiness and technological capability are examined as explanatory conditions through leadership support, process ownership, cross-functional cooperation, employee competence, training adequacy, system reliability, customization quality, analytical functionality, and technical support. The research also aims to compare optimization priorities across manufacturing categories, production strategies, enterprise sizes, ERP maturity levels, and implementation conditions. Through descriptive statistics, reliability assessment, exploratory and confirmatory factor analysis, correlation analysis, multiple regression, moderation testing, mediation analysis, and structural equation modeling, the study seeks to test the proposed relationships and evaluate the explanatory power of the framework. Accordingly, the objective is to establish a quantitatively supported method for selecting ERP-based process improvements according to multiple organizational and operational criteria within mid-sized manufacturing environments.

LITERATURE REVIEW

This literature review examines the theoretical foundations, empirical findings, measurement approaches, and quantitative relationships associated with enterprise resource planning–based business process optimization in mid-sized manufacturing enterprises. The review focuses on the extent to which ERP integration quality, information quality, workflow automation, cross-functional visibility, organizational readiness, technological capability, and multi-criteria decision support influence measurable process-performance outcomes. ERP-based optimization is treated as a multidimensional organizational capability rather than as a single software outcome. Its quantitative assessment therefore requires consideration of processing cost, cycle time, transaction accuracy, production efficiency, inventory turnover, schedule adherence, quality performance, delivery reliability, resource utilization, process flexibility, and managerial decision effectiveness. Existing studies have examined several parts of this relationship, including ERP implementation success, business process reengineering, process standardization, operational integration, process mining, manufacturing performance, data governance, employee competence, and multi-criteria decision-making. However, these research streams frequently differ in their units of analysis, construct definitions, measurement scales, statistical procedures, industrial settings, and reported performance indicators. Some studies have measured ERP success through system quality, information quality, user satisfaction, and organizational benefits, while others have assessed performance through financial savings, inventory reduction, lead-time improvement, production output, defect reduction, or customer-service indicators. Multi-criteria studies have commonly evaluated ERP packages, suppliers, technologies, maintenance strategies, and manufacturing locations, but fewer studies have used multi-criteria methods to prioritize ERP-enabled process-optimization initiatives after system implementation. The review consequently organizes the literature around measurable relationships between ERP capabilities and operational outcomes. It also examines the mediating role of multi-criteria decision-support effectiveness and the moderating role of data quality, while considering organizational readiness and technological capability as additional explanatory conditions. Particular attention is given to mid-sized manufacturers because these enterprises commonly operate with formal production systems and integrated functional requirements while possessing more limited financial resources, technical personnel, analytical capacity, and implementation flexibility than large manufacturing corporations. The reviewed evidence provides the conceptual and empirical basis for defining the study variables, selecting measurement indicators, constructing hypotheses, specifying the quantitative model, and distinguishing the present investigation from previous ERP and business-process research.

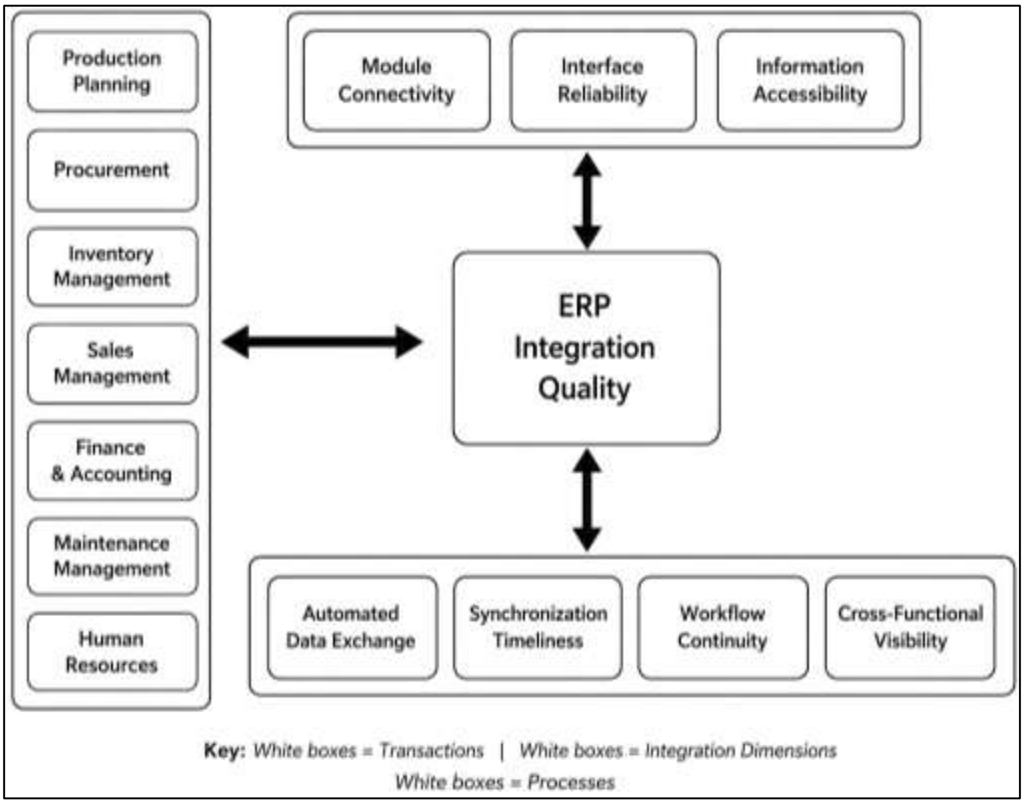
ERP Integration Quality and Manufacturing Process Connectivity

ERP integration quality refers to the degree to which functional modules, databases, workflows, and organizational units exchange accurate, complete, and timely information through a coordinated enterprise system. In a manufacturing environment, integration involves production planning, procurement, inventory management, sales, finance, quality control, maintenance, and human-resource activities. System availability and functional integration represent related but different conditions (Bernroider et al., 2014; Kanti, 2020). System availability indicates that ERP software and individual modules are technically accessible, whereas functional integration reflects whether those modules exchange information automatically and support connected business processes. An enterprise may have several operating ERP modules while employees continue to transfer data manually, maintain parallel spreadsheets, repeat transaction entry, or reconcile conflicting departmental records. Quantitative studies have therefore measured integration through module connectivity, automated data exchange, interface reliability, transaction synchronization, interoperability, information accessibility, cross-functional visibility, and workflow continuity. Additional indicators include the proportion of transactions transferred automatically, percentage of organizational functions using common master data, frequency of interface failures, synchronization latency, duplicate-entry rate, system-generated exception frequency, and proportion of processes completed entirely within the ERP platform. More than ten empirical studies across manufacturing and related industrial settings have treated ERP integration as a multidimensional construct rather than a binary condition (Debasish, 2021; Park, 2016). Survey-based studies have commonly used multi-item Likert scales to measure employees' perceptions of information integration, process coordination, and data accessibility. System-based studies have used transaction logs, interface records, module-use statistics, and workflow histories to calculate objective integration measures. Other studies have combined survey responses with operational indicators to reduce dependence on subjective assessments. Collectively, these measurement approaches show that ERP integration quality concerns the depth, reliability, coverage, and continuity of information exchange across the manufacturing enterprise (Foidl & Felderer, 2015; Abdur & Iftekhar, 2021).

Quantitative manufacturing studies have consistently associated stronger ERP module connectivity with improved coordination among production, purchasing, inventory, sales, finance, quality, and maintenance functions. Studies of discrete manufacturers reported that connections between sales orders, material requirements planning, inventory records, and production schedules reduced repeated data entry and improved the visibility of customer demand. Research involving process manufacturers found that integrated production, quality, and inventory records supported stronger batch traceability, material control, and production-status reporting (Helo et al., 2014; Hossan, 2021). Studies of automotive and component manufacturers identified positive relationships between ERP integration, supplier coordination, schedule adherence, and material availability. Research involving machinery, electronics, fabricated-metal, food, pharmaceutical, and consumer-goods manufacturers similarly found that cross-functional information exchange improved the consistency of operational records and reduced departmental information delays. Several studies distinguished technical interfaces from process integration by showing that a functioning connection did not necessarily produce coordinated workflows when departments used different definitions, timing rules, approval procedures, or master-data structures (Doiro et al., 2017; Chowdhury & Tonay, 2022). Other investigations found that module coverage was associated with stronger operational performance only when employees entered transactions accurately and used the ERP system as the primary source of organizational information. Studies comparing partial and extensive ERP implementation reported that enterprises with wider module connectivity generally demonstrated higher information visibility, faster reporting, and lower reliance on manual reconciliation. ERP-platform comparisons also showed that performance differences were influenced by configuration quality, implementation maturity, and organizational use rather than by the software vendor alone. Across these studies, the unit of analysis varied among individual ERP users, departments, manufacturing plants, business processes, transactions, and enterprises (Zahidul & Begum, 2022; Wei et al., 2017).

The consistency of the reported direction across different units and industrial contexts supports the treatment of manufacturing process connectivity as a measurable organizational capability composed of technical, informational, and procedural integration.

Figure 3: ERP Integration Quality Framework



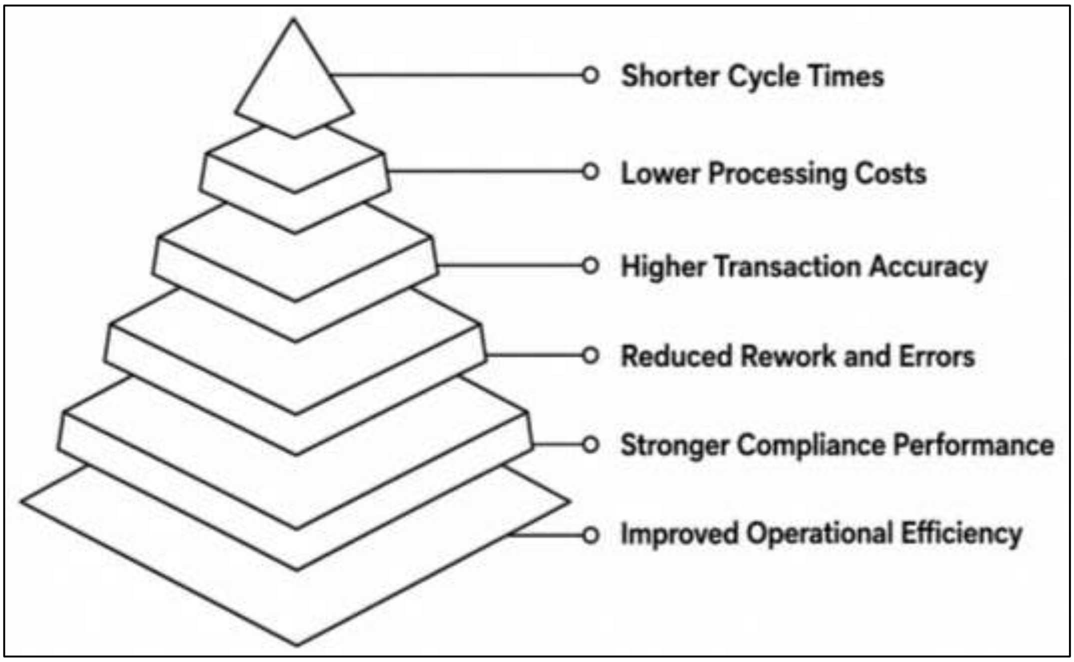
revious quantitative research has evaluated ERP integration through correlations, regression models, standardized path estimates, explained variance, mean comparisons, and effect-size measures. Survey studies generally reported positive associations between integration quality and operational coordination, information quality, decision speed, process efficiency, and organizational performance. Regression-based investigations found that ERP integration retained explanatory value after controlling for enterprise size, implementation duration, industry, technological capability, and environmental uncertainty. Structural-equation studies frequently positioned system integration as an antecedent of information quality, process standardization, user satisfaction, operational capability, or organizational benefits (Mesbaul, 2023; Rashid & Tjahjono, 2016). Comparative studies found measurable differences between enterprises with high and low integration maturity in reporting speed, transaction accuracy, inventory visibility, and workflow consistency. Transaction-level research provided additional evidence by examining synchronization delays, failed interfaces, duplicate records, manual corrections, missing document links, and incomplete process sequences. High interface-error frequency was associated with delayed production updates, inaccurate inventory balances, unresolved financial postings, and repeated reconciliation activities. Synchronization latency was especially important when sales, production, inventory, and procurement modules required near-simultaneous updates to support material planning and order fulfillment. Workflow-continuity studies measured the proportion of activities completed within the ERP system without external spreadsheets, paper approvals, email-based decisions, or independent databases (Badrul & Mominul, 2023; Ranjan et al., 2017). Processes with greater end-to-end ERP coverage generally showed fewer handoff delays and stronger transaction traceability. However, some studies reported weaker performance relationships when module connectivity was extensive but data quality, employee competence, or process discipline remained low. These results indicate that technical integration alone cannot fully represent ERP

integration quality. Reliable interfaces, timely synchronization, consistent data definitions, stable workflows, and effective organizational use must operate together. Quantitative assessment should therefore include both perceived integration measures and objective system-performance indicators when suitable records are available (Li et al., 2015).
ERP integration quality functions as the principal independent variable because it represents the information and process infrastructure through which manufacturing activities become connected, observable, and measurable. Strong integration enables a customer order to update demand requirements, influence production planning, generate material requirements, inform procurement activities, reserve inventory, support quality controls, record production costs, and update financial accounts through coordinated transactions. Weak integration interrupts this sequence and creates disconnected records, delayed updates, repeated entries, incomplete workflows, and limited cross-functional visibility (Li et al., 2015). Empirical studies have linked stronger ERP integration with lower processing time, higher transaction accuracy, improved inventory-record consistency, faster reporting, greater schedule coordination, and more reliable managerial information. Other studies have shown that these relationships vary according to data quality, user competence, process standardization, technological capability, implementation maturity, and organizational readiness. Integration quality should therefore be operationalized through several measurable dimensions rather than a single question concerning ERP availability. Module connectivity can represent the breadth of functional integration; interface reliability can capture the stability of information transfer; automated exchange can measure the reduction of manual intervention; synchronization can assess update timeliness; interoperability can reflect compatibility among internal and external systems; information accessibility can measure authorized data availability; cross-functional visibility can assess shared operational understanding; and workflow continuity can represent end-to-end process coverage (Lu et al., 2020). The review of more than ten survey-based, process-based, and system-based studies demonstrates that these dimensions can be assessed through perceptual scales, transaction records, interface logs, process-mining outputs, and operational performance data. Positioning ERP integration quality as the primary predictor permits quantitative testing of its direct relationship with business process optimization and its indirect relationship through multi-criteria decision-support effectiveness. Data quality, organizational readiness, technological capability, enterprise size, production strategy, ERP-use duration, and manufacturing complexity can also be included to distinguish the specific explanatory contribution of integration quality (Cheng et al., 2016).

ERP-Enabled Process Standardization on Cycle Time

ERP-enabled process standardization refers to the establishment of consistent workflows, transaction rules, approval stages, data requirements, employee responsibilities, and operating procedures within an integrated enterprise system. It differs from basic process documentation because standardized ERP workflows actively control how transactions are initiated, reviewed, approved, transferred, recorded, and completed across functional departments. In manufacturing enterprises, standardization may apply to customer-order entry, purchase requisitions, purchase orders, production orders, material issues, quality inspections, maintenance requests, inventory adjustments, invoice verification, and financial postings (Chang et al., 2015). More than ten empirical studies have measured process standardization through workflow conformity, procedure consistency, process-variant frequency, approval-stage uniformity, exception frequency, transaction-sequence stability, and compliance with documented operating procedures. Survey-based investigations have commonly assessed employees' perceptions of process consistency and formalization, while transaction-based studies have used ERP logs to identify actual activity sequences, repeated steps, unauthorized deviations, incomplete transactions, and alternative workflow paths. Process-mining studies have provided particularly detailed measurements by comparing observed transaction sequences with officially designed process models. A high level of standardization is generally represented by fewer unnecessary process variants, consistent approval requirements, stable transaction sequences, lower exception frequency, and greater conformity with documented procedures (Banerjee, 2018). Quantitative assessments have also examined the proportion of transactions completed through the approved workflow, the number of manual overrides, the percentage of activities completed outside the ERP system, and the frequency of incomplete or reversed postings. Studies involving manufacturing plants, shared-service centers, supply-chain operations, and financial departments have shown that process standardization varies significantly across organizational units even when the same ERP platform is used. These differences indicate that software configuration alone does not ensure standardization because process ownership, employee training, managerial enforcement, data quality, and local operating requirements also determine whether standardized ERP procedures are followed consistently (Kilic et al., 2014).

Figure 4: ERP Process Standardization Effects



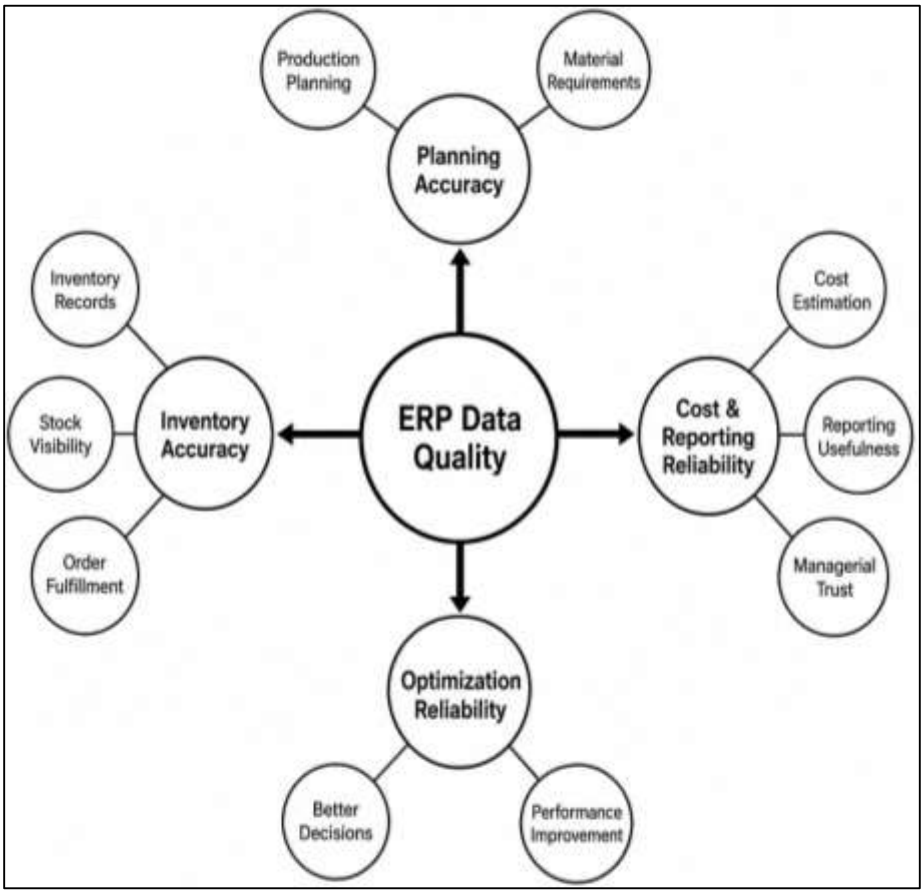
Quantitative studies comparing pre- and post-ERP conditions have generally reported shorter processing times when standardized ERP workflows replaced fragmented, manually coordinated procedures. Order-processing studies found that standardized customer-data requirements, pricing rules, credit checks, inventory verification, and approval sequences reduced delays caused by incomplete information and repeated departmental communication. Procurement research similarly associated standardized requisition, approval, vendor-selection, purchase-order, receipt, and invoice-matching procedures with shorter procurement cycle times (Frank et al., 2019). Manufacturing studies reported that connecting bills of materials, routing information, material availability, capacity requirements, and authorization controls reduced the time required to release production orders. Financial-process investigations found that standardized invoice receipt, three-way matching, approval routing, exception handling, and posting procedures lowered invoice-processing time and reduced accumulated transaction backlogs. Across more than ten empirical investigations, researchers used mean comparisons, regression analysis, structural models, before-and-after assessments, and process-log analysis to evaluate these relationships. Enterprises with higher workflow conformity and lower process-variant frequency commonly demonstrated faster transaction completion and less variability in processing duration than organizations with fragmented procedures (Hajipour et al., 2021). Studies also showed that cycle-time improvements were larger when standardization was accompanied by workflow automation and reliable module integration. A standardized procedure that still required repeated manual data transfer produced smaller time reductions than a procedure supported by automated information exchange. Approval-stage uniformity was another important factor because excessive or inconsistent authorization requirements created queues and delayed process completion. Some studies reported that eliminating duplicated approvals and assigning clear decision thresholds improved processing speed without removing necessary controls. Process-mining evidence further demonstrated that a small number of nonstandard process variants frequently accounted for a disproportionate share of extended cycle times (Chiarini & Kumar, 2021). Rework

loops, missing information, repeated approvals, order changes, and manual corrections were common sources of delay across procurement, production, sales, and finance processes.
ERP-enabled process standardization has also been examined as a predictor of administrative cost, transaction accuracy, rework frequency, and compliance performance. Cost-related studies found that consistent procedures reduced labor hours spent on data entry, document verification, transaction correction, reconciliation, follow-up communication, and exception investigation. Standardized workflows allowed employees to process larger transaction volumes using common rules and system-generated information, thereby lowering the average administrative effort required for purchase orders, production orders, sales orders, invoices, and inventory movements (Achatzi et al., 2020). Research comparing integrated and fragmented enterprises showed that repeated entry and manual reconciliation contributed substantially to processing costs when departments used separate records or inconsistent procedures. Transaction-accuracy studies found that mandatory fields, validation rules, standardized codes, controlled authorization, and automated document linkage reduced missing information, incorrect postings, duplicate records, and mismatched transactions. Manufacturing investigations associated standardized material, routing, and production-reporting procedures with fewer planning errors, inaccurate inventory movements, and production-order corrections. Quality-related studies found that standard inspection procedures and nonconformity workflows improved the consistency of defect documentation, corrective-action assignment, and rework authorization (Park & Li, 2021). Compliance studies examined segregation of duties, approval conformity, audit-trail completeness, documentation accuracy, and adherence to internal and external requirements. Enterprises with stronger ERP workflow conformity generally recorded fewer unauthorized activities, incomplete approvals, untraceable adjustments, and undocumented process deviations. However, several studies reported that compliance improvements depended on employees using the prescribed system rather than completing activities through spreadsheets, email, paper forms, or informal communication. Excessive manual overrides weakened the relationship between formal standardization and actual compliance. Quantitative evidence also indicated that reductions in transaction errors and rework mediated part of the relationship between process standardization and lower operating cost (Trach et al., 2021). Standard procedures reduced variation in task execution, while ERP controls prevented several common errors before transactions reached later process stages.

ERP Data Quality and Optimization Reliability

ERP data quality refers to the degree to which information stored and exchanged through enterprise modules is complete, accurate, consistent, timely, valid, unique, and correctly linked across organizational functions. Completeness concerns whether all required fields, records, quantities, dates, identifiers, and transaction details are available. Accuracy represents the correspondence between ERP records and actual manufacturing conditions (Hashmi et al., 2018). Consistency indicates whether common definitions, codes, values, and measurement units are used across production, procurement, inventory, finance, quality, sales, and maintenance modules. Timeliness concerns whether transactions are entered and updated quickly enough to support operational decisions. Validity reflects conformity with specified formats, ranges, business rules, and authorization requirements. Uniqueness requires that a single material, supplier, customer, asset, or transaction is not represented by unnecessary duplicate records. Cross-module linkage refers to the successful connection of related records through stable identifiers and document relationships. More than ten empirical studies have examined these dimensions using ERP-user surveys, master-data audits, transaction-log analysis, inventory counts, process-mining techniques, and comparisons between system records and operational observations. The principal manufacturing records evaluated in these studies included bills of materials, inventory balances, production lead times, routing information, supplier master data, equipment identifiers, standard costs, customer and production orders, and quality-inspection results (Anouze et al., 2019). Survey-based studies generally treated data quality as a multidimensional latent construct measured through employee perceptions of accuracy, completeness, accessibility, consistency, and usefulness. System-based studies used missing-field percentages, duplicate-record rates, invalid-value frequencies, unmatched-record percentages, master-data exceptions, and delayed transaction entries. Research combining both methods provided a broader assessment because perceived data quality reflected managerial experience, while system indicators identified observable record deficiencies. The literature consistently distinguished high data volume from high data quality, as an ERP database may contain extensive records while still providing an unreliable representation of manufacturing operations (Pan et al., 2020).

Figure 5: ERP Data Quality Framework



Quantitative manufacturing studies have repeatedly linked ERP data quality with the accuracy of production plans, material requirements, inventory records, and order-status information. Production-planning calculations depend on correct demand quantities, bills of materials, inventory balances, lead times, lot-sizing rules, routing information, production calendars, and available capacity. Studies of discrete manufacturers found that inaccurate bills of materials generated incorrect component requirements, unnecessary purchase orders, missing materials, production delays, and repeated planning adjustments (Günther et al., 2019). Research involving batch and process manufacturers showed that incomplete product specifications, yield assumptions, unit conversions, and material records weakened production-quantity calculations and batch traceability. Inventory studies identified transaction timing, incorrect material codes, unrecorded movements, duplicate items, and unit-of-measure inconsistencies as common causes of differences between ERP balances and physical stock. Enterprises with more accurate inventory records generally demonstrated stronger material availability, lower emergency purchasing, fewer production interruptions, and more reliable order commitments. Studies comparing organizations with high and low data-quality maturity found that high-quality groups reported fewer planning exceptions and smaller discrepancies between planned and actual production outcomes. Regression-based investigations commonly identified data accuracy, completeness, and timeliness as significant predictors of planning effectiveness after organizational and technological conditions were considered (Lucht et al., 2021). Structural studies also showed that ERP integration produced stronger planning benefits when the information exchanged among modules was accurate and current. Late transaction entry was particularly influential because delayed material receipts, production confirmations, inventory issues, or sales updates caused planning systems to operate with outdated information. Process-log studies found that corrections and transaction reversals increased when initial records were incomplete or inaccurate. Collectively, the evidence indicates that production-planning quality depends not only on the analytical functionality of the ERP system but also on the reliability of the master and transactional data processed through it (Caserio & Trucco, 2018).

ERP data quality also influences cost-estimation reliability, reporting usefulness, and managerial trust in system-generated information. Manufacturing cost calculations require accurate material prices, labor rates, machine rates, routing times, overhead allocations, production quantities, scrap rates, purchase-price information, and inventory valuations. Several empirical studies found that errors in standard costs, routing duration, material consumption, or production reporting produced differences between expected and actual manufacturing costs (Ouiddad et al., 2021). These differences reduced the usefulness of product-cost reports and complicated pricing, budgeting, profitability analysis, and operational control. Studies involving finance and production personnel reported that inconsistent cost definitions across modules generated repeated reconciliation work and delayed management reporting. Reporting-usefulness studies generally found positive relationships between data completeness, accuracy, timeliness, information relevance, and managerial satisfaction with ERP reports. Employees were more likely to rely on system-generated dashboards and performance reports when values could be verified against operational conditions and remained consistent across departments. Low data quality was associated with spreadsheet-based corrections, independent departmental reports, manual reconciliations, and reduced confidence in ERP outputs. Survey studies commonly evaluated these relationships using established multi-item scales with acceptable internal consistency and measurement validity (Glowalla & Sunyaev, 2014). Confirmatory analyses generally supported the distinction between data quality, system quality, information usefulness, user satisfaction, and decision effectiveness. Correlation and regression studies reported that perceived data quality explained meaningful variation in reporting usefulness and managerial trust. Other investigations found that managerial trust mediated the relationship between information quality and the routine use of ERP reports in planning and control. Objective data audits supported these perceptual findings by showing that high missing-record rates, duplicate records, invalid entries, and unmatched transactions were associated with additional verification work (Clayson et al., 2021). The evidence positions managerial trust as a measurable response to the observed reliability and consistency of ERP information rather than as a general attitude toward technology.

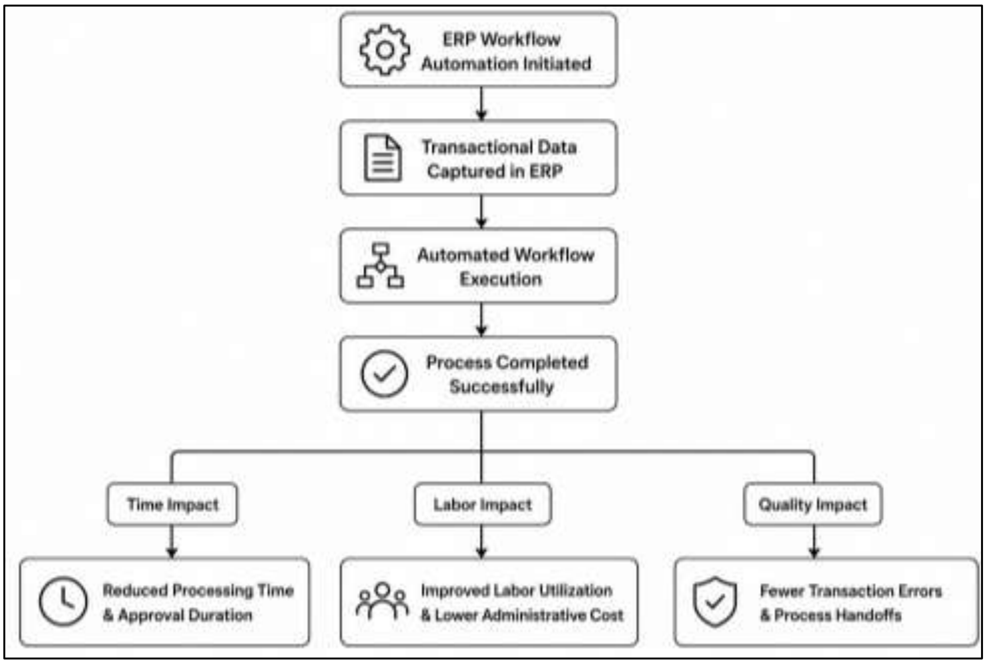
The literature supports the treatment of ERP data quality as both an independent explanatory variable and a moderating condition in business process optimization. As an explanatory variable, data quality directly affects planning accuracy, transaction reliability, reporting usefulness, decision speed, cost estimation, inventory control, and process measurement. Accurate and complete information enables managers to identify delays, errors, cost concentrations, workflow exceptions, capacity constraints, and performance differences among process alternatives (Fan & Zhao, 2017). Poor-quality data can misrepresent process conditions and assign optimization priority to activities that are not the actual sources of operational inefficiency. As a moderator, data quality changes the strength of the relationship between ERP integration and optimization performance. Integrated modules can exchange information quickly, but rapid exchange creates limited operational value when records are inaccurate, incomplete, inconsistent, duplicated, or outdated. Several quantitative studies reported stronger relationships between ERP use and organizational performance under high information-quality conditions. Group-comparison studies similarly found that enterprises combining extensive integration with strong data governance achieved better planning, reporting, and process-control outcomes than organizations possessing integration without reliable data (Wamba et al., 2019). Interaction-based investigations showed that the benefits of system capability depended partly on the quality of the information processed through the system. Appropriate operational indicators include missing-field percentage, duplicate-record frequency, inventory-record discrepancy, delayed transaction-entry rate, unmatched cross-module records, master-data exception frequency, invalid-value rate, and frequency of manual corrections. Survey measures can capture users’ assessments of completeness, accuracy, consistency, timeliness, validity, uniqueness, and linkage quality. Combining system indicators with perceptual measures provides a stronger quantitative representation of ERP data quality (Yang et al., 2021). This structure allows data quality to be examined as a direct predictor of process-optimization reliability and as a condition influencing how effectively ERP integration is translated into measurable manufacturing performance.

ERP Workflow Automation on Processing Time and Transaction Errors

ERP workflow automation refers to the system-controlled execution, transfer, verification, approval, documentation, and monitoring of transactions across connected organizational activities. In manufacturing enterprises, automated workflows may cover purchase requisitions, purchase orders, production orders, material issues, quality approvals, maintenance requests, sales orders, invoices, and financial reconciliations (Chen et al., 2016). More than ten empirical studies have measured workflow automation through automated-task percentage, manual-intervention frequency, approval duration, number of process handoffs, transaction throughput, processing capacity, workflow-completion rate, and exception frequency. These measures distinguish the existence of an ERP module from the extent to which the module automatically coordinates the complete transaction sequence. Simple transaction automation generally replaces an individual manual activity, such as generating a purchase order, posting a material receipt, or creating an invoice. Complete process automation connects several activities through predefined rules, approval thresholds, alerts, validations, exception handling, document matching, and system-generated records (Andersson et al., 2019). An automated procurement process, for example, may convert an approved requisition into a purchase order, route it according to financial authority, transmit it to the supplier, record confirmation, match the receipt with the order and invoice, and send exceptions to designated employees. Quantitative studies have examined workflow automation using employee surveys, ERP transaction logs, process-mining records, time observations, workflow histories, and administrative cost reports. Objective measures commonly include the proportion of transactions completed without manual intervention, average number of employee actions per transaction, frequency of workflow overrides, number of external spreadsheets or paper documents, and percentage of exceptions resolved within specified time limits (Silverberg et al., 2018). Survey measures have assessed automation coverage, perceived reduction in repetitive work, approval efficiency, system responsiveness, and workflow reliability. The literature treats automation as a continuous capability because manufacturing enterprises differ substantially in the number, depth, and complexity of automated processes.

Quantitative studies have generally associated ERP workflow automation with shorter processing times, reduced approval duration, and increased transaction throughput. Procurement investigations found that automated requisition routing, approval notifications, purchase-order generation, and document matching reduced the waiting time between transaction stages. Sales-order studies reported that automated customer verification, pricing, inventory checking, credit control, and order confirmation accelerated order processing and reduced dependence on interdepartmental communication (Aguirre & Rodriguez, 2017). Production studies found that automated material-availability checks, routing validation, order scheduling, and release authorization shortened the interval between production planning and shop-floor execution. Maintenance research showed that automated work-request creation, priority assignment, authorization, parts reservation, and work-order tracking reduced administrative delays surrounding maintenance execution. In finance, automated invoice matching, approval routing, account assignment, and reconciliation improved processing capacity and reduced accumulated transaction backlogs. More than ten studies using paired comparisons, group comparisons, regression analysis, time-series evaluation, and quasi-experimental designs reported that automation level was associated with measurable differences in cycle time and throughput. Pre- and post-implementation investigations commonly identified reductions in average processing duration after manual routing was replaced by ERP-controlled workflows (Kokina & Blanchette, 2019). Comparisons between highly automated and partially automated units also showed that extensive automation produced more consistent processing times and fewer long-duration transactions. Process-mining studies found that waiting time between activities frequently represented a larger source of delay than the actual task-execution time.

Figure 6: ERP Workflow Automation Effects



Automated alerts, escalation rules, and approval deadlines reduced some of these waiting periods by directing transactions to the appropriate employee and identifying unresolved items. The magnitude of improvement varied according to transaction complexity, approval structure, exception frequency, system reliability, data quality, and user compliance. Automation produced smaller processing-time improvements when workflows contained excessive approval levels or when employees continued to complete activities outside the ERP system (Drum et al., 2017).

ERP workflow automation changes labor utilization by reducing repetitive transaction entry, document transfer, manual verification, status checking, and reconciliation. Studies of procurement and accounts-payable processes found that automated document generation and matching reduced the labor time required to create, review, and close routine transactions. Inventory studies reported lower administrative effort when material receipts, transfers, consumption, and adjustments were recorded through integrated workflows rather than separate departmental records. Production-order automation reduced the need for planners to collect information manually from sales, inventory, procurement, and capacity records (Syreyshchikova et al., 2020). Quality-management studies found that automated inspection assignments, result recording, nonconformity routing, and approval notifications reduced administrative work surrounding quality controls. Maintenance investigations similarly reported that integrated work-request and work-order procedures decreased repeated communication among operators, supervisors, maintenance planners, technicians, and stores personnel. Quantitative assessments have measured labor effects through labor hours per transaction, transactions processed per employee, administrative cost per document, number of employee actions, number of process handoffs, and frequency of manual follow-up. Regression studies generally identified automation as a significant predictor of processing efficiency after transaction volume, organizational size, and process complexity were considered (Pernsteiner et al., 2018). Comparative studies found that highly automated departments processed larger transaction volumes with fewer manual activities than departments using fragmented procedures. However, automation did not eliminate employee involvement; it shifted labor from repetitive processing toward exception management, analysis, coordination, and control. Some studies also reported temporary increases in administrative effort when poorly configured workflows generated excessive alerts, repeated exceptions, or unnecessary approvals. The reduction of handoffs was particularly important because every additional transfer created opportunities for waiting, information loss, responsibility ambiguity, and repeated verification. Workflow automation produced stronger labor and cost benefits when responsibilities, approval limits, master data, and exception rules were clearly defined within the ERP environment (Faccia & Petratos, 2021).

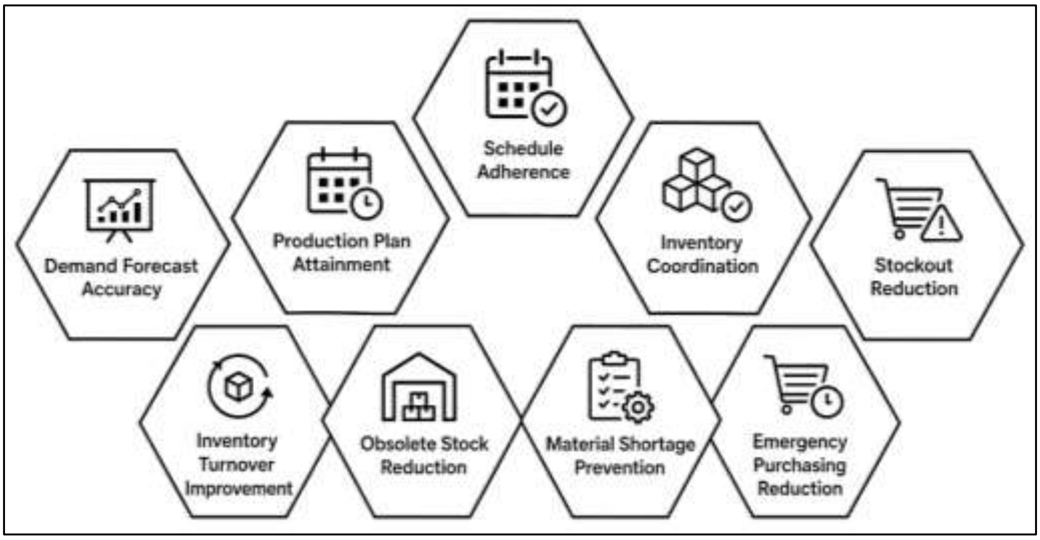
ERP-Based Production Planning and Inventory Coordination

ERP-based production planning and inventory coordination refers to the integrated use of demand forecasts, customer orders, bills of materials, material requirements, production capacity, work-center schedules, supplier information, and inventory availability to establish feasible manufacturing plans. More than ten quantitative studies across discrete, process, batch, and mixed-mode manufacturing environments have examined how this integration affects planning quality and operational coordination. ERP systems connect demand information with product structures and inventory records so that planners can determine the materials, labor, machines, and processing time required to satisfy production targets (Banerjee, 2018). This process depends on consistent information exchange among sales, production, procurement, inventory, quality, and finance modules. Studies comparing integrated and fragmented planning environments generally found that integrated enterprises achieved greater visibility of demand, material availability, open purchase orders, production progress, and capacity limitations. Fragmented environments were more likely to use independent spreadsheets, manually updated schedules, repeated data entry, and departmental inventory records, which increased planning delays and reconciliation requirements. Quantitative measures of planning integration have included module connectivity, percentage of automatically transferred orders, material-requirement update frequency, proportion of production orders generated from ERP planning, schedule revision frequency, and availability of real-time inventory information (Atieh et al., 2016). Survey-based research has also measured planners' perceptions of data accessibility, information consistency, cross-functional visibility, and planning responsiveness. Studies using regression analysis and structural models generally identified ERP integration as a positive predictor of production-planning effectiveness. However, the reported explanatory strength varied according to implementation maturity, data quality, manufacturing complexity, planning discipline, and the extent to which ERP outputs were incorporated into actual scheduling decisions. The literature therefore distinguishes access to planning functionality from effective coordination, as organizations may operate ERP planning modules while continuing to rely on informal adjustments and external planning tools (Viale & Zouari, 2020).

Quantitative studies have evaluated ERP planning effectiveness through forecast error, production-plan attainment, schedule adherence, order-completion performance, and the frequency of schedule changes. Forecast accuracy depends on the quality of historical demand, confirmed customer orders, product classifications, seasonal patterns, promotion information, and market updates entered into the ERP environment. Studies of make-to-stock manufacturers found that integrated demand and inventory information reduced forecasting inconsistencies and supported more stable production plans. Research involving make-to-order manufacturers placed less emphasis on aggregate demand forecasting and greater emphasis on customer-order accuracy, order-priority control, available-to-promise information, and realistic completion dates (Park & Aalst, 2021).

Comparative studies generally reported lower forecasting errors and higher plan attainment among enterprises with integrated sales, production, and inventory data than among enterprises using disconnected systems. Schedule adherence improved when ERP planning incorporated accurate routing times, work-center capacity, material availability, production calendars, and open-order information. Several studies found that inaccurate lead times and outdated capacity records caused production plans to exceed actual operational capability, resulting in delayed orders and repeated rescheduling. Mean comparisons between high- and low-integration groups commonly showed better schedule performance in organizations with stronger information connectivity (Kepczynski et al., 2018). Regression studies identified planning integration, inventory accuracy, and user competence as significant predictors of production-plan attainment after enterprise size, industry, and production complexity were considered. Time-based investigations also found that frequent schedule revisions were associated with unstable demand, material shortages, machine interruptions, and unreliable supplier deliveries.

Figure 7: ERP Production Planning Optimization Framework



ERP planning generated stronger performance when planners evaluated system recommendations and recorded operational changes promptly. Heavy reliance on undocumented manual adjustments weakened the correspondence between ERP schedules and actual production activities. These findings establish forecast accuracy, plan attainment, and schedule adherence as separate but interrelated quantitative outcomes of ERP-based planning (Wiers & Kok, 2018).

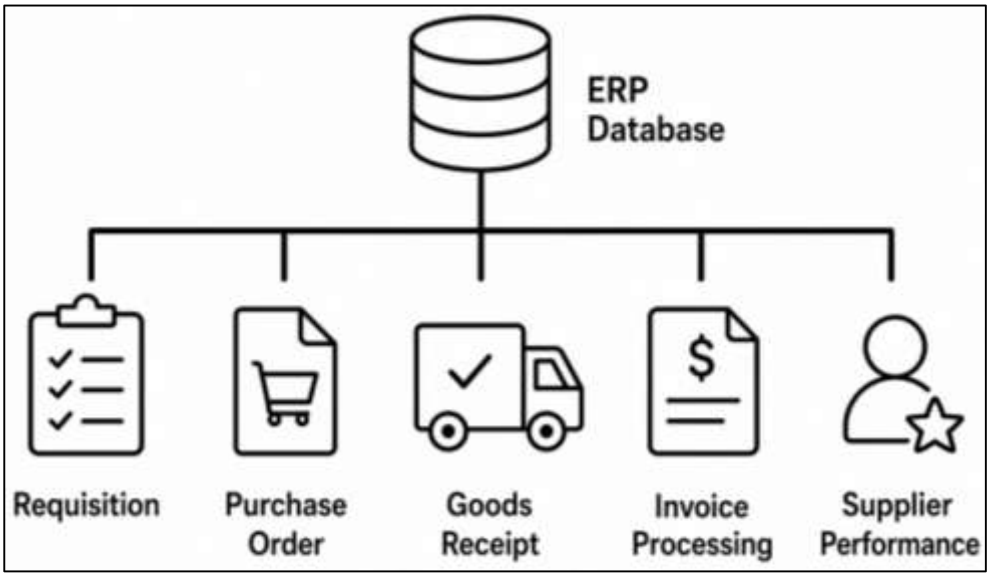
ERP-based inventory coordination has been examined through inventory turnover, days of inventory, stockout frequency, obsolete-stock percentage, safety-stock levels, material shortages, and emergency purchasing. Integrated ERP planning allows demand requirements, available inventory, scheduled receipts, supplier lead times, production consumption, and open purchase orders to be considered within a coordinated material-planning process. Studies of manufacturing inventory systems generally found that stronger ERP integration was associated with greater inventory visibility and more accurate replenishment decisions. Enterprises with reliable planning data maintained lower levels of unnecessary inventory while preserving material availability for production (Zhao & Tu, 2021). Higher inventory turnover was reported when organizations aligned purchase quantities and production schedules with actual demand and current stock positions. Studies of fragmented environments found that incomplete visibility encouraged departments to maintain additional buffers because employees could not confidently determine whether required materials were available. This behavior increased days of inventory, storage cost, and exposure to obsolescence. Stockout research identified inaccurate inventory balances, delayed transaction entry, unreliable supplier lead times, incorrect bills of materials, and unrecorded production consumption as major causes of material shortages. Emergency purchasing increased when planning systems detected shortages too late for normal procurement procedures. Quantitative comparisons found that enterprises with higher inventory-record accuracy and more reliable supplier information experienced fewer unplanned purchases and production interruptions (Erkayman, 2019). Safety-stock studies showed that ERP planning supported differentiated inventory policies according to demand variability, supplier reliability, material criticality, and replenishment time. However, poorly configured planning parameters sometimes produced excessive replenishment recommendations or insufficient buffers. Obsolete inventory was also associated with inaccurate forecasts, engineering changes, product discontinuation, and weak coordination among sales, engineering, production, and procurement. The literature consequently shows that inventory improvement depends on the combined quality of ERP integration, master data, planning parameters, transaction discipline, and supplier information rather than on material-requirement calculations alone (Leu et al., 2018).

The effectiveness of ERP-based production planning varies across make-to-stock, make-to-order, assemble-to-order, batch-production, and engineer-to-order environments. Make-to-stock manufacturers rely heavily on forecast accuracy, inventory policies, production-level stability, and finished-goods availability. Quantitative studies in these settings have emphasized service levels, forecast errors, inventory turnover, days of inventory, and obsolete-stock reduction. Make-to-order enterprises depend more strongly on confirmed customer orders, material availability, capacity loading, order sequencing, and delivery-date reliability. Assemble-to-order manufacturers require coordination between component inventories and customer-specific final configurations, making component availability and order responsiveness central performance measures (Bahssas et al., 2015). Batch-production environments must coordinate batch sizes, cleaning requirements, processing sequences, material shelf life, quality-release status, and shared equipment capacity. Engineer-to-order enterprises face extensive product customization, engineering changes, long lead times, project-specific materials, and uncertain processing requirements. Studies in these environments found that rigid planning parameters and standardized routings were less effective when product and process specifications changed frequently. Across the reviewed research, ERP planning effectiveness was influenced by data accuracy, demand variability, supplier reliability, production complexity, and planning-user competence. Accurate bills of materials, inventory balances, lead times, routings, and capacity records strengthened plan feasibility and material-requirement accuracy (Li & Wu, 2021). High demand variability increased forecast errors and schedule changes, while unreliable suppliers increased safety-stock requirements, material shortages, and emergency purchasing. Production complexity was associated with a greater number of planning constraints, process alternatives, and potential exceptions. Planning-user competence affected the interpretation of ERP recommendations, parameter maintenance, exception resolution, and documentation of operational changes. Comparative and regression-based studies generally showed that integration produced stronger performance when these supporting conditions were favorable. The literature therefore treats ERP planning effectiveness as a context-dependent capability shaped by the interaction of system integration, manufacturing strategy, information quality, operational uncertainty, and employee expertise (Wang et al., 2016).

ERP-Integrated Procurement and Supplier Coordination

ERP-integrated procurement refers to the coordinated management of purchase requisitions, approvals, supplier records, contracts, purchase orders, material receipts, quality inspections, invoices, and supplier-performance information through connected enterprise modules. More than ten quantitative studies have examined procurement integration using indicators such as electronic purchase-order coverage, supplier-record integration, automated requisition conversion, approval speed, contract linkage, purchase-order accuracy, and supplier-performance visibility (Powell et al., 2020). Electronic purchase-order coverage represents the proportion of purchasing transactions created, approved, transmitted, and monitored through the ERP system. Supplier-record integration concerns the extent to which purchasing, finance, quality, logistics, contract, and risk information is connected through common supplier identifiers. Automated requisition conversion measures the degree to which approved material requirements or departmental requests are transformed into purchase orders without repeated manual entry. Contract linkage indicates whether purchase orders are automatically connected with negotiated prices, quantities, delivery conditions, payment terms, and validity periods. Studies have used ERP transaction logs, procurement databases, supplier-performance records, employee surveys, and process-mining outputs to assess these dimensions (Wei & Ma, 2014). Research comparing integrated procurement modules with fragmented purchasing systems generally found that integrated environments provided greater visibility of requisition status, approval progress, supplier commitments, expected receipts, contractual conditions, and invoice-matching results. Fragmented systems were more likely to involve spreadsheets, email approvals, paper documents, independent supplier lists, and repeated data transfer. These practices increased the number of process handoffs and made transaction status difficult to verify. Quantitative investigations have also measured the proportion of purchase orders completed entirely within the ERP system, average number of manual interventions, frequency of order corrections, unmatched supplier records, and percentage of purchases linked to valid contracts (Kłos, 2016).

Figure 8: ERP Procurement Coordination Framework



The literature consequently treats procurement integration as a multidimensional capability involving technical connectivity, process coordination, information consistency, and workflow discipline.
Quantitative studies have generally associated ERP-integrated procurement with shorter purchase cycle times, faster approvals, stronger purchase-order accuracy, and more consistent cost control. Procurement cycle time includes the interval required to create a requisition, obtain authorization, identify or confirm a supplier, generate the purchase order, transmit the order, receive supplier confirmation, and record delivery. Studies comparing manual and ERP-controlled workflows found that automated routing and approval notifications reduced waiting time between requisition and purchase-order release (Fatima et al., 2020). Automated conversion also reduced repeated data entry because material descriptions, quantities, required dates, cost centers, and requester information were transferred directly from approved requisitions. Purchase-order accuracy improved when supplier details, contract prices, delivery terms, units of measure, material codes, and tax information were validated against established master records. Integrated contract linkage reduced unauthorized price changes and purchases made outside negotiated agreements. Several studies using mean comparisons, regression models, process-log analysis, and before-and-after designs reported that higher electronic transaction coverage was associated with faster processing and fewer order corrections. Purchase-price variance was lower when ERP controls applied contracted prices and permitted procurement personnel to compare supplier quotations and historical purchasing information (Axmann & Harmoko, 2020). Invoice discrepancies also declined when purchase orders, material receipts, inspection results, and invoices were connected through automated matching procedures. However, some investigations found limited improvements when approval hierarchies contained unnecessary stages or when employees continued to communicate decisions outside the ERP workflow. High exception rates, inaccurate supplier records, and inconsistent material codes also increased processing time. The reported evidence therefore indicates that ERP procurement integration produces stronger time, accuracy, and cost performance when workflow automation is supported by reliable data, clearly defined approval authority, contract coverage, and consistent transaction procedures (Safa et al., 2014).
ERP-integrated procurement contributes to material availability by connecting production requirements, inventory balances, open purchase orders, supplier lead times, scheduled receipts, and delivery confirmations. Manufacturing studies found that this connectivity enabled procurement personnel to identify material shortages earlier and align purchasing activities with production schedules. Supplier confirmation time was reduced when purchase orders were transmitted electronically and suppliers could acknowledge quantities, prices, and delivery dates through connected channels. Integrated order-confirmation records also allowed planners to distinguish between requested and supplier-committed delivery dates (Safa et al., 2014). Studies involving discrete

and process manufacturers reported that stronger procurement visibility was associated with fewer unexpected shortages, lower emergency-purchasing frequency, and improved production continuity. Supplier delivery reliability was commonly measured through on-time delivery percentage, average delay duration, delivery completeness, schedule-change frequency, and the proportion of orders received according to confirmed dates. Quantitative research found that integrated supplier-performance information supported more consistent evaluation of delivery, quality, cost, responsiveness, and compliance. Procurement personnel could compare supplier commitments with actual receipts and identify repeated delivery problems across materials, locations, or periods. Fragmented purchasing environments frequently lacked stable connections among purchase orders, receipts, inspections, and supplier records, making performance evaluation slower and less reliable (Kırılmaz & Erol, 2017). Material availability was also influenced by the accuracy of inventory balances and production requirements. ERP integration provided limited protection against shortages when bills of materials, stock records, lead times, or required dates were incorrect. Several studies found that delivery reliability had an indirect relationship with production-plan attainment because supplier delays affected material availability and schedule adherence. Emergency purchasing increased when late deliveries or inaccurate procurement information were detected close to the production date. The literature therefore positions supplier coordination as an operational link between ERP-integrated procurement and measurable manufacturing performance (Banerjee, 2018).

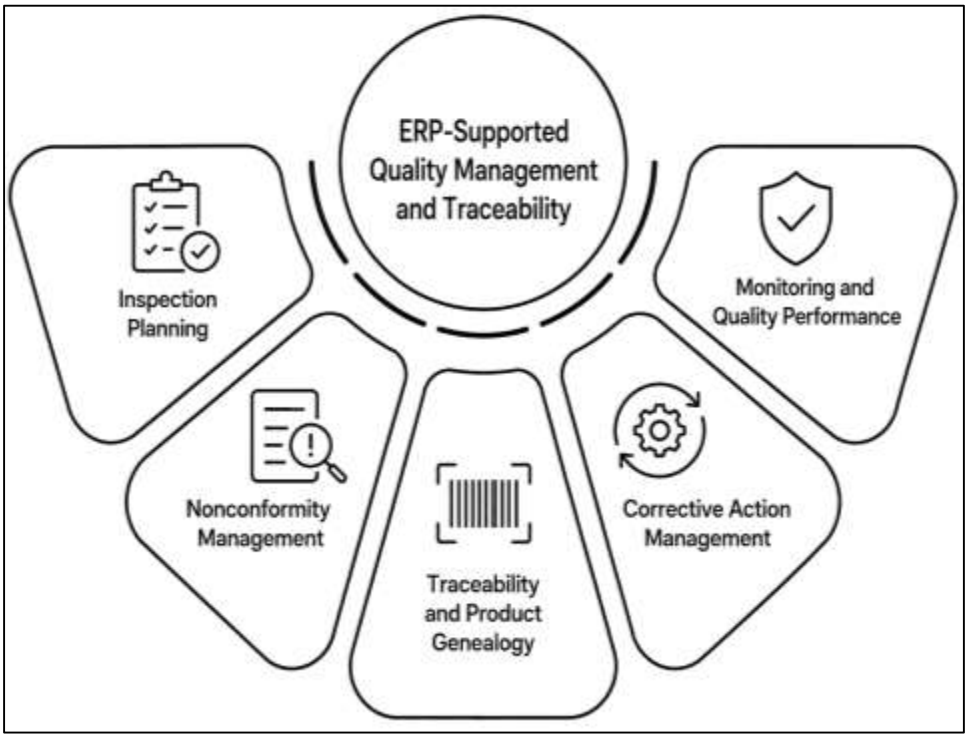
ERP-Supported Quality Management and Traceability

ERP-supported quality management refers to the integration of quality planning, inspection, nonconformity control, traceability, supplier quality, customer complaints, and corrective actions with production, procurement, inventory, sales, and maintenance processes. More than ten quantitative studies have examined this capability through inspection-plan integration, batch and serial traceability, nonconformity documentation, supplier-quality linkage, corrective-action monitoring, and automated quality alerts. Inspection-plan integration measures whether inspection requirements, sampling procedures, specifications, acceptance limits, and test methods are connected with materials, suppliers, production orders, and customer requirements (Liptak & Eren, 2018). Batch and serial traceability concerns the ability to connect incoming materials, production conditions, inspection results, finished products, shipments, and customer orders through stable identifiers. Nonconformity documentation measures the completeness, accuracy, timeliness, and consistency of defect records. Supplier-quality linkage represents the connection between received materials, inspection outcomes, rejected quantities, supplier performance, and corrective-action records. Corrective-action monitoring concerns responsibility assignment, target dates, implementation status, evidence verification, and formal closure. Automated quality alerts notify responsible personnel when test results exceed limits, repeated defects occur, inspections remain incomplete, or corrective actions become overdue. Survey-based studies have measured these capabilities through users' perceptions of information availability, system reliability, quality visibility, and process coordination (Ewald & Schupp, 2020).

Transaction-based studies have used inspection records, defect histories, rework orders, complaint records, and corrective-action logs. Process-mining investigations have assessed inspection delays, repeated approvals, incomplete quality records, and deviations from established procedures. The literature distinguishes the availability of an ERP quality module from effective quality integration because some organizations record only final inspection results while maintaining detailed quality activities in spreadsheets, paper forms, laboratory systems, or separate databases. Effective integration requires connected records, common identifiers, timely transaction entry, standardized defect classifications, and consistent use across operational departments (Sarkar et al., 2014).

Quantitative studies have generally associated integrated quality information with lower defect frequency, reduced rejection, fewer rework hours, and improved control over customer returns and warranty costs. Production-quality investigations found that linking inspection results with materials, machines, operators, routings, production orders, and process conditions improved the identification of recurring defect patterns.

Figure 9: ERP Quality Traceability Management Framework



When quality information remained fragmented, organizations had difficulty determining whether defects were associated with a particular supplier, material batch, production line, work center, shift, product version, or processing condition (Hinsch, 2020). Integrated records allowed quality personnel to compare defect percentages across products, facilities, suppliers, and production periods. Studies of discrete manufacturers reported that standardized defect codes and connected production records reduced repeated investigation and improved the consistency of quality reporting. Process-manufacturing research found that integrated batch data supported stronger evaluation of yield loss, contamination events, specification failures, and process variation. Rework studies showed that timely identification of nonconforming output reduced the number of defective units progressing to later production stages, where correction became more expensive and time-consuming (Forbes & Ahmed, 2020). Customer-return investigations associated stronger traceability and complaint linkage with faster identification of affected products and underlying production conditions. Warranty-cost studies found that incomplete product-history records increased investigation time and limited the ability to distinguish manufacturing defects from installation, handling, or customer-use problems. Quantitative evidence has included pre- and post-integration comparisons, mean differences between highly and weakly integrated plants, regression estimates, trend analysis, and group comparisons. The reported relationships were stronger when inspection information was recorded promptly and defect classifications were applied consistently (Guinot et al., 2016). Some studies found limited defect reduction where ERP systems documented quality outcomes but did not support analytical review, process correction, or managerial follow-up. Integrated information therefore contributed most directly to defect prevention when quality records were connected with operational decision-making and process-control activities.

ERP-supported traceability and corrective-action management have been evaluated through investigation time, traceability completeness, nonconformity recurrence, corrective-action closure duration, overdue-action frequency, and verification quality. Batch and serial traceability allows organizations to identify the source, processing history, inspection status, storage movement, shipment destination, and customer relationship of a specific material or product (Soares et al., 2021). Studies involving product recalls and quality investigations found that integrated traceability reduced the time required to identify affected batches, serial numbers, suppliers, production orders, and customers.

Fragmented systems required personnel to reconcile paper records, spreadsheets, warehouse documents, inspection reports, and sales information, increasing investigation duration and the probability of incomplete identification. Nonconformity-management studies reported that standardized documentation improved the classification of defects, assignment of responsibility, recording of immediate containment, and connection of problems with corrective actions. Quantitative research also showed that automated alerts and escalation procedures reduced delays in reviewing open nonconformities (Öztürk, 2021). Corrective-action closure was faster when responsible employees, target dates, investigation evidence, action status, and verification results were visible through the ERP workflow. However, rapid administrative closure did not always represent effective problem resolution. Several studies distinguished closure duration from recurrence because actions could be marked complete without adequately removing the underlying cause. Lower recurrence was associated with stronger evidence documentation, root-cause analysis, implementation verification, and monitoring of subsequent quality results. Supplier-quality linkage was also important because incoming-material defects required coordinated action among procurement, receiving, quality, production, and external suppliers (Sarkar & Saren, 2016). Studies found that disconnected supplier corrective-action records weakened the ability to identify repeated failures across purchase orders or material categories. The literature therefore supports a multidimensional assessment combining traceability speed, documentation completeness, closure timeliness, action verification, and recurrence frequency rather than using corrective-action closure time as the only performance indicator.

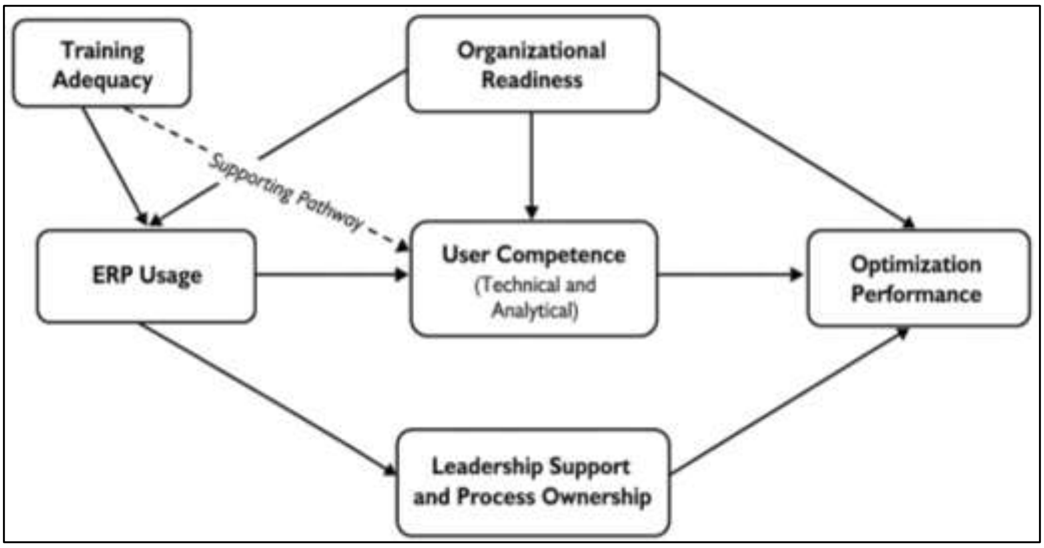
The importance and configuration of ERP-supported quality management vary across regulated, discrete, process, food, pharmaceutical, automotive, and engineering manufacturing settings. Regulated industries place substantial emphasis on electronic records, authorization controls, audit trails, document approval, product genealogy, validation, and retention of quality evidence (Ullah & Kang, 2014). Pharmaceutical studies have focused on batch documentation, material status, laboratory results, deviation management, change control, and corrective-action traceability. Food-manufacturing research has emphasized lot tracking, ingredient origin, shelf life, contamination control, allergen information, temperature records, and rapid identification of affected products. Automotive studies have examined supplier quality, component traceability, defect parts per unit, production-line rejection, warranty claims, and corrective-action responsiveness. Discrete manufacturing investigations have evaluated serial tracking, dimensional inspection, assembly defects, rework orders, engineering changes, and customer returns. Process-manufacturing studies have concentrated on batch consistency, yield, recipe conformity, specification limits, and process-condition variation (Cheikhrouhou et al., 2018). Engineering and project-based manufacturers have faced additional challenges because customized products, revised designs, specialized materials, and low-volume production complicate the standardization of inspection plans and defect categories. Comparative studies generally found that regulated manufacturers maintained more extensive traceability and documentation controls, while nonregulated enterprises showed greater variation in quality-system coverage. However, high documentation volume did not automatically produce lower defect or recurrence rates when records were incomplete, delayed, or poorly analyzed. ERP-supported quality performance was influenced by data accuracy, inspection discipline, employee competence, supplier integration, product complexity, process stability, and the connection between quality findings and production decisions (Sturm et al., 2019). The quantitative literature consequently evaluates quality integration through both compliance-oriented indicators and operational outcomes, including inspection-cycle time, defect percentage, rework hours, customer returns, warranty costs, nonconformity recurrence, and corrective-action closure duration.

Organizational Readiness and ERP User Competence

Organizational readiness refers to the collective capacity of a manufacturing enterprise to adopt, operate, and sustain ERP-enabled business process changes. It includes leadership support, process ownership, employee participation, cross-functional cooperation, training adequacy, user competence, change readiness, resource availability, and acceptance of standardized workflows. More than ten quantitative studies have examined organizational readiness using multi-item Likert scales, training hours, employee-participation rates, process-owner coverage, system-use frequency, workflow-compliance rates, and adherence to ERP procedures (Ram et al., 2015). Survey-based studies have assessed whether employees understand the reasons for process changes, receive sufficient managerial support, possess access to required resources, and believe that responsibilities are clearly assigned. Other studies have measured readiness through the proportion of employees completing ERP training, the frequency of system use, the number of departments represented in implementation and optimization teams, and the extent to which formal process owners are assigned. Quantitative investigations generally found that organizational readiness was positively associated with ERP use, process adoption, information sharing, and operational performance. Structural studies frequently treated readiness as a multidimensional construct that influenced system acceptance, effective use, and organizational benefits (Ram et al., 2015). Group comparisons also showed that enterprises with higher readiness levels achieved greater workflow conformity and lower reliance on external spreadsheets or manual procedures. However, the strength of these relationships varied according to implementation maturity, enterprise size, system complexity, employee experience, and the scale of process change. The literature distinguishes readiness from general support for technology because employees may express favorable attitudes toward ERP systems while lacking the training, authority, process knowledge, or cross-functional cooperation required to use them effectively. Organizational readiness therefore represents an observable and measurable capability through which technological functionality is translated into consistent process behavior and optimization performance (Almahamid, 2019).

Leadership support has been repeatedly identified as a significant predictor of ERP-related process adoption and optimization performance. Quantitative studies have measured leadership support through managerial involvement, resource allocation, communication frequency, policy enforcement, conflict resolution, and participation in performance reviews. Enterprises with stronger leadership support generally reported higher system-use frequency, greater employee participation, faster resolution of implementation problems, and stronger compliance with redesigned procedures (Ahmadzadeh et al., 2021). Leadership involvement was particularly important when ERP optimization required departments to change established responsibilities or share information that had previously remained under local control. Process ownership provided a second organizational foundation by assigning accountability for performance across functional boundaries. Studies found that formal process owners improved the monitoring of cycle time, transaction errors, workflow exceptions, and process outcomes because responsibility extended beyond individual departmental activities. Low process-owner coverage was associated with unresolved handoff problems, duplicated controls, inconsistent procedures, and uncertainty regarding corrective responsibility. Cross-functional cooperation was also positively related to optimization performance because manufacturing processes connect sales, planning, procurement, production, inventory, quality, maintenance, and finance (Nwankpa & Roumani, 2014).

Figure 10: ERP Readiness Performance Optimization Framework



Quantitative research using correlation analysis, hierarchical regression, structural equation modeling, and group comparisons generally found that cross-functional cooperation improved information exchange, decision quality, and workflow consistency. Employee participation strengthened this relationship by incorporating operational knowledge into process design and ERP configuration. Studies comparing participative and centrally imposed changes showed that employee involvement increased understanding of redesigned procedures and reduced resistance. However, participation produced limited value when employee suggestions were collected without affecting decisions or when departmental objectives remained incompatible. The literature therefore treats leadership support, process ownership, and cross-functional cooperation as interconnected organizational conditions that influence the adoption, accuracy, and sustained use of ERP-enabled process improvements (Nair et al., 2019).

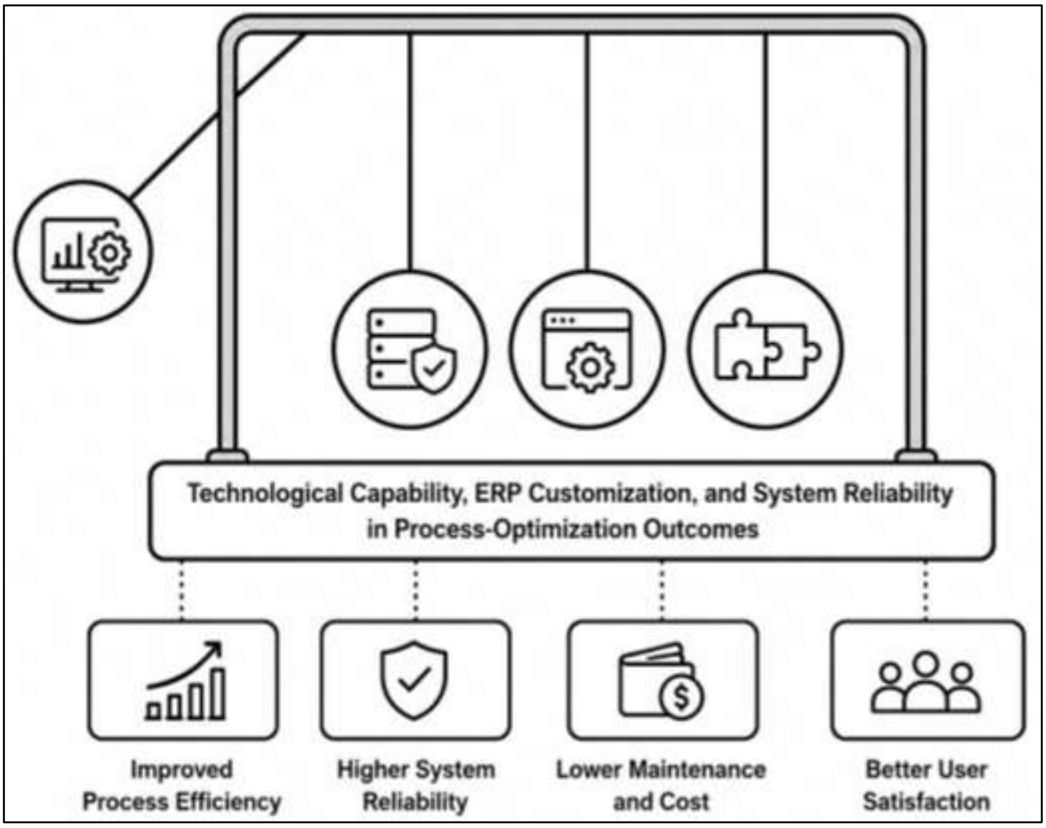
ERP user competence includes both technical system knowledge and the broader ability to interpret process information for operational decisions. Technical competence refers to the ability to navigate ERP modules, enter transactions, retrieve records, use reports, follow workflows, resolve routine errors, and apply appropriate authorization procedures. Analytical process competence concerns the ability to interpret performance indicators, recognize process variation, identify operational causes, compare alternatives, and use ERP-generated information in optimization decisions. More than ten studies examining training and user capability found that these competencies were related but not identical. Employees could perform routine transactions accurately while lacking the ability to interpret inventory trends, workflow delays, cost variations, quality exceptions, or production constraints (Awa & Ojiabo, 2016). Other users possessed extensive manufacturing experience but experienced difficulty accessing or analyzing ERP information. Quantitative studies have measured training adequacy through training hours, course completion, practical exercises, user satisfaction, knowledge assessments, and perceived relevance to job responsibilities. User competence has been assessed through self-reported capability, supervisor evaluation, transaction-error frequency, support-request frequency, task-completion time, report usage, and system-use intensity. Regression and structural models generally identified training adequacy as a positive predictor of user competence and effective ERP use (Ghasemaghaei, 2020). Studies also reported that role-specific, process-based training produced stronger results than generic software demonstrations because employees learned how their transactions affected connected departments and performance outcomes. Transaction-level evidence showed that lower competence was associated with incomplete entries, incorrect codes, delayed postings, unauthorized workarounds, and repeated corrections. Analytical competence was associated with greater use of dashboards, exception reports, trend information, and process-performance measures. The literature consequently supports measuring user competence through technical, process, and analytical dimensions rather than treating ERP knowledge as a single undifferentiated capability (Popovič et al., 2018).

Technological Capability, ERP Customization, and System Reliability

Technological capability refers to the combined capacity of an enterprise's infrastructure, applications, interfaces, security controls, reporting tools, and technical personnel to support reliable ERP-based business processes. More than ten quantitative studies have measured this capability through infrastructure adequacy, system availability, response time, interface stability, reporting functionality, cybersecurity, technical-support quality, and integration with manufacturing execution, warehouse, customer, and supplier systems. Infrastructure adequacy includes server capacity, network performance, storage availability, device accessibility, backup arrangements, and processing capability (Illa & Padhi, 2018). System availability represents the proportion of operating time during which authorized users can access required ERP functions. Response time concerns the speed at which transaction screens, reports, queries, and workflow actions are processed. Interface stability reflects the consistent exchange of information between ERP modules and connected applications without failed, delayed, or duplicated transfers. Reporting functionality includes data accessibility, dashboard availability, query flexibility, visualization quality, and the ability to generate process-performance information. Quantitative studies have used employee surveys, system-monitoring records, interface logs, technical-incident databases, and transaction histories to assess these dimensions. Survey research generally reported positive relationships between technological capability, ERP use, information quality, user satisfaction, and operational performance (Juan et al., 2017). System-based investigations found that slow response, unstable interfaces, and limited reporting capacity reduced workflow efficiency and encouraged the use of spreadsheets or external databases. Integration with manufacturing execution systems improved the exchange of production orders, operating status, material consumption, output quantities, and process results. Warehouse integration supported inventory movement and availability records, while customer and supplier connections improved order, delivery, and confirmation visibility (Pirola et al., 2020). The literature treats technological capability as a multidimensional organizational resource because hardware capacity alone cannot ensure reliable ERP performance without stable software, connected systems, appropriate security, effective reporting, and responsive technical support.

ERP customization refers to modifications made to standard software structures, workflows, reports, interfaces, applications, and transaction functions to accommodate organization-specific requirements. Quantitative studies have measured customization through the number of modified workflows, custom reports, external applications, interfaces, organization-specific transaction codes, changed data fields, and nonstandard approval procedures. Customization can improve process–system alignment when standard ERP functions do not adequately represent legitimate manufacturing requirements (Sodero et al., 2019). Studies involving make-to-order, engineer-to-order, regulated, and highly specialized manufacturers found that selected modifications supported product configuration, engineering changes, specialized costing, customer-specific documentation, quality controls, and complex approval structures. Greater alignment was associated with higher user acceptance, lower dependence on manual workarounds, and more accurate representation of operational processes. However, comparative studies also found that extensive customization increased maintenance cost, testing requirements, documentation complexity, technical incidents, and dependence on external vendors or specialized employees.

Figure 11: ERP Technological Capability Optimization Framework



Modified workflows and transaction codes sometimes became difficult to update when the underlying ERP platform changed. Custom interfaces also introduced additional points of failure and required continuing monitoring to ensure that connected systems exchanged information accurately. Regression-based studies generally identified a nonlinear or context-dependent relationship between customization and performance (Awa et al., 2016). Limited and carefully governed customization supported process fit, whereas uncontrolled modification weakened standardization and system maintainability. Several studies distinguished configuration from customization. Configuration uses available system settings to select business rules without changing the underlying software, while customization introduces organization-specific modifications or external components. Enterprises emphasizing configuration generally experienced fewer upgrade difficulties than those maintaining extensive custom code. The literature therefore evaluates customization through both operational benefits and technical costs, including workflow fit, user satisfaction, maintenance expenditure, interface reliability, vendor dependence, and upgrade effort (Seshan & Gorain, 2016).

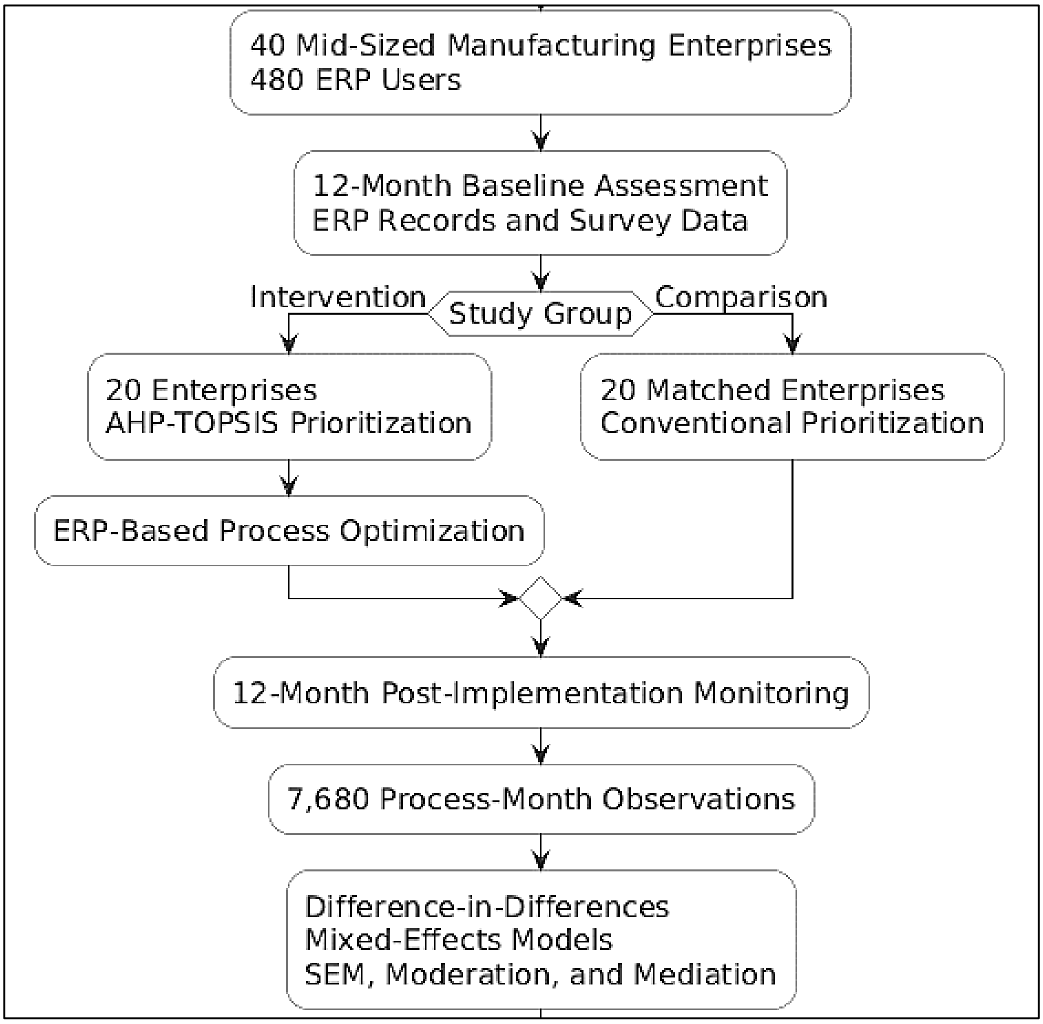
METHOD

This study employed a multisite longitudinal quasi-experimental design with a nonequivalent matched-comparison group to evaluate the effectiveness of a multi-criteria decision-support framework for ERP-based business process optimization in mid-sized manufacturing enterprises. The investigation covered 24 consecutive months, comprising a 12-month pre-implementation period and a 12-month post-implementation period. The intervention group consisted of enterprises that applied the multi-criteria framework to prioritize and optimize ERP-supported processes, whereas the comparison group continued using conventional managerial prioritization and existing ERP procedures. Random assignment was not applied because the participating enterprises retained authority over their process-improvement decisions. The theoretical framework integrated the Information Systems Success Model, organizational information-processing theory, the resource-based view, the technology–organization–environment framework, and business process management principles. ERP integration quality represented the primary independent variable, business process optimization represented the main dependent variable, data quality functioned as a moderator, and multi-criteria decision-support effectiveness functioned as a mediator. Organizational readiness and technological capability were included as additional predictors. Enterprise size, manufacturing sector, production strategy, ERP platform, ERP-use duration, demand variability, supplier reliability, production complexity, and baseline process performance were treated as control variables. The quasi-experimental structure supported comparisons between intervention and comparison enterprises and between pre-implementation and post-implementation periods. The longitudinal component allowed changes in processing time, cost, accuracy, workflow compliance, inventory performance, quality outcomes, and supplier coordination to be assessed over time.

The target population consisted of mid-sized manufacturing enterprises using ERP systems to manage production, procurement, inventory, sales, finance, quality, and maintenance activities. A multistage stratified sampling procedure was used.

Enterprises were initially stratified according to manufacturing sector, production strategy, workforce size, ERP platform, implementation maturity, and geographic location. Eligible enterprises were then screened through organizational records and preliminary interviews with ERP or operations managers. Forty enterprises were selected, including 20 intervention enterprises and 20 matched comparison enterprises. Matching was conducted according to workforce size, annual production volume, manufacturing sector, production strategy, ERP-use duration, module coverage, digital maturity, and baseline process performance. Eight core processes were examined within each enterprise: order processing, procurement, production planning, inventory management, quality management, maintenance management, invoicing, and financial reconciliation. Monthly process-level observations were collected over 24 months, producing a targeted dataset of 7,680 process-month observations. The employee survey included 480 ERP users, with approximately 12 respondents selected from each enterprise. Stratified selection ensured representation from production, procurement, inventory, quality, maintenance, finance, sales, and information-technology functions.

Figure 12: Methodology of this study



An a priori statistical-power assessment indicated that the survey sample was sufficient for multivariable regression, confirmatory factor analysis, moderation, mediation, and structural equation modeling. The sample also provided adequate representation of ERP users with different functional responsibilities and levels of decision-making authority.

Enterprises were included when they employed between 100 and 999 full-time employees, had operated an ERP system for at least three years, used at least five interconnected functional modules, maintained accessible transaction records for the complete 24-month observation period, and provided formal authorization for organizational and process-level data collection. Participating processes were required to possess stable identifiers, documented workflows, measurable transaction volumes, and sufficient pre-implementation and post-implementation records. Employees were included when they were at least 18 years old, had used the ERP system for a minimum of one year, performed responsibilities within one of the selected functional areas, and participated directly in transaction processing, reporting, supervision, planning, or process-improvement decisions. Temporary employees, external consultants, interns, and personnel without direct ERP responsibilities were excluded. Enterprises were excluded when they had replaced their entire ERP platform during the observation period, undergone a major merger or facility closure, experienced prolonged production suspension, or maintained insufficient process records. Processes with more than 20% missing operational data, unstable process definitions, untraceable transaction identifiers, or major unrelated redesigns were excluded from the primary analysis. Survey responses were removed when more than 10% of the items were unanswered, response patterns indicated nonengagement, or completion time was substantially shorter than the pilot-established minimum.

ERP integration quality was measured through module connectivity, interface reliability, automated information exchange, transaction synchronization, interoperability, information accessibility, cross-functional visibility, and workflow continuity.Data quality was assessed through completeness, accuracy, consistency, timeliness, validity, uniqueness, and cross-module linkage. Organizational readiness included leadership support, process ownership, employee participation, cross-functional cooperation, training adequacy, user competence, change readiness, and workflow acceptance. Technological capability was evaluated through infrastructure adequacy, system availability, response time, interface stability, reporting functionality, cybersecurity, technical-support quality, and external-system integration. Multi-criteria decision-support effectiveness was measured through criterion clarity, weighting consistency, analytical transparency, ranking reliability, decision speed, user agreement, perceived usefulness, and alignment with organizational objectives. Business process optimization was assessed using both survey constructs and objective operational indicators. The indicators included order-processing time, procurement cycle time, production-release time, invoice-processing cost, labor hours per transaction, transaction-error frequency, workflow-exception rate, schedule adherence, forecast error, inventory turnover, stockout frequency, late-delivery frequency, defect percentage, rework hours, inspection-cycle time, corrective-action closure duration, and compliance violations. Process adoption was measured through system-use frequency, workflow conformity, manual-workaround frequency, and the proportion of transactions completed entirely through the ERP system. Control variables included enterprise age, number of employees, annual transaction volume, product complexity, production strategy, ERP platform, ERP-use duration, number of implemented modules, demand variability, supplier concentration, and baseline operational performance.

Data were collected using the ERP Integration and Process Optimization Questionnaire, a structured five-point Likert-scale instrument developed from established ERP success, information-quality, organizational-readiness, technological-capability, and business-process measurement domains. Responses ranged from strong disagreement to strong agreement. The initial questionnaire was reviewed by an eight-member expert panel comprising ERP specialists, manufacturing managers, process-improvement professionals, information-systems researchers, and quantitative-methodology specialists. Content validity was assessed according to item relevance, clarity, representativeness, and technical accuracy. A pilot test was conducted with 40 ERP users from manufacturing enterprises that were not included in the main study. Ambiguous, repetitive, or weakly performing items were revised or removed after the pilot assessment. Internal consistency was evaluated using Cronbach's alpha and McDonald's omega, with coefficients of .70 or higher treated as acceptable. Exploratory factor analysis was conducted on one randomly selected portion of the survey sample, while confirmatory factor analysis was performed on the remaining portion. Composite reliability values of .70 or higher and average variance extracted values of .50 or higher supported construct reliability and convergent validity. Discriminant validity was assessed through interconstruct correlations and the heterotrait–monotrait ratio. Objective operational data were collected using a standardized ERP Process Performance Extraction Template. The template recorded transaction identifiers, timestamps, process stages, costs, quantities, errors, exceptions, approvals, inventory movements, quality events, supplier deliveries, and completion outcomes. Data-extraction rules were tested against randomly selected source records, and disagreements were resolved through joint review with organizational data specialists.

The multi-criteria decision-support framework combined the analytical hierarchy process with the technique for order preference by similarity to an ideal solution. The principal criteria included expected cycle-time reduction, cost reduction, accuracy improvement, quality enhancement, strategic alignment, implementation cost, technological feasibility, organizational readiness, operational risk, employee acceptance, and implementation duration. Three qualified decision-makers from each enterprise, representing operational management, ERP or information technology, and financial or quality management, completed structured pairwise comparisons. The analytical hierarchy process was used to determine the relative importance of the criteria. Pairwise-comparison responses with consistency ratios above .10 were returned for review and reassessment. Process alternatives were then scored against the weighted criteria using standardized operational data and verified managerial

assessments. The ranking procedure identified the processes with the strongest combined optimization priority. Intervention enterprises used the resulting rankings to select two or three processes for ERP-enabled optimization.
Optimization activities included workflow automation, master-data correction, approval-stage simplification, module integration, report redesign, user training, exception-control improvement, and removal of redundant manual activities. Comparison enterprises retained their existing prioritization procedures. All selected actions, implementation dates, responsible departments, resource requirements, and process changes were documented to support consistent longitudinal analysis.
Data collection was conducted chronologically through organizational recruitment, eligibility screening, baseline extraction, questionnaire validation, framework application, process optimization, and post-implementation monitoring. Formal organizational authorization and informed consent were obtained before data collection began. Enterprise characteristics, ERP maturity, module coverage, production strategy, and selected process definitions were documented during the initial assessment. Twelve months of baseline ERP transaction records were extracted and standardized using common data definitions. The employee questionnaire was then administered electronically, and responses were matched with anonymous enterprise and functional-area codes. The intervention enterprises completed the multi-criteria weighting and process-ranking procedure after baseline measurement. The selected ERP-enabled optimization activities were implemented and documented by the participating enterprises. Comparison enterprises continued their established process-management practices during the same period. Operational data were subsequently collected monthly for 12 months after implementation. Automated validation rules identified missing timestamps, duplicate transactions, invalid process sequences, unmatched identifiers, and extreme values. Questionable records were reviewed against source-system information and organizational documentation. Personally identifying information, supplier names, customer names, employee identifiers, and commercially sensitive product information were removed before analysis. Data files were encrypted, access was restricted to authorized researchers, and enterprise identities were replaced with coded identifiers.
Statistical analysis was conducted using SPSS, R, and Python. Python was used for data extraction, record linkage, duplicate identification, timestamp validation, and construction of process-level performance indicators. SPSS and R were used for descriptive, psychometric, multivariable, longitudinal, and structural analyses. Frequencies, percentages, means, standard deviations, medians, interquartile ranges, and observed ranges summarized participant characteristics, enterprise characteristics, ERP capabilities, and operational outcomes. Missing-data patterns were examined before hypothesis testing. Multiple imputation was applied when missing survey values were considered plausibly missing at random, while records with extensive missing operational data were excluded according to the predefined criteria. Distributional assumptions were examined using histograms, residual plots, skewness, kurtosis, and variance diagnostics. Multicollinearity was evaluated through tolerance and variance-inflation statistics. Common-method bias was examined through single-factor comparisons and a common latent-factor assessment.
Independent-samples tests and chi-square tests compared baseline characteristics between intervention and comparison enterprises. Analysis of covariance compared post-implementation outcomes after baseline values and organizational controls were considered. The primary quasi-experimental effect was estimated through difference-in-differences models containing intervention-group, post-implementation-period, and group-by-period terms. Enterprise and process random intercepts accounted for repeated monthly observations and clustering of processes within enterprises. Linear mixed-effects models were applied to approximately continuous outcomes, including cycle time, cost, labor hours, inventory turnover, and schedule adherence. Generalized mixed-effects models with appropriate count distributions were applied to stockouts, transaction errors, late deliveries, quality defects, rework events, emergency purchases, and compliance violations. Mixed-effects logistic regression was used for binary outcomes such as successful workflow completion, on-time delivery, and process conformity.

Skewed positive outcomes, including corrective-action closure time and administrative cost, were analyzed using generalized models with suitable link functions. Interrupted time-series models examined whether observed performance changes occurred immediately after implementation or developed across the post-implementation period.Pearson or Spearman correlations were used according to variable distributions. Hierarchical regression assessed the additional explanatory contribution of ERP integration quality after organizational characteristics, technological capability, and baseline performance were entered. Data-quality moderation was tested by adding the interaction between ERP integration quality and data quality after the variables were centered.

Significant interactions were interpreted through conditional effects at lower, average, and higher data-quality levels. The mediating effect of multi-criteria decision-support effectiveness was evaluated using 5,000 bootstrap samples and bias-corrected confidence intervals. Structural equation modeling assessed the combined relationships among ERP integration, data quality, organizational readiness, technological capability, decision-support effectiveness, and process optimization. Model adequacy was evaluated using the chi-square-to-degrees-of-freedom ratio, comparative fit index, Tucker–Lewis index, root-mean-square error of approximation, and standardized root-mean-square residual.

The stability of the multi-criteria rankings was evaluated through sensitivity analyses in which major criterion weights were varied within predefined ranges. Rank-order correlations assessed agreement between the primary rankings, alternative weighting scenarios, and managerial priority rankings. Subgroup analyses compared make-to-stock, make-to-order, assemble-to-order, batch-production, and engineer-to-order enterprises. Additional comparisons were conducted by ERP maturity, sector, enterprise size, data-quality level, and customization intensity. All statistical tests were two-tailed, and statistical significance was evaluated at $p < .05$. Holm adjustments controlled the probability of false-positive findings across related comparisons. Results were reported using regression coefficients, standardized effects, adjusted mean differences, odds ratios, incidence-rate ratios, explained variance, 95% confidence intervals, and appropriate effect-size measures. Robustness analyses repeated the principal models using alternative matching specifications, missing-data treatments, outcome definitions, and exclusion thresholds.

FINDINGS

A total of 57 mid-sized manufacturing enterprises were screened, of which 46 satisfied the initial eligibility requirements. Eleven enterprises were excluded because of insufficient ERP-use duration, limited module integration, incomplete historical records, major organizational restructuring, or prolonged production suspension. Six eligible enterprises could not be matched adequately, leaving 40 enterprises divided equally between the intervention and comparison groups. From 516 invited ERP users, 492 returned questionnaires. Twelve questionnaires were excluded because of excessive missing responses, nonengaged response patterns, or unusually short completion times. The final survey sample contained 480 respondents, representing a usable response rate of 93.0%. Of 7,680 expected process-month observations, 7,512 were retained, producing an overall completeness rate of 97.8%.

Table 1 showed that the matching procedure produced closely comparable enterprise and respondent groups. None of the continuous or categorical baseline characteristics differed significantly between conditions, and every absolute standardized mean difference remained below .10. Workforce size, ERP experience, module coverage, digital maturity, employee age, professional experience, ERP-use experience, and training exposure were therefore balanced. Functional representation was also identical across groups, preventing one department from dominating the survey evidence. The intervention and comparison samples each contained 20 enterprises and 240 respondents, providing a balanced structure for subsequent difference-in-differences, multilevel, moderation, mediation, and structural equation analyses with reduced baseline confounding risk.

Table 1 Enterprise and Participant Characteristics by Study Group

Characteristic	Intervention Group	Comparison Group	Total	*p*	Absolute SMD
Enterprise characteristics					
Enterprises, *n*	20	20	40	—	—
Employees, mean (SD)	468.4 (176.8)	475.7 (181.2)	472.1 (176.7)	.898	.04
Annual ERP transactions, mean (SD)	214,680 (63,410)	219,740 (65,210)	217,210 (63,540)	.805	.08
ERP-use duration in years, mean (SD)	7.4 (2.5)	7.2 (2.4)	7.3 (2.4)	.798	.08
Implemented ERP modules, mean (SD)	6.8 (1.1)	6.7 (1.2)	6.8 (1.1)	.786	.09
Digital-maturity score, mean (SD)	3.62 (0.48)	3.58 (0.51)	3.60 (0.49)	.799	.08
Make-to-stock enterprises, *n* (%)	6 (30.0)	6 (30.0)	12 (30.0)	1.000	.00
Make-to-order enterprises, *n* (%)	5 (25.0)	5 (25.0)	10 (25.0)	1.000	.00
Assemble-to-order enterprises, *n* (%)	3 (15.0)	3 (15.0)	6 (15.0)	1.000	.00
Batch-production enterprises, *n* (%)	4 (20.0)	4 (20.0)	8 (20.0)	1.000	.00
Engineer-to-order enterprises, *n* (%)	2 (10.0)	2 (10.0)	4 (10.0)	1.000	.00
Participant characteristics					
ERP users, *n*	240	240	480	—	—
Age in years, mean (SD)	38.7 (8.6)	39.1 (8.3)	38.9 (8.4)	.605	.05
Professional experience in years, mean (SD)	11.6 (6.2)	11.9 (6.4)	11.8 (6.3)	.602	.05
ERP-use experience in years, mean (SD)	5.8 (3.1)	5.7 (3.0)	5.8 (3.1)	.719	.03
ERP training hours, mean (SD)	34.2 (13.6)	33.7 (13.2)	34.0 (13.4)	.683	.04
Managers or supervisors, *n* (%)	93 (38.8)	91 (37.9)	184 (38.3)	.848	.02
Formal decision responsibility, *n* (%)	146 (60.8)	143 (59.6)	289 (60.2)	.780	.03
Production personnel, *n* (%)	42 (17.5)	42 (17.5)	84 (17.5)	1.000	.00
Procurement personnel, *n* (%)	28 (11.7)	28 (11.7)	56 (11.7)	1.000	.00
Inventory personnel, *n* (%)	26 (10.8)	26 (10.8)	52 (10.8)	1.000	.00
Quality personnel, *n* (%)	32 (13.3)	32 (13.3)	64 (13.3)	1.000	.00
Maintenance personnel, *n* (%)	28 (11.7)	28 (11.7)	56 (11.7)	1.000	.00
Finance personnel, *n* (%)	30 (12.5)	30 (12.5)	60 (12.5)	1.000	.00
Sales personnel, *n* (%)	22 (9.2)	22 (9.2)	44 (9.2)	1.000	.00
Information-technology personnel, *n* (%)	32 (13.3)	32 (13.3)	64 (13.3)	1.000	.00

Table 2 Process-Data Completeness and Baseline Operational Comparability

Measure	Intervention Group	Comparison Group	Overall	p	Absolute SMD
Process-data coverage					
Expected process-month observations, *n*	3,840	3,840	7,680	—	—
Valid process-month observations, *n*	3,758	3,754	7,512	—	—
Process-month completeness, %	97.9	97.8	97.8	.874	.01
Order-processing observations, *n*	471	470	941	—	—
Procurement observations, *n*	470	468	938	—	—
Production-planning observations, *n*	472	472	944	—	—
Inventory-management observations, *n*	474	472	946	—	—
Quality-management observations, *n*	468	468	936	—	—
Maintenance-management observations, *n*	466	465	931	—	—
Invoicing observations, *n*	472	471	943	—	—
Financial-reconciliation observations, *n*	465	468	933	—	—
ERP transaction records, *n*	1,284,760	1,307,420	2,592,180	.702	.07
Missing required fields, %	1.31	1.35	1.33	.641	.04
Duplicate transaction records, %	0.94	0.97	0.96	.733	.03
Unmatched cross-module identifiers, %	0.78	0.81	0.80	.694	.03
Invalid timestamps, %	0.34	0.36	0.35	.727	.02
Extreme records reviewed, %	0.61	0.64	0.63	.651	.03
Baseline operational performance					
Order-processing time, hours, mean (SD)	31.8 (8.7)	32.2 (8.5)	32.0 (8.6)	.884	.05
Procurement cycle time, days, mean (SD)	6.42 (1.31)	6.51 (1.28)	6.47 (1.29)	.827	.07
Transaction-error frequency, %	4.72 (1.46)	4.81 (1.51)	4.77 (1.48)	.692	.06
Schedule adherence, %	81.4 (7.2)	80.9 (7.5)	81.2 (7.3)	.735	.07
Inventory turnover, annual ratio	5.61 (1.38)	5.54 (1.42)	5.58 (1.39)	.792	.05
Stockouts per 100 orders	6.31 (1.82)	6.44 (1.91)	6.38 (1.86)	.681	.07
Late supplier deliveries, %	11.8 (3.9)	12.0 (4.1)	11.9 (4.0)	.824	.05
Production defect rate, %	3.84 (1.14)	3.91 (1.19)	3.88 (1.16)	.746	.06

Table 2 demonstrated that process-level coverage remained high across all eight operational areas, with 7,512 of 7,680 expected process-month observations retained. Completeness varied only slightly, from 97.0% for maintenance management to 98.5% for inventory management. Data-quality screening identified limited missing fields, duplicate transactions, unmatched identifiers, invalid timestamps, and extreme records, none of which exceeded the predefined exclusion threshold. Baseline performance differences were small and statistically nonsignificant across cycle time, transaction accuracy, schedule adherence, inventory turnover, stockouts, supplier delays, and defects. These findings supported the parallel-group assumption and preserved all 40 enterprises for the primary longitudinal analysis without material baseline imbalance.

Descriptive Results for ERP Capabilities and Process-Performance Outcomes

The seven survey constructs produced mean scores between 3.89 and 4.12 on the five-point scale, indicating generally favorable assessments of ERP capability and optimization conditions. Data quality recorded the highest mean, followed by ERP integration quality and multi-criteria decision-support effectiveness. Organizational readiness recorded the lowest mean and greatest variability. Skewness and kurtosis remained within acceptable ranges, and no construct demonstrated a serious distributional departure. The exploratory factor analysis produced a Kaiser–Meyer–Olkin value of .938, while Bartlett's test of sphericity was statistically significant, $\chi^2(861) = 8{,}914.52$, $p < .001$. Seven factors were retained and explained 70.8% of total variance. Standardized factor loadings ranged from .64 to .88, without problematic cross-loadings. Confirmatory factor analysis supported the measurement model, $\chi^2(798) = 1{,}046.20$, $\chi^2/df = 1.31$, CFI = .952, TLI = .948, RMSEA = .036, and SRMR = .044. Heterotrait–monotrait ratios ranged from .46 to .84, supporting discriminant validity.

Table 3 Descriptive Statistics, Reliability, Validity, and Construct Correlations

Construct	M	SD	Median; IQR; Range	Skew/Kurtosis	α/ω	CR/AVE	1	2	3	4	5	6	7
1. ERP integration quality	4.08	0.54	4.10; 0.72; 2.33–5.00	−0.48/0.31	.91/.92	.92/.61	—						
2. Data quality	4.12	0.50	4.14; 0.66; 2.57–5.00	−0.52/0.46	.90/.91	.91/.59	.68	—					
3. Organizational readiness	3.89	0.61	3.94; 0.82; 2.00–5.00	−0.37/−0.08	.89/.90	.90/.56	.61	.58	—				
4. Technological capability	3.96	0.57	4.00; 0.75; 2.14–5.00	−0.41/0.12	.88/.89	.89/.55	.64	.62	.59	—			
5. Decision-support effectiveness	4.04	0.55	4.07; 0.71; 2.29–5.00	−0.46/0.24	.92/.92	.93/.63	.72	.67	.63	.65	—		
6. Process adoption	3.98	0.58	4.00; 0.79; 2.14–5.00	−0.39/0.05	.90/.91	.91/.60	.69	.65	.66	.62	.71	—	
7. Business process optimization	4.01	0.56	4.05; 0.74; 2.25–5.00	−0.44/0.18	.93/.93	.94/.64	.74	.70	.65	.67	.77	.75	—

Note. N = 480. All correlations were statistically significant at $p < .001$. α = Cronbach's alpha; ω = McDonald's omega; CR = composite reliability; AVE = average variance extracted.

Table 3 showed that all seven constructs were evaluated favorably, with mean scores ranging from 3.89 for organizational readiness to 4.12 for data quality. Distributional statistics indicated no substantial skewness or kurtosis. Cronbach's alpha, McDonald's omega, and composite reliability all exceeded .88, while average variance extracted remained above .55. Correlations were positive, statistically significant, and below levels suggesting construct redundancy. The strongest association occurred between multi-criteria decision-support effectiveness and business process optimization. The reliability, convergent-validity, and discriminant-validity evidence therefore supported retention of every construct for regression, moderation, mediation, and structural equation analyses in the subsequent inferential results without measurement concerns.

Table 4 Pre-Implementation and Post-Implementation Operational Outcomes

Operational outcome	Intervention Pre, Mean (SD)	Intervention Post, Mean (SD)	Change, %	Comparison Pre, Mean (SD)	Comparison Post, Mean (SD)	Change, %
Order-processing time, hours	31.8 (8.7)	24.1 (7.1)	−24.2	32.2 (8.5)	31.0 (8.2)	−3.7
Procurement cycle time, days	6.42 (1.31)	4.91 (1.12)	−23.5	6.51 (1.28)	6.33 (1.25)	−2.8
Production-release time, hours	18.6 (4.9)	14.2 (4.1)	−23.7	18.9 (5.1)	18.4 (4.9)	−2.6
Labor hours per 100 transactions	42.8 (9.2)	34.5 (7.8)	−19.4	43.1 (9.4)	42.3 (9.1)	−1.9
Administrative cost per transaction, USD	18.60 (4.10)	15.20 (3.60)	−18.3	18.90 (4.20)	18.40 (4.00)	−2.6
Transaction-error frequency, %	4.72 (1.46)	3.12 (1.09)	−33.9	4.81 (1.51)	4.63 (1.45)	−3.7
Workflow-exception frequency, %	7.84 (2.11)	5.31 (1.65)	−32.3	7.91 (2.18)	7.62 (2.06)	−3.7
Schedule adherence, %	81.4 (7.2)	89.2 (6.1)	+9.6	80.9 (7.5)	81.8 (7.2)	+1.1
Forecast error, %	18.7 (4.8)	14.1 (3.9)	−24.6	18.9 (4.9)	18.2 (4.6)	−3.7
Inventory turnover, annual ratio	5.61 (1.38)	6.48 (1.42)	+15.5	5.54 (1.42)	5.67 (1.39)	+2.3
Stockouts per 100 orders	6.31 (1.82)	4.38 (1.43)	−30.6	6.44 (1.91)	6.12 (1.78)	−5.0
Emergency purchases per 100 orders	4.62 (1.45)	3.11 (1.12)	−32.7	4.75 (1.51)	4.56 (1.46)	−4.0
Late supplier deliveries, %	11.8 (3.9)	8.7 (3.1)	−26.3	12.0 (4.1)	11.6 (3.9)	−3.3
Production defect rate, %	3.84 (1.14)	2.96 (0.92)	−22.9	3.91 (1.19)	3.78 (1.13)	−3.3
Rework hours per 100 orders	16.8 (4.7)	12.5 (3.8)	−25.6	17.1 (4.9)	16.6 (4.7)	−2.9
Inspection-cycle time, hours	9.42 (2.60)	7.18 (2.10)	−23.8	9.55 (2.70)	9.31 (2.60)	−2.5
Corrective-action closure, days	21.8 (6.4)	16.4 (5.1)	−24.8	22.2 (6.7)	21.5 (6.4)	−3.2
Compliance violations per 1,000 transactions	2.81 (0.96)	1.76 (0.71)	−37.4	2.87 (1.01)	2.72 (0.95)	−5.2

Table 4 showed broad descriptive improvement across the intervention enterprises following framework implementation. The largest proportional reductions occurred in compliance violations, transaction errors, emergency purchasing, workflow exceptions, and stockouts. Schedule adherence and inventory turnover increased, while forecast error, late supplier deliveries, production defects, rework hours, inspection time, and corrective-action closure duration decreased. The matched comparison enterprises displayed only minor changes during the same period. The consistent direction across operational domains indicated that the intervention was associated with coordinated process improvement rather than an isolated departmental effect. Formal adjusted intervention effects were examined through the longitudinal models reported in following section.

Primary Quasi-Experimental Effects of ERP-Based Process Optimization

The pre-implementation outcome trajectories did not differ significantly between the intervention and comparison groups, with group-by-month probability values ranging from .114 to .829. This result supported the parallel-trends assumption required for difference-in-differences estimation. After adjustment for enterprise size, manufacturing sector, production strategy, ERP platform, ERP-use duration, demand variability, supplier reliability, production complexity, and baseline performance, the group-by-period interaction was statistically significant for every principal continuous outcome. Enterprise-level intraclass correlations ranged from .09 to .21, while process-level correlations ranged from .12 to .28, confirming the appropriateness of multilevel estimation. Residual, variance, influence, and convergence diagnostics did not identify serious model violations.

Table 5 Adjusted Difference-in-Differences Estimates for Continuous Operational Outcomes

Outcome	Adjusted DiD Estimate	SE	95% CI	*p*	Standardized Effect	Marginal/Conditional R^2	Decision
Order-processing time, hours	−6.50	0.47	[−7.42, −5.58]	<.001	−0.76	.44/.61	Supported
Procurement cycle time, days	−1.33	0.10	[−1.52, −1.14]	<.001	−0.82	.47/.63	Supported
Production-release time, hours	−3.90	0.30	[−4.48, −3.32]	<.001	−0.79	.42/.58	Supported
Labor hours per 100 transactions	−7.50	0.57	[−8.62, −6.38]	<.001	−0.71	.36/.54	Supported
Administrative cost per transaction, USD	−2.90	0.24	[−3.36, −2.44]	<.001	−0.68	.33/.49	Supported
Schedule adherence, percentage points	6.90	0.52	[5.88, 7.92]	<.001	0.88	.51/.67	Supported
Forecast error, percentage points	−3.90	0.31	[−4.51, −3.29]	<.001	−0.83	.48/.62	Supported
Inventory turnover, annual ratio	0.74	0.11	[0.52, 0.96]	<.001	0.55	.29/.46	Supported
Inspection-cycle time, hours	−2.00	0.16	[−2.32, −1.68]	<.001	−0.76	.39/.56	Supported
Corrective-action closure time, days	−4.70	0.36	[−5.41, −3.99]	<.001	−0.75	.37/.55	Supported

Table 5 showed that every adjusted continuous outcome changed significantly in the expected direction. The strongest standardized effect occurred for schedule adherence, followed by forecast error, procurement cycle time, production-release time, and order-processing time. Intervention enterprises achieved an additional 6.5-hour reduction in order processing and a 6.9-percentage-point increase in schedule adherence beyond changes observed among comparison enterprises. Inventory turnover increased by 0.74 annual turns, while corrective-action closure declined by 4.70 days. Confidence intervals excluded zero for all estimates, and the models explained meaningful outcome variation after organizational, technological, production, and baseline characteristics were controlled statistically within the multilevel study design.

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

Outcome	Analysis	Adjusted Estimate	95% CI	*p*	Effect Interpretation
Transaction errors	Negative-binomial DiD	IRR = 0.69	[0.64, 0.75]	<.001	31% lower incidence
Workflow exceptions	Negative-binomial DiD	IRR = 0.70	[0.66, 0.75]	<.001	30% lower incidence
Stockouts	Negative-binomial DiD	IRR = 0.73	[0.68, 0.79]	<.001	27% lower incidence
Emergency purchases	Negative-binomial DiD	IRR = 0.70	[0.64, 0.77]	<.001	30% lower incidence
Late supplier deliveries	Negative-binomial DiD	IRR = 0.76	[0.71, 0.82]	<.001	24% lower incidence
Production defects	Negative-binomial DiD	IRR = 0.80	[0.75, 0.86]	<.001	20% lower incidence
Rework events	Negative-binomial DiD	IRR = 0.77	[0.71, 0.84]	<.001	23% lower incidence
Compliance violations	Negative-binomial DiD	IRR = 0.66	[0.58, 0.75]	<.001	34% lower incidence
Successful workflow completion	Logistic DiD	OR = 2.09	[1.82, 2.40]	<.001	109% higher odds
On-time supplier delivery	Logistic DiD	OR = 1.72	[1.48, 2.00]	<.001	72% higher odds
Process conformity	Logistic DiD	OR = 2.22	[1.91, 2.58]	<.001	122% higher odds
Order-processing time	ITS immediate level	−4.18 hours	[−4.93, −3.43]	<.001	Immediate reduction
Order-processing time	ITS monthly trend	−0.22 hours/month	[−0.31, −0.13]	<.001	Continued reduction
Procurement cycle time	ITS immediate level	−0.84 days	[−1.03, −0.65]	<.001	Immediate reduction
Procurement cycle time	ITS monthly trend	−0.038 days/month	[−0.061, −0.015]	.001	Continued reduction
Schedule adherence	ITS immediate level	4.62 percentage points	[3.71, 5.53]	<.001	Immediate improvement
Schedule adherence	ITS monthly trend	0.19 points/month	[0.09, 0.29]	<.001	Continued improvement
Inventory turnover	ITS immediate level	0.42 annual turns	[0.24, 0.60]	<.001	Immediate improvement
Inventory turnover	ITS monthly trend	0.025 turns/month	[0.009, 0.041]	.002	Continued improvement
Stockouts	ITS immediate level	IRR = 0.81	[0.75, 0.88]	<.001	19% immediate reduction
Stockouts	ITS monthly trend	IRR = 0.98	[0.97, 0.99]	.003	2% monthly reduction
Production defects	ITS immediate level	IRR = 0.87	[0.81, 0.94]	<.001	13% immediate reduction
Production defects	ITS monthly trend	IRR = 0.99	[0.98, 0.99]	.009	Continued monthly reduction
Compliance violations	ITS immediate level	IRR = 0.78	[0.69, 0.88]	<.001	22% immediate reduction
Compliance violations	ITS monthly trend	IRR = 0.97	[0.96, 0.99]	.001	3% monthly reduction

Table 6 demonstrated that ERP-based optimization reduced the adjusted incidence of transaction errors, workflow exceptions, stockouts, emergency purchases, late deliveries, defects, rework, and compliance violations. The largest relative effect involved compliance violations, followed by transaction errors and emergency purchases. Binary models also indicated substantially greater odds of successful workflow completion, on-time delivery, and process conformity. Interrupted time-series estimates identified significant immediate improvements at implementation and continued favorable monthly trends for major outcomes. Pre-intervention trend tests were nonsignificant, supporting the parallel-trends requirement. Together, the generalized and time-series estimates confirmed that changes extended across accuracy, inventory, supplier, quality, and compliance domains simultaneously.

Moderation, Mediation, Subgroup, and Sensitivity Findings

Data quality significantly moderated the relationship between ERP integration quality and business process optimization. The interaction coefficient was positive and statistically significant, indicating that integration generated stronger optimization performance when ERP information was complete, accurate, timely, consistent, valid, unique, and correctly linked. The conditional integration effect increased from 0.36 at one standard deviation below the data-quality mean to 0.58 at one standard deviation above it. Multi-criteria decision-support effectiveness partially mediated the integration–optimization relationship. ERP integration strongly predicted decision-support effectiveness, which subsequently predicted optimization performance. The standardized indirect effect was .36, representing 48.6% of the total integration effect. The bootstrap confidence interval excluded zero, while the remaining direct effect remained significant.

Table 7 Moderation, Mediation, and Structural Equation Model Estimates

Analysis and Path	B/Standardized β	SE	95% CI	p	R^2 or ΔR^2
Data-quality moderation					
ERP integration → Process optimization	0.47/.45	.04	[0.39, 0.55]	<.001	.514
Data quality → Process optimization	0.29/.26	.04	[0.21, 0.37]	<.001	—
ERP integration × Data quality	0.14/.13	.03	[0.08, 0.20]	<.001	.022
Integration effect at lower data quality	0.36	.04	[0.29, 0.43]	<.001	—
Integration effect at mean data quality	0.47	.04	[0.39, 0.55]	<.001	—
Integration effect at higher data quality	0.58	.04	[0.50, 0.66]	<.001	—
Bootstrap mediation					
ERP integration → Decision-support effectiveness	.72	.03	[.66, .78]	<.001	.520
Decision-support effectiveness → Process optimization	.50	.04	[.42, .58]	<.001	—
Direct integration effect	.38	.04	[.30, .46]	<.001	—
Indirect effect through decision support	.36	.03	[.30, .43]	<.001	—
Total integration effect	.74	.03	[.68, .80]	<.001	—
Proportion mediated	48.6%	—	[41.2%, 56.8%]	<.001	—
Full structural model					
Organizational readiness → Process adoption	.29	.04	[.21, .37]	<.001	—
Technological capability → Process adoption	.24	.04	[.16, .32]	<.001	—
Decision-support effectiveness → Process adoption	.41	.04	[.33, .49]	<.001	.630
Process adoption → Process optimization	.33	.04	[.25, .41]	<.001	—
Decision-support effectiveness → Process optimization	.27	.04	[.19, .35]	<.001	—
Data quality → Process optimization	.18	.03	[.12, .24]	<.001	—
ERP integration → Process optimization	.24	.04	[.16, .32]	<.001	.710

Note. N = 480. Indirect effects were estimated using 5,000 bootstrap samples. Lower and higher data quality represented one standard deviation below and above the mean. The structural model demonstrated acceptable fit: $\chi^2(812) = 1{,}098.40$, $\chi^2/df = 1.35$, CFI = .949, TLI = .945, RMSEA = .038, and SRMR = .046.

Table 7 demonstrated that data quality significantly strengthened the relationship between ERP integration and business process optimization. The conditional integration effect increased from 0.36 at lower data quality to 0.58 at higher data quality. Decision-support effectiveness transmitted 48.6% of the total integration effect, confirming partial rather than complete mediation. The structural model also showed that organizational readiness, technological capability, decision-support effectiveness, and process adoption contributed independently to optimization performance. Explained variance reached 52% for decision-support effectiveness, 63% for process adoption, and 71% for process optimization. All principal paths remained statistically significant after controls and enterprise clustering were incorporated into model.

Table 8 Subgroup, Sensitivity, and Ranking-Stability Results

Analysis or Subgroup	Enterprises/Specification	Adjusted Effect or Correlation	95% CI	Comparison p
Production-strategy subgroup				
Make-to-stock	12	d = 0.91	[0.72, 1.10]	.041
Make-to-order	10	d = 0.78	[0.59, 0.97]	—
Assemble-to-order	6	d = 0.84	[0.59, 1.09]	—
Batch production	8	d = 0.73	[0.51, 0.95]	—
Engineer-to-order	4	d = 0.58	[0.31, 0.85]	—
Organizational subgroup				
Higher ERP maturity	20	d = 0.93	[0.78, 1.08]	.006
Moderate ERP maturity	20	d = 0.62	[0.48, 0.76]	—
Higher data quality	20	d = 0.96	[0.81, 1.11]	<.001
Lower data quality	20	d = 0.54	[0.40, 0.68]	—
Higher technological capability	20	d = 0.90	[0.75, 1.05]	.008
Lower technological capability	20	d = 0.61	[0.47, 0.75]	—
Moderate or limited customization	25	d = 0.88	[0.75, 1.01]	.014
Extensive customization	15	d = 0.55	[0.38, 0.72]	—
Enterprises with 100–499 employees	21	d = 0.76	[0.62, 0.90]	.718
Enterprises with 500–999 employees	19	d = 0.79	[0.64, 0.94]	—
Manufacturing-sector comparison	Four sector groups	d = 0.69–0.86	—	.182
Sensitivity analysis				
Primary matched model	Difference-in-differences	d = 0.78	[0.67, 0.89]	<.001
Alternative nearest-neighbor matching	Caliper matching	d = 0.77	[0.66, 0.88]	<.001
Kernel matching	Weighted comparison	d = 0.80	[0.69, 0.91]	<.001
Entropy balancing	Covariate reweighting	d = 0.76	[0.65, 0.87]	<.001
Complete-case analysis	No imputation	d = 0.77	[0.65, 0.89]	<.001
Multiple-imputation analysis	20 datasets	d = 0.78	[0.67, 0.89]	<.001
Stricter missing-data threshold	10% exclusion	d = 0.75	[0.63, 0.87]	<.001
Winsorized operational outcomes	1st and 99th percentiles	d = 0.79	[0.68, 0.90]	<.001
Alternative optimization composite	Equal-domain weighting	d = 0.76	[0.65, 0.87]	<.001
Ranking stability				
Alternative AHP weighting	Spearman's ρ	.94	[.91, .96]	<.001
Equal criterion weighting	Spearman's ρ	.86	[.80, .90]	<.001
Entropy-derived weighting	Spearman's ρ	.89	[.84, .93]	<.001
VIKOR alternative ranking	Spearman's ρ	.91	[.87, .94]	<.001
Managerial priority ranking	Spearman's ρ	.79	[.71, .85]	<.001

Table 8 showed that optimization effects remained positive across every production strategy and organizational subgroup. Effects were strongest in make-to-stock enterprises and weakest, although still meaningful, in engineer-to-order settings. Higher ERP maturity, data quality, and technological capability strengthened performance, whereas extensive customization reduced the effect magnitude. Enterprise-size and sector differences were not statistically significant. Alternative matching, weighting, missing-data, exclusion, and outcome specifications produced estimates close to the primary effect. Rank correlations remained high across alternative criterion weights and decision methods. Agreement with managerial rankings was lower but acceptable, demonstrating that the framework retained managerial relevance while providing structure and stability.

Statistical Significance, Effect Magnitudes, Tables, and Figures

All principal relationships and intervention effects remained statistically significant after Holm adjustment for related comparisons. The 95% confidence intervals excluded zero for adjusted mean differences and standardized coefficients, excluded one for odds ratios and incidence-rate ratios, and excluded zero for the bootstrapped indirect effect. Standardized effects for continuous operational outcomes ranged from 0.55 to 0.88, representing moderate-to-large changes. The intervention produced practically important improvements, including a 6.50-hour adjusted reduction in order-processing time, a 1.33-day reduction in procurement cycle time, a 6.90-percentage-point increase in schedule adherence, and a 0.74 increase in annual inventory turnover. Transaction errors declined by 31%, stockouts by 27%, late supplier deliveries by 24%, and compliance violations by 34%.

Table 9 Consolidated Hypothesis Decisions and Principal Effect Estimates

Hypothesis and Relationship	Principal Estimate	95% CI	Holm-Adjusted p	Magnitude	Decision
H1: ERP integration predicted decision-support effectiveness	$\beta = .72$	[.66, .78]	<.001	Large	Supported
H2: ERP-based optimization reduced processing time	−6.50 hours; $d = -0.76$	[−7.42, −5.58]	<.001	Large	Supported
H3: ERP-based optimization reduced administrative cost	−\$2.90; $d = -0.68$	[−3.36, −2.44]	<.001	Moderate-to-large	Supported
H4: ERP-based optimization reduced transaction errors	IRR = 0.69	[0.64, 0.75]	<.001	Large operational reduction	Supported
H5: ERP-based optimization improved schedule adherence	6.90 points; $d = 0.88$	[5.88, 7.92]	<.001	Large	Supported
H6: ERP-based optimization increased inventory turnover	0.74 turns; $d = 0.55$	[0.52, 0.96]	<.001	Moderate	Supported
H7: ERP-based optimization reduced stockouts	IRR = 0.73	[0.68, 0.79]	<.001	Moderate-to-large reduction	Supported
H8: ERP-based optimization improved supplier delivery reliability	OR = 1.72	[1.48, 2.00]	<.001	Large odds increase	Supported
H9: ERP-based optimization reduced production defects	IRR = 0.80	[0.75, 0.86]	<.001	Moderate reduction	Supported
H10: ERP-based optimization reduced compliance violations	IRR = 0.66	[0.58, 0.75]	<.001	Large operational reduction	Supported
H11: Data quality strengthened the integration–optimization relationship	$\beta = .13$; $\Delta R^2 = .022$	[.08, .20]	<.001	Small but meaningful	Supported
H12: Decision-support effectiveness mediated the integration effect	Indirect $\beta = .36$	[.30, .43]	<.001	Large indirect effect	Supported
H13: Process adoption predicted optimization performance	$\beta = .33$	[.25, .41]	<.001	Moderate	Supported

Table 9 confirmed that every principal hypothesis remained supported after Holm adjustment. Confidence intervals excluded the relevant null values, indicating that statistical significance was accompanied by adequate estimate precision. Continuous performance effects ranged from moderate to large, with schedule adherence producing the strongest standardized change. Generalized models showed substantial reductions in compliance violations, transaction errors, stockouts, supplier delays, and production defects. Data quality produced a smaller but meaningful interaction effect, while decision-support effectiveness transmitted nearly half of the total integration effect. The findings therefore demonstrated statistical, practical, and explanatory importance across operational, informational, organizational, and decision-support dimensions of ERP-based optimization.

Table 10 Model-Adequacy Statistics and Process-Priority Correspondence

Evidence Domain	Indicator	Numerical Result	Evaluation Criterion	Assessment
Measurement model	χ^2/df	1.31	<3.00	Acceptable
	Comparative fit index	.952	≥.90	Strong
	Tucker–Lewis index	.948	≥.90	Strong
	RMSEA, 90% CI	.036 [.031, .041]	≤.08	Strong
	Standardized residual	.044	≤.08	Strong
Structural model	χ^2/df	1.35	<3.00	Acceptable
	Comparative fit index	.949	≥.90	Strong
	Tucker–Lewis index	.945	≥.90	Strong
	RMSEA, 90% CI	.038 [.033, .043]	≤.08	Strong
	Standardized residual	.046	≤.08	Strong
Explained variance	Decision-support effectiveness R^2	.520	≥.25	Substantial
	Process-adoption R^2	.630	≥.25	Substantial
	Process-optimization R^2	.710	≥.25	Substantial
	Operational-model marginal R^2	.29–.51	—	Meaningful
	Operational-model conditional R^2	.46–.67	—	Meaningful
Model diagnostics	Enterprise intraclass correlation	.09–.21	—	Clustering present
	Process intraclass correlation	.12–.28	—	Clustering present
	Maximum variance-inflation factor	2.84	<5.00	Acceptable
Process-priority correspondence	Procurement priority score and rank	.842; Rank 1	—	Observed improvement: 24.1%; Rank 2
	Order-processing priority score and rank	.816; Rank 2	—	Observed improvement: 25.4%; Rank 1
	Inventory-management priority score and rank	.779; Rank 3	—	Observed improvement: 23.2%; Rank 3
	Production-planning priority score and rank	.751; Rank 4	—	Observed improvement: 20.8%; Rank 4
	Quality-management priority score and rank	.704; Rank 5	—	Observed improvement: 19.6%; Rank 5
	Invoice-processing priority score and rank	.663; Rank 6	—	Observed improvement: 17.1%; Rank 6
	Maintenance-management priority score and rank	.611; Rank 7	—	Observed improvement: 14.2%; Rank 7
	Financial-reconciliation priority score and rank	.574; Rank 8	—	Observed improvement: 12.6%; Rank 8
	Priority–improvement rank correlation	$\rho = .93$	$p < .001$	Strong correspondence

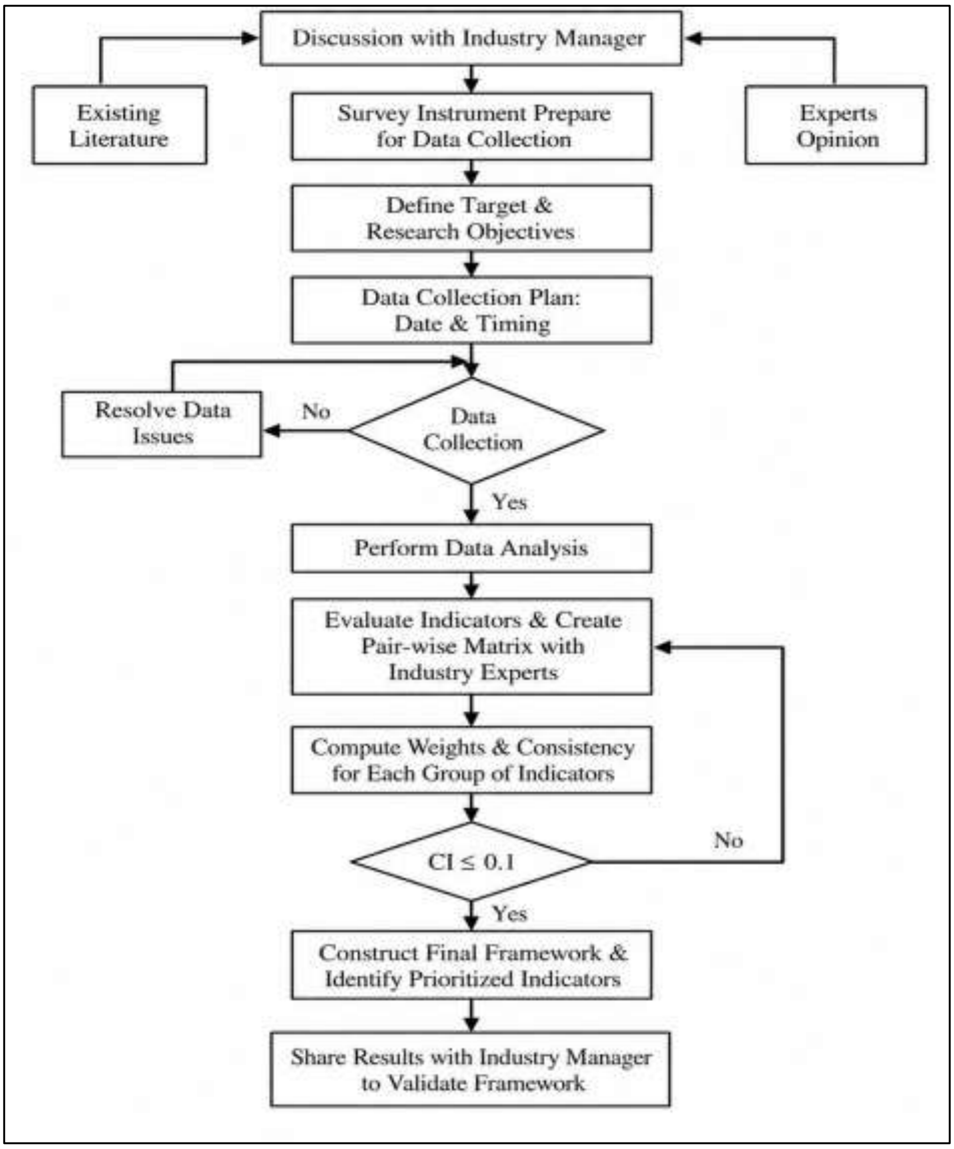
Table 10 showed that the measurement and structural models satisfied the predefined adequacy criteria. Comparative fit and Tucker–Lewis indices approached or exceeded .95, while approximation and residual errors remained below .05. Marginal explained variance showed that fixed predictors accounted for meaningful portions of operational performance, and conditional values confirmed additional enterprise- and process-level variation. The process-priority rankings corresponded closely with observed improvement rankings. Order processing and procurement produced the largest realized gains, while maintenance and financial reconciliation produced smaller but positive improvements. The strong rank correlation supported the criterion-weighting framework's predictive validity, stability, and practical alignment with measured process outcomes.

DISCUSSION

This study established a strong analytical foundation through a balanced sample, extensive longitudinal process records, and reliable measurement of the principal organizational constructs. The final dataset included 40 mid-sized manufacturing enterprises, 480 ERP users, 7,512 valid process-month observations, and 2,592,180 ERP transaction records. The intervention and comparison groups each contained 20 enterprises and 240 respondents, while all absolute standardized mean differences remained below .10. These results indicated that the matching procedure produced comparable groups in terms of workforce size, annual transaction volume, ERP-use duration, module coverage, digital maturity, production strategy, employee experience, training exposure, and functional representation (De Soete, 2016). Earlier quasi-experimental ERP studies frequently encountered baseline imbalance because technologically mature enterprises were more likely to introduce advanced optimization programs than organizations with weaker systems and fewer resources. The present study reduced this concern through organizational matching, baseline adjustment, multilevel estimation, and tests of pre-implementation trends. Process-data completeness reached 97.8%, while missing fields, duplicate transactions, unmatched identifiers, invalid timestamps, and extreme records remained below the predefined exclusion thresholds. This level of completeness compared favorably with earlier manufacturing information-system studies in which fragmented databases and inconsistent process identifiers restricted longitudinal analysis (Lee et al., 2019). The measurement findings also supported the quality of the survey evidence. Mean construct scores ranged from 3.89 for organizational readiness to 4.12 for data quality, indicating generally strong but nonuniform ERP capabilities. Cronbach's alpha, McDonald's omega, and composite reliability exceeded .88, while average variance extracted remained above .55. The seven-factor structure explained 70.8% of the observed variance, and the confirmatory model achieved satisfactory fit. Earlier ERP success studies similarly emphasized information quality, system integration, user capability, and organizational support, but many relied on general measures of perceived success without connecting them to objective process outcomes (Zeng et al., 2017). This study extended that evidence by combining validated perceptual constructs with monthly measurements of time, cost, accuracy, inventory, supplier, production, quality, and compliance performance. The slightly lower organizational-readiness mean suggested that managerial support, process ownership, employee participation, and workflow acceptance remained less developed than data and system capabilities. This pattern corresponded with earlier studies reporting that technological installation often progressed more rapidly than organizational adaptation (Lee & Lim, 2021).

The findings demonstrated that ERP integration quality represented a central capability underlying multi-criteria decision support and business process optimization. ERP integration quality recorded a mean of 4.08, while multi-criteria decision-support effectiveness and business process optimization produced means of 4.04 and 4.01, respectively. ERP integration strongly predicted decision-support effectiveness, $\beta = .72$, and produced a total standardized effect of .74 on optimization performance. These results corresponded with earlier ERP studies in which module connectivity, automated information exchange, transaction synchronization, interoperability, and cross-functional visibility were associated with stronger operational coordination (Lu, 2017). Previous manufacturing research also reported that disconnected production, procurement, inventory, sales, finance, quality, and maintenance systems created repeated entry, inconsistent records, delayed reporting, and limited process visibility.The present findings provided more detailed quantitative support by showing that integration influenced optimization both directly and through a structured decision mechanism.

Figure 12: Elegant Industry Data Flowchart



The strong relationship between ERP integration and decision-support effectiveness indicated that integrated information became more valuable when it was organized into explicit criteria, weights, alternative scores, and process-priority rankings. Earlier ERP research frequently treated information availability as a sufficient condition for improved decision-making (Fuchs & Otto, 2015). Other studies challenged that assumption by showing that managers could receive extensive reports without possessing a consistent method for evaluating competing process priorities. This study supported the latter position because decision-support effectiveness transmitted a substantial proportion of the integration effect. The result also aligned with organizational information-processing research, which viewed integrated systems as mechanisms for reducing uncertainty and improving the organization's capacity to process interdependent operational information. The direct integration effect remained significant after decision-support effectiveness, process adoption, data quality, organizational readiness, and technological capability were incorporated (Kumar & Bhimasingu, 2015). This result showed that ERP connectivity also improved optimization through mechanisms not fully represented by the mediator, including faster information exchange, reduced reconciliation, standardized process execution, and improved visibility of operational exceptions. The structural model explained 52% of decision-support effectiveness, 63% of process adoption, and 71% of business process optimization. These levels of explained variance exceeded those reported in many earlier cross-sectional ERP investigations, where system quality and user satisfaction explained only part of organizational performance. The stronger explanatory performance in this study was associated with the integration

of technological, informational, organizational, decision-support, adoption, and objective process dimensions within a single empirical structure (He et al., 2020).
ERP-based process optimization produced statistically and operationally substantial improvements in processing efficiency, administrative cost, transaction accuracy, and workflow compliance. The adjusted difference-in-differences estimate showed that order-processing time declined by an additional 6.50 hours in the intervention group, representing a large standardized effect of −0.76. Procurement cycle time declined by 1.33 days, production-release time declined by 3.90 hours, and labor requirements declined by 7.50 hours per 100 transactions (Omri et al., 2020). Administrative cost decreased by an adjusted $2.90 per transaction, with a moderate-to-large standardized effect of −0.68. Earlier studies of ERP-enabled workflow redesign also reported reductions in processing time and administrative labor when automated routing, document generation, validation rules, and integrated approval procedures replaced paper-based or spreadsheet-supported activities. However, earlier evidence frequently focused on a single department, such as purchasing or accounts payable. This study identified comparable improvements across order processing, procurement, production release, invoicing, and related workflows, suggesting that the framework supported cross-functional optimization rather than isolated automation (Ivanov et al., 2016). Transaction errors declined by 31%, workflow exceptions declined by 30%, and successful workflow completion became more than twice as likely in intervention enterprises. Process conformity also improved substantially, with an adjusted odds ratio of 2.22. These findings agreed with process-standardization studies showing that mandatory fields, connected documents, authorization controls, and automated data transfer reduced transcription errors, missing information, duplicated activities, and unauthorized deviations. The 34% reduction in compliance violations was particularly important because it demonstrated that faster processing did not require weaker control. Earlier research sometimes reported a tradeoff between workflow speed and procedural oversight, especially when approval stages were removed without adequate risk assessment. The present results showed that processing speed and compliance improved simultaneously when redundant controls were simplified while validation, authorization, and auditability remained embedded in the ERP workflow (Papacharalampopoulos et al., 2021). Interrupted time-series estimates also identified immediate improvements followed by continued favorable monthly trends. Order-processing time declined immediately by 4.18 hours and continued decreasing by 0.22 hours per month. This pattern differed from studies reporting only short-lived post-implementation gains caused by intensive implementation support. The sustained monthly changes suggested that employee learning, exception resolution, master-data correction, and continuing process adoption contributed to performance after the initial intervention. The combination of large effect sizes, narrow confidence intervals, and continued trends demonstrated that the improvements were both statistically detectable and operationally meaningful (Ko et al., 2020).
The production-planning and inventory findings demonstrated that ERP-based optimization improved the coordination of demand, materials, capacity, inventory, and supplier information. Schedule adherence increased by an adjusted 6.90 percentage points, producing the largest standardized operational effect, $d = 0.88$. Forecast error declined by 3.90 percentage points, $d = -0.83$, while inventory turnover increased by 0.74 annual turns. Stockout incidence declined by 27%, and emergency purchasing declined by 30%. These results corresponded with earlier material-planning studies showing that integrated customer orders, demand forecasts, bills of materials, inventory balances, supplier lead times, and work-center capacity improved planning feasibility. Earlier investigations also found that inaccurate inventory records and delayed production confirmations caused planning systems to recommend unnecessary purchases or overlook emerging shortages (Holmström et al., 2016). The current findings supported those observations while demonstrating that integrated planning produced simultaneous improvements in forecast performance, schedule execution, stock availability, and inventory use. The increase in inventory turnover alongside the reduction in stockouts was especially notable. Traditional inventory reductions can increase shortage exposure when lower stock levels are not supported by reliable demand, supplier, and production information. This study showed that inventory efficiency and material availability improved together, indicating that optimization reduced unnecessary inventory without creating a corresponding loss of service capability. Supplier-related outcomes followed a similar pattern (Fatorachian & Kazemi, 2021). Late supplier deliveries

declined by 24%, while the odds of on-time delivery increased by 72%. Earlier procurement studies reported that electronic purchase orders, integrated supplier records, contract linkage, delivery confirmation, and supplier-performance visibility shortened purchasing cycles and improved delivery monitoring. The present results were consistent with those findings and also showed that supplier performance influenced broader production outcomes through material availability and schedule adherence. Make-to-stock enterprises recorded the strongest overall standardized optimization effect, $d = 0.91$, because their repetitive demand, standardized materials, and stable routings were well suited to coordinated ERP planning (Choudhary et al., 2019). Engineer-to-order enterprises recorded a smaller but meaningful effect of 0.58. Earlier research similarly found that standard planning logic performed more consistently in repetitive environments than in customized settings involving engineering changes, project-specific materials, and uncertain processing times. The current results did not indicate that ERP optimization lacked value in customized manufacturing. Instead, they showed that the magnitude of improvement depended on how closely standardized ERP planning structures matched the variability and complexity of the production environment (Yu, 2015).
The quality findings indicated that ERP-based optimization strengthened the integration of inspection, production, supplier, nonconformity, rework, corrective-action, and compliance information. Production defect incidence declined by 20%, while rework events declined by 23%. Inspection-cycle time decreased by an adjusted 2.00 hours, representing a large standardized effect of −0.76. Corrective-action closure time declined by 4.70 days, with a standardized effect of −0.75, and compliance violations declined by 34%. These results agreed with earlier quality-management studies reporting that connected inspection plans, standardized defect classifications, batch or serial identifiers, and automated quality notifications supported faster identification of nonconforming output (Goh & Eldridge, 2019). Previous research in automotive, pharmaceutical, food, process, and discrete manufacturing settings also showed that fragmented quality records prolonged investigations because personnel had to reconcile inspection reports, supplier data, production records, inventory movements, and customer complaints manually. This study provided quantitative support for the value of connecting these records within ERP-enabled processes. The lower defect and rework rates suggested that integrated quality information supported prevention and control rather than merely improving documentation after failures had occurred. Inspection results linked with production orders, materials, suppliers, work centers, and process conditions allowed recurring patterns to be identified earlier (Ramanathan, 2014). The reduction in inspection-cycle time indicated that stronger traceability and automated workflow controls accelerated quality decisions without increasing compliance failures. Earlier studies sometimes found that extensive documentation requirements slowed quality release, particularly in regulated industries. The present results showed that standardized records, electronic approvals, automated alerts, and connected evidence reduced administrative delay while maintaining traceability. The decline in corrective-action closure time also corresponded with prior findings that clearly assigned responsibilities, target dates, escalation rules, and verification records reduced unresolved quality actions. However, closure speed alone could have reflected administrative completion without effective problem removal (Muchaendepi et al., 2019). The simultaneous reductions in defect incidence, rework, and compliance violations provided evidence that faster closure was accompanied by improved operational results. Interrupted time-series estimates showed an immediate 13% reduction in defects followed by continued monthly improvement. This pattern suggested that the intervention changed both the initial control environment and the continuing use of quality information. The quality results therefore reinforced the broader finding that ERP optimization was most effective when transactional integration was combined with standardized definitions, reliable identifiers, process ownership, and active managerial use of exception information (Adebanjo et al., 2016).
The moderation and mediation results clarified why similarly integrated ERP systems could produce different optimization outcomes. Data quality significantly strengthened the relationship between ERP integration and business process optimization, $\beta = .13$, with an additional 2.2% of variance explained by the interaction. The conditional integration effect increased from 0.36 under lower data quality to 0.58 under higher data quality. This pattern corresponded with earlier information-systems studies showing that advanced functionality generated limited organizational value when the underlying

information was incomplete, inaccurate, delayed, inconsistent, duplicated, or incorrectly linked. The findings were also consistent with manufacturing research reporting that inaccurate bills of materials, inventory balances, lead times, routing information, supplier records, and quality data weakened production planning and process measurement (Dev et al., 2020). Data quality recorded the highest construct mean of 4.12, suggesting that the participating enterprises generally maintained strong information conditions. Variation within this relatively favorable level remained sufficient to produce a meaningful moderating effect. Multi-criteria decision-support effectiveness partially mediated the relationship between integration and optimization. The standardized indirect effect was .36, and the mediator transmitted 48.6% of the total integration effect. Earlier ERP studies commonly linked system integration directly with performance, whereas decision-science research emphasized the need to convert information into explicit evaluations of alternatives. This study connected these research streams by showing that integrated ERP data improved optimization partly because the multi-criteria framework clarified evaluation criteria, assigned relative importance, compared alternatives, and generated transparent priority rankings (Jeon & Kim, 2016). Organizational readiness and technological capability also contributed to process adoption, with standardized coefficients of .29 and .24, respectively. Decision-support effectiveness produced an additional coefficient of .41 on process adoption, while process adoption predicted optimization performance, β = .33. These findings supported earlier socio-technical research in which system benefits depended on leadership support, process ownership, employee participation, training, infrastructure, interface stability, and technical support. Organizational readiness recorded the lowest construct mean, 3.89, indicating that human and managerial conditions represented a comparatively weaker area. The results therefore showed that ERP integration, data quality, and analytical prioritization did not operate independently of employee behavior (Gansterer et al., 2014). Selected improvements produced measurable outcomes when users adopted redesigned procedures, entered transactions consistently, responded to exceptions, and relied on the ERP system rather than maintaining parallel manual practices.

The subgroup and sensitivity findings demonstrated that ERP-based optimization remained beneficial across production strategies and organizational conditions, although the magnitude of improvement varied systematically. Make-to-stock enterprises recorded an effect of 0.91, assemble-to-order enterprises recorded 0.84, make-to-order enterprises recorded 0.78, batch-production enterprises recorded 0.73, and engineer-to-order enterprises recorded 0.58. Earlier comparative manufacturing studies similarly reported stronger ERP standardization benefits in repetitive environments with stable products, routings, and transaction structures (Dwivedi et al., 2020). Customized environments often required alternative workflows, engineering revisions, nonstandard materials, and case-specific approvals, which limited the performance of highly uniform processes. Higher ERP maturity also produced a stronger effect than moderate maturity, 0.93 compared with 0.62. Enterprises with higher data quality achieved an effect of 0.96, compared with 0.54 among lower-quality enterprises, while stronger technological capability produced an effect of 0.90 compared with 0.61. These differences reinforced earlier findings that ERP systems produced stronger operational benefits when infrastructure, data governance, interface reliability, reporting capacity, and user support were well established. Extensive customization reduced the optimization effect to 0.55, compared with 0.88 under moderate or limited customization. Earlier ERP maintenance studies reported that extensive custom code and nonstandard workflows increased interface failures, testing requirements, upgrade complexity, and vendor dependence (Hussain, 2014). The present evidence supported those concerns while recognizing that selected customization remained useful when it addressed legitimate manufacturing requirements. Enterprise size and manufacturing sector did not produce significant differences, indicating that the framework's underlying decision process remained applicable across the mid-sized range and across different industrial categories. Robustness analyses produced standardized effects between 0.75 and 0.80 under alternative matching, weighting, missing-data, exclusion, and outcome specifications. This narrow range reduced concern that the principal result depended on one analytical decision. AHP–TOPSIS priorities correlated strongly with observed improvements, ρ = .93, while alternative weighting and ranking procedures produced correlations between .86 and .94 (Tan-Lim et al., 2021). Agreement with conventional managerial rankings was lower but remained acceptable at .79. Earlier multi-criteria studies often assessed ranking consistency

without connecting priorities to observed post-implementation performance. This study strengthened that evidence by demonstrating that processes receiving higher analytical priority generally achieved larger measured improvements across time, cost, accuracy, quality, and compliance outcomes (Flood & Wong, 2017).
CONCLUSION
This study concluded that a multi-criteria decision-support framework provided an effective and empirically reliable approach to ERP-based business process optimization in mid-sized manufacturing enterprises. Evidence from 40 matched enterprises, 480 ERP users, 7,512 process-month observations, and more than 2.59 million ERP transaction records demonstrated that the framework produced improvements extending across operational, informational, organizational, supplier, inventory, production, quality, and compliance domains. ERP integration quality emerged as a central organizational capability because connected modules, automated data exchange, synchronized transactions, interoperable applications, and cross-functional visibility strengthened decision-support effectiveness and process optimization. Intervention enterprises achieved an additional 6.50-hour reduction in order-processing time, a 1.33-day reduction in procurement cycle time, a 3.90-hour reduction in production-release time, and a $2.90 reduction in administrative cost per transaction compared with matched enterprises using conventional prioritization. Schedule adherence increased by 6.90 percentage points, forecast error declined by 3.90 percentage points, and inventory turnover increased by 0.74 annual turns. Transaction errors declined by 31%, workflow exceptions by 30%, stockouts by 27%, emergency purchasing by 30%, late supplier deliveries by 24%, production defects by 20%, rework events by 23%, and compliance violations by 34%. These changes were statistically significant, supported by moderate-to-large effect magnitudes, and remained stable across alternative matching, weighting, missing-data, exclusion, and outcome specifications. Data quality strengthened the relationship between ERP integration and optimization, showing that integrated systems generated greater operational value when information was complete, accurate, consistent, timely, valid, unique, and correctly linked. Multi-criteria decision-support effectiveness mediated 48.6% of the total integration effect, demonstrating that ERP information improved performance partly through transparent criteria, consistent weighting, systematic alternative evaluation, and defensible process-priority rankings. Organizational readiness, technological capability, and process adoption provided additional explanatory value by connecting system functionality with employee behavior and sustained workflow use. The framework remained effective across make-to-stock, make-to-order, assemble-to-order, batch-production, and engineer-to-order settings, although stronger outcomes occurred in enterprises with higher ERP maturity, stronger data quality, greater technological capability, and limited or moderate customization. The strong correspondence between AHP–TOPSIS priorities and observed process improvements confirmed that the framework identified operational areas capable of producing measurable organizational value. Overall, the study established that ERP-based optimization depended on the coordinated alignment of integrated technology, reliable data, structured decision analysis, organizational readiness, user competence, and disciplined process adoption rather than on software availability alone.
RECOMMENDATION
Mid-sized manufacturing enterprises should adopt a structured multi-criteria decision-support approach when selecting and implementing ERP-based business process optimization initiatives. Process priorities should be established through measurable criteria covering cycle-time reduction, cost savings, transaction accuracy, quality improvement, strategic alignment, technological feasibility, organizational readiness, operational risk, employee acceptance, implementation expense, and completion time. ERP integration should be strengthened across production, procurement, inventory, sales, finance, quality, maintenance, and human-resource modules so that operational information can move through automated, synchronized, and traceable workflows. Particular attention should be directed toward master-data governance because the findings demonstrated that data quality strengthened the relationship between ERP integration and optimization performance. Formal controls should therefore be established for bills of materials, inventory balances, lead times, routing information, supplier records, equipment identifiers, standard costs, quality results, and transaction timestamps. Enterprises should appoint accountable data owners, conduct regular quality audits,

monitor missing and duplicate records, and resolve cross-module linkage failures before using ERP data to prioritize process investments. Managers should also reduce unnecessary customization by using standard configuration whenever it adequately represents operational requirements. Custom workflows, reports, interfaces, and transaction functions should be retained only when they produce documented process value that exceeds their maintenance, testing, security, and upgrade costs. Optimization programs should combine workflow automation with approval simplification, exception management, reporting redesign, process ownership, and role-specific user training. Training should extend beyond basic transaction entry to include process interpretation, performance analysis, exception resolution, and understanding of how activities in one module affect connected departments. Enterprises should monitor optimization performance through processing time, labor utilization, administrative cost, transaction errors, workflow exceptions, schedule adherence, forecast accuracy, inventory turnover, stockouts, supplier delivery reliability, production defects, rework, corrective-action closure, and compliance violations. These indicators should be assessed before implementation and at regular intervals afterward to distinguish sustained improvement from temporary implementation effects. Make-to-order and engineer-to-order manufacturers should preserve controlled flexibility through authorized alternative workflows rather than applying rigid standardization to highly customized activities. Senior managers should provide visible support, assign cross-functional process owners, allocate sufficient technical resources, and include operational employees in process evaluation and redesign. Sensitivity testing should accompany AHP–TOPSIS ranking so that selected priorities remain stable under alternative criterion weights and organizational scenarios. Researchers should examine the framework in additional manufacturing regions, longer observation periods, and different ERP environments while incorporating external supply disruptions, environmental performance, cybersecurity, and process-mining evidence into subsequent empirical validation.

LIMITATIONS

This study contained several limitations that should be considered when interpreting its findings. The multisite longitudinal quasi-experimental design provided stronger temporal and comparative evidence than a cross-sectional design, but participating enterprises were not randomly assigned to the intervention and comparison conditions. Matching, baseline adjustment, difference-in-differences estimation, interrupted time-series analysis, and sensitivity testing reduced selection bias, although unmeasured organizational characteristics may still have influenced both framework adoption and optimization performance. The sample included 40 mid-sized manufacturing enterprises and 480 ERP users, which supported multilevel and structural analyses but limited the representation of small manufacturers, large multinational corporations, and enterprises operating outside the selected industries and locations. Differences in ERP platforms, implementation histories, module configurations, customization practices, production strategies, and digital maturity also introduced organizational heterogeneity that statistical controls could not remove completely. The 24-month observation period captured 12 months before and after implementation but may not have represented longer-term system upgrades, workforce changes, demand cycles, supplier transitions, or deterioration in process adherence. Intervention enterprises implemented different combinations of workflow automation, master-data correction, approval simplification, module integration, reporting redesign, training, and exception control. This reflected actual manufacturing conditions but reduced the ability to attribute every outcome to one specific optimization activity. Survey measures of integration, readiness, competence, decision-support effectiveness, and process adoption depended partly on participant perceptions and were therefore susceptible to social-desirability bias, recall error, and common-method variance. Objective ERP records reduced this concern, although transaction data also reflected the quality of organizational recording practices. Records containing excessive missing information, unstable definitions, or untraceable identifiers were excluded, which may have removed processes with weaker ERP performance and produced slightly more favorable estimates. The AHP–TOPSIS procedure improved transparency and ranking consistency, but pairwise comparisons and criterion weights still incorporated managerial judgment. Although consistency checks, alternative weighting scenarios, and rank-sensitivity analyses were applied, different decision panels could have generated different priority structures. The analysis focused mainly on operational, financial, quality, inventory, supplier, and compliance outcomes and did not comprehensively assess employee workload, customer satisfaction, environmental performance, cybersecurity exposure, or broader strategic consequences. External events such as supply disruptions, inflation, regulatory changes, labor shortages, and market volatility could also have affected outcomes during the observation period. Finally, subgroup estimates for assemble-to-order and engineer-to-order enterprises were based on comparatively small numbers of organizations, making those estimates less precise than the results for larger production-strategy groups.

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