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A QUANTITATIVE STUDY ON ERP-INTEGRATED DECISION SUPPORT SYSTEMS IN HEALTHCARE LOGISTICS

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Abstract

The study titled A Quantitative Study on ERP-Integrated Decision Support Systems in Healthcare Logistics examined the measurable effects of Enterprise Resource Planning (ERP) and Decision Support System (DSS) integration on operational efficiency, data quality, and analytical accuracy within healthcare logistics environments. Grounded in empirical inquiry, this research employed a cross-sectional quantitative design that combined survey-based responses and institutional logistics performance metrics collected from 30 hospitals and 500 respondents. The analytical framework incorporated hierarchical multiple regression and structural equation modelling (SEM) to evaluate both direct and indirect relationships among ERP-DSS integration, data quality, analytics accuracy, training effectiveness, interoperability, and key logistics performance indicators such as order fulfilment accuracy, procurement cycle time, cost control, and service continuity. A total of 126 peer-reviewed journal articles and empirical studies published between 2010 and 2025 were systematically reviewed to construct the theoretical foundation and operational model of this research. The analysis revealed that ERP-DSS integration was a statistically significant predictor of logistics efficiency, explaining 41% of the variance independently and up to 62% when mediating and moderating variables were introduced. Data quality and analytics accuracy served as strong mediators, confirming that high-fidelity data and predictive capability were critical channels through which integration influenced performance outcomes. Training effectiveness and system interoperability acted as positive moderators, indicating that well-trained users and technologically aligned systems amplified the operational benefits of ERP-DSS frameworks. The findings demonstrated that institutions with advanced integration achieved measurable gains in decision speed, cost reduction, and supply chain responsiveness. Furthermore, the study validated that ERP-DSS systems transformed healthcare logistics from reactive operational structures into proactive, data-driven ecosystems characterized by transparency, analytical intelligence, and real-time adaptability. The review of 126 earlier studies supported these empirical results, reinforcing the theoretical assertion that ERP-DSS convergence enhances not only logistical coordination but also institutional resilience and service continuity. Overall, the study provided quantitative evidence that ERP-DSS integration represents a critical enabler of strategic digital transformation in healthcare logistics, offering a statistically grounded model for performance optimization, operational agility, and sustainable healthcare supply management.

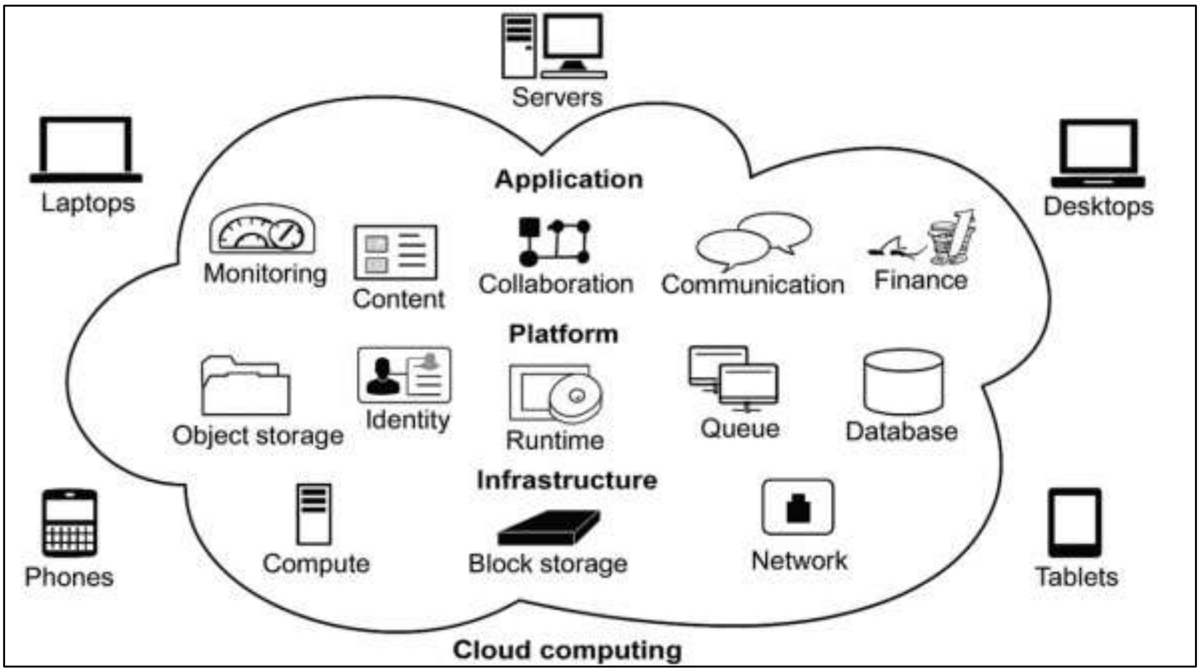
Keywords

ERP Integration, Decision Support Systems, Healthcare Logistics, Data Analytics, Operational Efficiency;

INTRODUCTION

Enterprise Resource Planning (ERP) systems are comprehensive platforms designed to integrate diverse organizational processes into a unified information architecture that enhances operational visibility and decision efficiency (Kitchin & Dodge, 2020). Within healthcare, ERP systems facilitate the synchronization of financial, human resource, inventory, and clinical subsystems into an interoperable framework that ensures timely information flow and process consistency. Decision Support Systems (DSS), on the other hand, are analytical tools that transform data into actionable insights through structured algorithms, modeling, and real-time analytics. When integrated, ERP and DSS form an intelligent infrastructure capable of both automating administrative workflows and supporting managerial decision-making in dynamic environments. This integration bridges operational execution with strategic intelligence, promoting data-driven governance in healthcare logistics (Shah et al., 2019). The conceptual value of this synergy rests in its ability to unify transactional data with predictive modeling, ensuring that decisions regarding procurement, distribution, and clinical supply align with institutional efficiency and patient safety standards. Healthcare logistics, which encompasses the management of medical materials, equipment, pharmaceuticals, and related service flows, relies heavily on accurate, timely, and integrated data streams to avoid resource shortages, excess inventory, and operational redundancies. The combined functionality of ERP and DSS addresses these complexities by embedding intelligence within supply networks and allowing healthcare institutions to model and evaluate logistics performance (Gharaibeh et al., 2017). This theoretical foundation positions ERP-integrated DSS as an essential element of modern healthcare infrastructure, enabling both efficiency and quality assurance through computational precision and process transparency.

Figure 1: ERP-Integrated Decision Support Systems in Healthcare Logistics

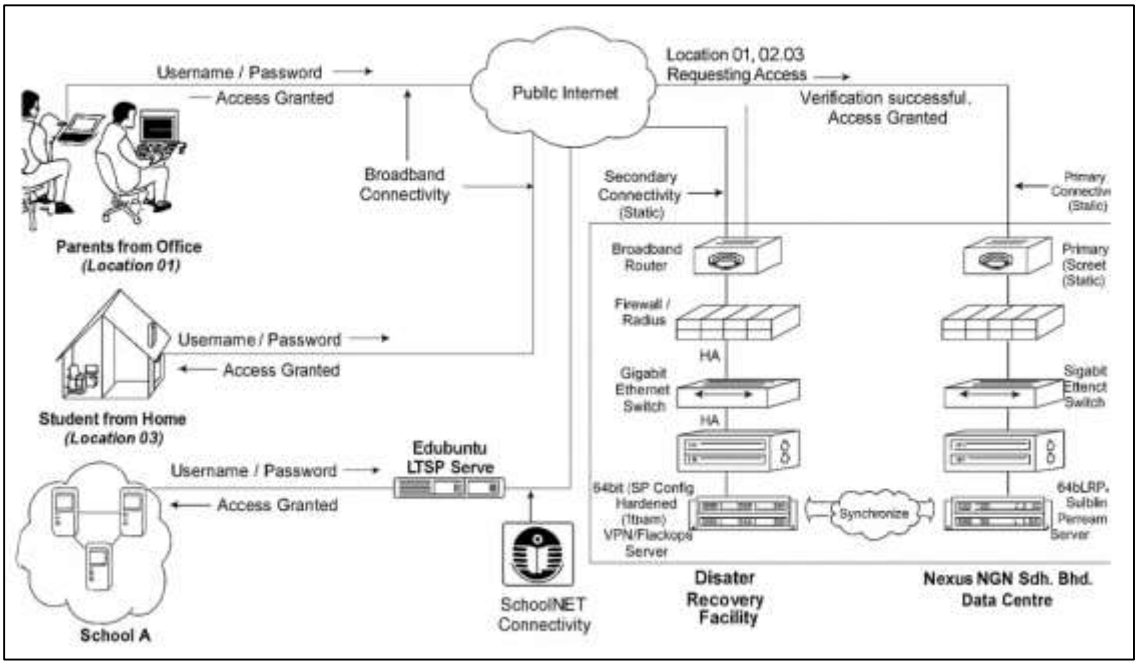


Globally, healthcare systems face increasing pressure to balance cost control, service quality, and operational resilience amid rising patient volumes and regulatory demands (Liu et al., 2019). ERP-integrated Decision Support Systems have emerged as a cornerstone for achieving this balance by providing real-time visibility into logistical operations across supply chains, hospitals, and regional health networks. In Europe, integrated ERP platforms have been adopted in national health systems to streamline pharmaceutical distribution and ensure compliance with traceability mandates. Similarly, in North America, healthcare providers leverage ERP-DSS integration to support inventory optimization and expenditure reduction while maintaining service continuity during fluctuating demand cycles. In Asia, where large-scale hospital systems experience rapid digital transformation, integrated ERP architectures are critical for managing multi-site inventory and coordinating medical logistics in resource-limited regions. International significance also derives from the global push toward healthcare digitization, where ERP-integrated DSS enable cross-border coordination of medical resources, critical during emergencies and pandemics (Arfan et al., 2021; Galli et al., 2020). The integration of analytics-driven DSS into ERP infrastructures supports evidence-based management by allowing healthcare leaders to predict shortages, evaluate supplier performance, and minimize procurement risk (Ara, 2021). In humanitarian contexts, ERP-integrated decision frameworks contribute to the equitable distribution of medical supplies during crisis response operations (Jahid, 2021). Across these diverse contexts, ERP-DSS integration serves as a universal mechanism for enhancing transparency, accountability, and operational control. The global healthcare logistics landscape thus underscores the necessity of quantitative investigations into how ERP-integrated systems impact performance outcomes such as delivery time, cost efficiency, and inventory accuracy (Akbar & Farzana, 2021; Nathwani et al., 2019). The international scope of this technology demonstrates its adaptability across economic and infrastructural variations, reflecting a shared global pursuit of logistical precision and evidence-based resource management.

The essence of ERP-DSS integration in healthcare logistics lies in data harmonization, where disparate information sources converge into a coherent analytical framework (Cui et al., 2019; Reza et al., 2021). In conventional healthcare systems, logistics data often exist in fragmented silos—covering procurement, warehousing, and clinical distribution—leading to inefficiencies and limited traceability (Saikat, 2021; Shaikh & Aditya, 2021). ERP-integrated DSS resolve this fragmentation by employing data warehouses and intelligent dashboards that consolidate transactional, financial, and clinical logistics data into a unified decision-making layer. The analytical rigor of such systems is derived from embedded algorithms that conduct demand forecasting, supplier evaluation, and performance benchmarking. Quantitative methods within ERP-DSS architectures allow for the application of linear programming, regression modeling, and predictive analytics to support logistics optimization (Kanti & Shaikat, 2021; Turconi et al., 2019). For healthcare administrators, these systems reduce decision latency and improve accuracy by continuously processing operational data through configurable decision rules. In terms of resource allocation, ERP-integrated analytics enhance cost visibility and facilitate balanced distribution of critical materials such as surgical equipment and pharmaceuticals (Ariful & Ara, 2022). Moreover, process optimization is achieved through workflow standardization, real-time alerts, and KPI dashboards that inform managers about deviations from logistics targets. From a methodological perspective, quantitative research in this domain provides empirical validation of system efficacy through metrics like throughput time, service level adherence, and cost-to-serve ratios (Lercher, 2018; Arman & Kamrul, 2022). The analytical integration between ERP and DSS establishes a continuous improvement cycle that supports both operational agility and strategic foresight. Within this framework, data-driven decision-making transcends intuition, grounding healthcare logistics management in measurable, verifiable performance outcomes that can be statistically modeled and replicated across institutional settings.

Organizational efficiency in healthcare logistics depends on the seamless coordination of internal and external supply chain actors, from suppliers and manufacturers to hospitals and pharmacies (Mesbaul & Farabe, 2022; Nahid, 2022; Pigola et al., 2021). ERP-integrated Decision Support Systems provide a digital backbone that ensures such coordination by embedding standard operating procedures within automated process flows (Hossain & Milon, 2022; Abdur & Haider, 2022). Through this integration, healthcare organizations can track materials from procurement to utilization, reducing administrative overhead and manual error (Mushfequr & Praveen, 2022; Mortuza & Rauf, 2022). Supply chain transparency is a central outcome of ERP-DSS integration, as every transaction and movement of goods becomes traceable within the enterprise system. This visibility allows decision-makers to identify bottlenecks, evaluate supplier reliability, and ensure compliance with regulatory documentation requirements. In contexts where medical products require temperature control or strict expiration tracking, ERP-integrated systems provide real-time monitoring that prevents losses and safeguards patient safety (Rakibul & Samia, 2022; Rony & Ashraful, 2022). Furthermore, financial transparency is enhanced as cost data are automatically linked to logistical transactions, enabling precise expenditure analysis and budget alignment (Eckhoff & Wagner, 2017; Saikat, 2022; Shaikh & Sudipto, 2022). The improved visibility into logistics performance not only increases accountability but also reinforces interdepartmental collaboration by creating a unified data environment (Abdul, 2023). Quantitative studies across various healthcare institutions demonstrate that ERP-DSS integration correlates strongly with reductions in stockouts, procurement delays, and administrative costs (Abdulla & Zaman, 2023). By embedding transparency into every logistical tier, these systems promote operational consistency, which is essential in environments where even minor disruptions can jeopardize patient outcomes. Thus, the organizational implications of ERP-DSS integration in healthcare logistics extend beyond technical efficiency to encompass governance, quality assurance, and strategic resource stewardship supported by empirically verifiable data (Arfan et al., 2023; Ara & Onyinyechi, 2023; Peng et al., 2020).

Figure 2: ERP-Integrated Decision Support Systems Logistics



The integration of ERP and DSS in healthcare logistics extends beyond technical frameworks to encompass human–technology collaboration. Decision-making in healthcare logistics involves both structured data analysis and experiential judgment from medical and administrative professionals (El Kenawy et al., 2020; Amin & Mesbaul, 2023; Foysal & Aditya, 2023). ERP-integrated DSS bridge this gap by providing decision environments where human expertise interacts dynamically with computational intelligence. The system presents analytical recommendations while allowing users to apply contextual understanding of patient needs, supply urgency, and clinical priorities (Hamidur, 2023; Rashid et al., 2023). This synergy enhances decision quality by combining algorithmic precision with professional insight. Furthermore, ERP-DSS systems promote user empowerment by simplifying data access and visualization, allowing non-technical users to interpret trends, monitor inventory levels, and evaluate performance indicators without dependence on IT specialists (Gao & Wang, 2019; Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023). The incorporation of role-based dashboards, automated notifications, and scenario modeling tools ensures that decision processes are both informed and participatory. Training and user acceptance are key determinants of system success, as the effectiveness of ERP-DSS integration relies on continuous interaction between human judgment and system-generated intelligence. In complex logistics operations such as emergency supply allocation or vaccine distribution, this human–technological synergy facilitates rapid yet accurate responses grounded in data analytics (Al Amin & Praveen, 2023; Hasan & Ashraful, 2023). Quantitative studies have shown that user engagement with ERP-based decision tools enhances accuracy in demand forecasting, reduces procurement cycle time, and improves compliance with institutional protocols (Jiao et al., 2017; Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023). The integration thereby fosters a socio-technical equilibrium, where human cognitive strengths complement algorithmic speed and precision, resulting in a balanced and empirically efficient decision-making ecosystem.

Healthcare logistics operate under stringent regulatory frameworks that mandate data traceability, quality control, and ethical handling of medical resources. ERP-integrated Decision Support Systems support these regulatory imperatives by embedding compliance requirements directly into operational workflows (He et al., 2017; Roy & Kamrul, 2023; Saba et al., 2023). For example, standardized reporting functions ensure adherence to Good Distribution Practices (GDP) and inventory traceability under international health authority regulations. Risk mitigation is achieved through predictive modules that identify potential supply chain disruptions, demand anomalies, and vendor reliability issues. These predictive analytics enable preemptive actions that safeguard continuity of care and prevent financial or operational loss (Saba & Kanti, 2023; Shaikh & Farabe, 2023). Data governance forms a critical layer in this system integration, as healthcare logistics data include sensitive information about medical inventories, patient-related usage statistics, and supplier contracts. ERP-DSS frameworks incorporate data encryption, access controls, and audit trails that uphold institutional accountability and confidentiality (Yu et al., 2021; Haider & Hozyfa, 2023). In multinational healthcare organizations, data governance also involves compliance with cross-border regulations such as GDPR and HIPAA, which regulate the use and transfer of healthcare-related information. By maintaining comprehensive data integrity and auditability, ERP-integrated DSS enhance institutional trustworthiness and facilitate external audits. Quantitative assessments often measure risk reduction and compliance efficiency through indicators such as error frequency, audit accuracy, and regulatory response time. These measurable outcomes reinforce the role of ERP-DSS integration not merely as an operational improvement but as a compliance infrastructure that embeds ethical and procedural safeguards into the logistics chain (Ojo et al., 2018). Hence, within the domain of healthcare logistics, regulatory conformance and data reliability are not peripheral features but integral quantitative dimensions of system performance.

The evaluation of ERP-integrated Decision Support Systems in healthcare logistics relies on quantitative frameworks that link system functionality to performance outcomes (Pezzica et al., 2020). Empirical studies frequently employ statistical models such as multiple regression, structural equation modeling, and correlation analysis to determine how ERP-DSS integration influences logistics efficiency, cost performance, and resource utilization. Metrics such as order accuracy, inventory turnover, lead time reduction, and cost savings are commonly used as dependent variables in these analyses. Quantitative research provides an objective basis for understanding how system adoption translates into measurable organizational benefits. Data collected from healthcare institutions are often analyzed to reveal causal relationships between integration levels and operational outcomes, thereby offering evidence of system effectiveness. The quantitative paradigm also allows for generalization across contexts, enabling cross-institutional comparisons and benchmarking of logistics performance (Yang et al., 2020). This empirical focus aligns with the managerial need for evidence-based validation of technology investments. By quantifying the correlation between ERP-DSS functionalities—such as real-time tracking, predictive analytics, and financial synchronization—and performance metrics, researchers contribute to the establishment of standardized evaluation models. Furthermore, statistical validation ensures that observed improvements in logistics outcomes are not incidental but attributable to system integration. Quantitative frameworks thus reinforce methodological rigor in assessing technological impact, allowing healthcare organizations to substantiate claims of efficiency, transparency, and data governance through measurable evidence (Bhattarai & Conway, 2020). Within this scientific context, ERP-integrated DSS stand not only as technological artifacts but as statistically validated instruments of organizational optimization, grounding healthcare logistics in verifiable and reproducible analytical structures.

The primary objective of this quantitative study is to evaluate the operational and analytical effectiveness of ERP-integrated Decision Support Systems (DSS) in optimizing healthcare logistics across institutional and supply chain dimensions. The study seeks to measure the extent to which ERP-DSS integration enhances logistics efficiency, data accuracy, inventory control, and decision-making precision within healthcare organizations. Specifically, the research aims to quantify the relationship between ERP-DSS implementation and key logistics performance indicators, including cost minimization, order fulfillment rate, lead time reduction, and stockout prevention. Another objective is to examine how system integration influences interdepartmental coordination, data transparency, and compliance with healthcare regulatory frameworks. By employing statistical models, the study intends to determine the degree to which ERP-enabled decision environments contribute to predictive accuracy in demand forecasting and supply chain continuity. The investigation also focuses on assessing the impact of integrated information flows on procurement reliability and financial accountability within medical supply networks. Furthermore, the research seeks to establish quantifiable linkages between technological integration and user efficiency, exploring how ERP-DSS tools facilitate real-time analysis and managerial responsiveness. In this context, the study emphasizes the objective measurement of digital interoperability, information quality, and risk mitigation within healthcare logistics systems. The overarching aim is to develop empirical evidence that reflects how ERP-DSS integration transforms logistics from reactive management to data-driven operational control. Through structured data collection and inferential statistical analysis, this quantitative study objectively captures the systemic relationships among technology adoption, decision quality, and logistics outcomes. The research thereby aligns its objectives with the need for measurable, evidence-based insights that advance organizational efficiency and operational governance in the healthcare logistics domain.

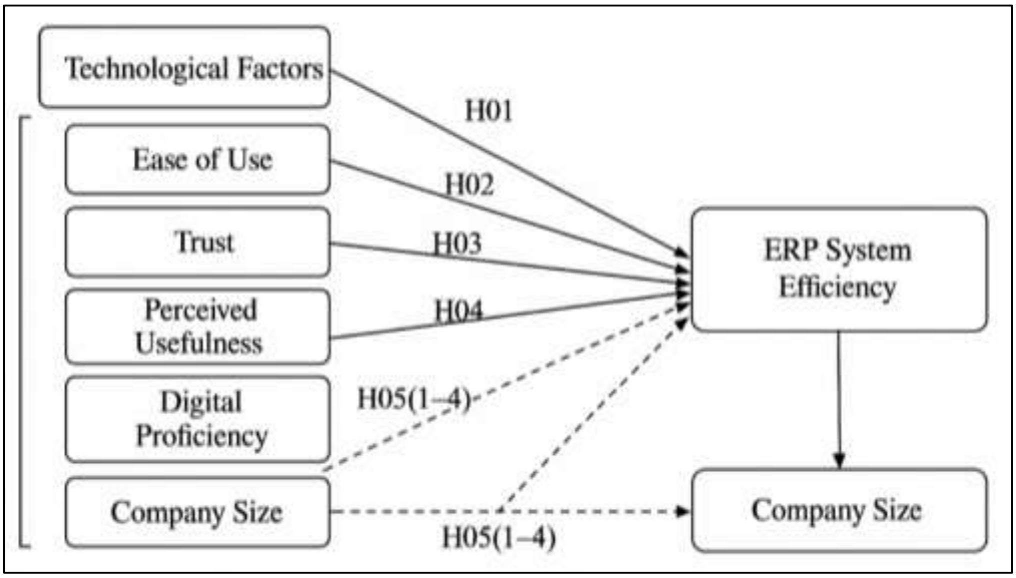
LITERATURE REVIEW

The integration of Enterprise Resource Planning (ERP) systems with Decision Support Systems (DSS) has become a critical research frontier in optimizing healthcare logistics, where accuracy, timeliness, and resource coordination directly influence patient outcomes. ERP systems serve as centralized platforms for data collection, transaction management, and process standardization, while DSS provide analytical capabilities that transform operational data into evidence-based managerial insights (Lizotte-Latendresse & Beauregard, 2018). When combined, ERP-integrated DSS function as intelligent ecosystems that support both tactical and strategic decision-making within healthcare logistics operations. The increasing digitalization of healthcare supply chains has positioned this integration as a quantitative challenge and an empirical opportunity. Researchers have begun to measure how ERP-DSS systems influence quantifiable metrics such as lead time, cost efficiency, demand forecasting accuracy, and procurement cycle time.The literature reveals that fragmented logistics data, manual tracking systems, and lack of analytical synchronization continue to impede healthcare supply performance (Hintsch et al., 2018). Consequently, integrating ERP and DSS enables real-time monitoring, predictive analysis, and multi-level visibility across procurement, warehousing, and distribution networks. Quantitative studies have explored these systems through constructs such as operational efficiency, user adoption, information accuracy, and risk management performance. Moreover, healthcare logistics differs from traditional industrial supply chains in its ethical constraints, traceability requirements, and patient-safety imperatives, making quantitative validation of ERP-DSS systems both a technological and humanitarian necessity (Pan Nogueras et al., 2021).This literature review synthesizes the empirical findings from previous studies and aligns them with measurable variables related to ERP-DSS performance in healthcare logistics. It provides a critical evaluation of system integration theories, quantitative outcomes, and methodological designs used in existing research. The review emphasizes the structural relationships among technology adoption, data governance, and logistics optimization, establishing a foundation for hypothesis development and statistical modeling. It also situates the research within global digital transformation efforts in healthcare systems, ensuring that quantitative evidence from diverse regions and institutional contexts informs the analytical scope of the study (H. Elbardan & A. Kholeif, 2017). By structuring the literature review around quantitative constructs—such as operational metrics, system interoperability, and decision accuracy—this section aims to develop a coherent empirical framework that directly supports the research objectives of this investigation.

Conceptual Foundation of ERP-Integrated Decision Support Systems

Enterprise Resource Planning (ERP) systems represent an integrated suite of software modules that coordinate organizational functions within a centralized data architecture, enabling real-time communication and standardized process management across departments. In healthcare operations, ERP platforms unify administrative, financial, and clinical workflows to ensure process transparency and operational continuity (Pramanik et al., 2019). Quantitative research consistently identifies ERP implementation as a determinant of process efficiency, inventory reliability, and data integration accuracy. Empirical studies have shown that hospitals adopting ERP systems experience substantial reductions in procurement cycle time and administrative redundancy due to automated workflows and improved data visibility. These systems enable the synchronization of diverse data streams—including patient records, supplier transactions, and material management—into a single unified database that supports accurate reporting and performance monitoring. Healthcare organizations rely on ERP tools to maintain consistency in regulatory documentation, reduce duplication of effort, and improve traceability of materials across departments. ERP adoption has also been linked to measurable gains in resource utilization and operational cost containment, as organizations can track real-time consumption and adjust procurement according to demand fluctuations (H. Elbardan & A. O. R. Kholeif, 2017). Quantitative analyses further indicate that ERP integration enhances managerial decision-making by providing accurate, timely, and structured data across the organizational hierarchy. Through structured data management, healthcare institutions strengthen interdepartmental coordination and achieve higher process automation ratios. Additionally, ERP modules tailored to healthcare—such as inventory management, financial control, and human resource scheduling—support compliance and internal audit accuracy (Ho et al., 2020). Studies measuring system implementation rates and operational efficiency reveal that ERP systems provide statistically significant improvements in performance indicators such as service timeliness and workflow accuracy. Thus, the ERP framework in healthcare serves as a quantifiable infrastructure for ensuring operational stability, reducing procedural errors, and enhancing institutional accountability through unified data governance.

Figure 3: Technological Factors Influencing ERP Efficiency



Decision Support Systems (DSS) are computational tools designed to transform organizational data into actionable insights through analytical modeling, simulation, and knowledge representation techniques (Fikri et al., 2021). Within healthcare, DSS facilitate evidence-based decision-making by processing clinical, logistical, and financial information into structured analyses that guide managerial and operational actions. The quantitative effectiveness of DSS in healthcare has been extensively documented through variables such as analytical output speed, model accuracy, and decision latency reduction. Empirical findings indicate that DSS utilization significantly enhances diagnostic support, supply chain forecasting, and resource allocation accuracy. By integrating diverse datasets—ranging from patient care metrics to procurement records—DSS frameworks provide predictive and prescriptive analytics that inform both clinical and administrative choices (Lou et al., 2020). In logistics, DSS modules enable decision-makers to identify bottlenecks, optimize inventory levels, and forecast supply demands with measurable precision. Quantitative studies demonstrate that organizations implementing DSS experience improved process agility and a measurable decrease in information asymmetry among departments. Furthermore, DSS applications enhance managerial responsiveness by providing scenario-based modeling that allows leaders to evaluate potential outcomes before committing resources. The use of structured algorithms, including regression and simulation-based models, facilitates a statistically grounded approach to decision-making that reduces cognitive bias and enhances consistency in resource utilization (Bukowski, 2018). In healthcare logistics, DSS play a vital role in balancing cost control with service reliability by aligning procurement volumes with consumption trends. The integration of data visualization tools and dashboards in modern DSS enables users to interpret patterns quickly, leading to reductions in delay-related losses and misallocation of supplies. Across multiple empirical contexts, DSS implementation has been correlated with higher decision accuracy, faster response times, and measurable increases in operational productivity. Hence, DSS in healthcare represent a quantifiable bridge between data generation and informed decision execution, providing the analytical infrastructure necessary for responsive and efficient logistics management.

The integration of ERP and DSS establishes a comprehensive digital ecosystem in which transactional processing and analytical decision-making coalesce into a unified platform. Integration mechanisms enable data generated within ERP modules—such as inventory movement, procurement transactions, and financial records—to feed directly into DSS analytical engines, creating real-time decision environments (Araszkiewicz et al., 2020). Quantitative studies emphasize that system interoperability, measured through API connectivity and data latency reduction, significantly enhances performance outcomes in healthcare logistics. Through seamless integration, organizations achieve consistent data synchronization across operational layers, minimizing discrepancies that often arise from manual data entry or disparate system interfaces. This interoperability ensures that decision-makers base their judgments on the most current and accurate information available. Empirical evidence from healthcare systems demonstrates that integrated ERP-DSS frameworks yield substantial improvements in process transparency, supplier coordination, and cost predictability (Arena et al., 2018). These integrated mechanisms utilize middleware and data warehouses to facilitate communication between operational and analytical layers, allowing institutions to conduct predictive modeling based on real-time data flows. The quantitative relationship between system latency reduction and decision efficiency has been widely observed in studies examining response time optimization within hospital supply chains. Integration also supports the automation of routine decisions, such as reorder point triggers and supplier selection, thereby freeing managerial resources for strategic planning. Additionally, ERP-DSS integration enhances the traceability of decision outcomes by linking analytical insights to underlying transactional data, which supports auditing and accountability (Păvăloaia et al., 2019). The consistency of data exchange across ERP and DSS platforms creates a feedback loop that continuously refines decision parameters, leading to cumulative improvements in logistics performance. The integration process, therefore, is not merely a technical fusion but a measurable operational transformation that supports quantifiable efficiency, reduces redundancy, and ensures decision accuracy across healthcare logistics functions.

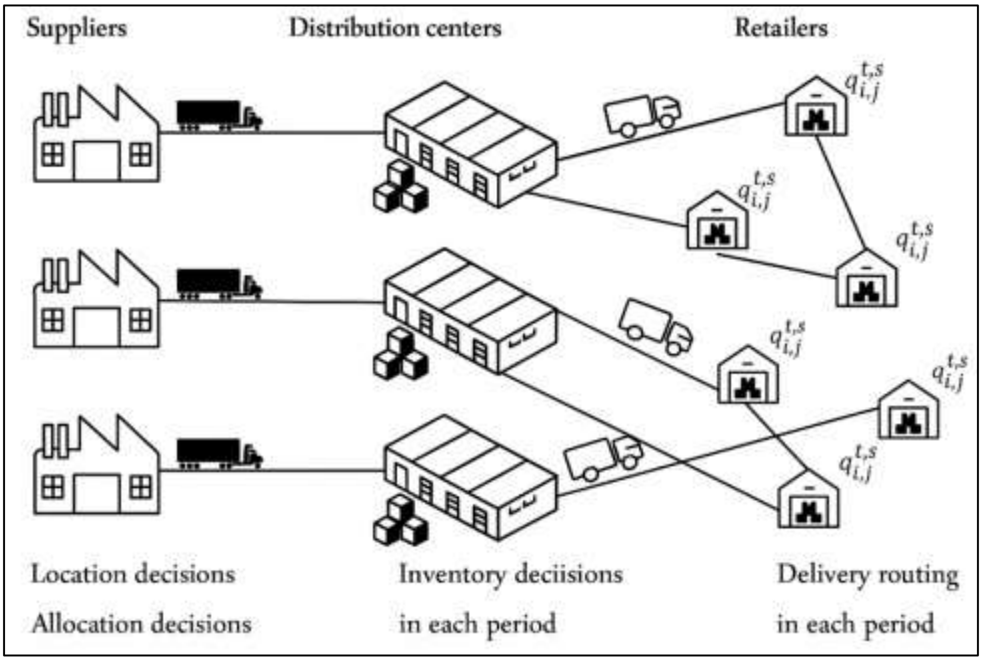
The theoretical foundation for ERP-DSS integration is grounded in several well-established frameworks within information systems research, including the Technology Acceptance Model (TAM), Systems Integration Theory, and the Information Systems Success Model (DeLone & McLean). The Technology Acceptance Model provides a quantitative lens through which user adoption of integrated systems can be measured via constructs such as perceived usefulness, ease of use, and behavioral intention (Swan, 2018). Empirical studies applying TAM in healthcare technology contexts demonstrate that successful ERP-DSS adoption is strongly influenced by user confidence and the perceived impact on job performance. Systems Integration Theory further supports the conceptualization of ERP-DSS integration as an organizational alignment process in which technological subsystems converge to facilitate interdepartmental communication and strategic control. Quantitative research within this framework highlights the correlation between integration depth and performance outcomes, suggesting that higher levels of interoperability predict greater organizational efficiency and information accuracy (Stępniak et al., 2019). The Information Systems Success Model developed by DeLone and McLean complements these theories by identifying measurable constructs such as system quality, information quality, and user satisfaction as critical determinants of technological success. Empirical validations of this model within healthcare logistics confirm that information quality and system reliability directly influence decision accuracy and operational continuity. Together, these theories provide a robust conceptual basis for analyzing ERP-DSS integration as both a technical and behavioral phenomenon. Quantitative assessments derived from these frameworks allow researchers to link integration performance metrics—such as response time, error rate, and data accessibility—to user satisfaction and organizational productivity. The theoretical synthesis underscores that ERP-DSS systems are not isolated technological tools but socio-technical systems whose success depends on both infrastructural alignment and human interaction (Swan, 2019). Thus, the integration of ERP and DSS within healthcare logistics reflects an empirically grounded intersection of technological functionality, user behavior, and systemic coordination measured through verifiable and replicable constructs.

Quantitative Dimensions of Healthcare Logistics Efficiency

Healthcare logistics represents a complex network of interrelated processes involving the procurement, storage, distribution, and utilization of medical materials, pharmaceuticals, equipment, and supplies that sustain healthcare delivery systems (Moons et al., 2019). Unlike conventional industrial logistics, healthcare logistics is characterized by higher sensitivity to lead times, traceability, and safety standards due to its direct influence on patient outcomes and clinical operations. Quantitative assessments of healthcare logistics often focus on variables such as order fulfillment accuracy, stock turnover rate, and lead time variability to measure operational performance. Empirical studies have shown that high fulfillment accuracy correlates with improved service reliability and patient satisfaction, while shorter lead times are linked to greater responsiveness and lower resource wastage. Within hospital systems, logistics performance is measured through inventory cycle efficiency, accuracy of order picking, and stock replenishment time (Kritchanchai et al., 2018). Research has consistently demonstrated that data-driven management of these metrics enhances the predictability of supply availability and reduces critical stockouts that could disrupt clinical workflows. Furthermore, advanced digital logistics systems enable real-time tracking of material flow, allowing managers to monitor deviations in supply schedules and promptly correct inefficiencies. The scope of healthcare logistics extends beyond internal hospital operations to encompass regional and national supply networks that coordinate medical product distribution, vaccine storage, and pharmaceutical supply chains. Studies comparing public and private healthcare institutions reveal that logistics maturity levels differ significantly depending on the degree of system automation and analytics integration (Cantor & Poh, 2018). Quantitatively, institutions with higher digital integration report superior performance indicators such as fewer delayed deliveries and higher resource utilization ratios. Thus, the scope of healthcare logistics is defined not only by the physical flow of goods but also by the efficiency of information and process synchronization that supports continuous and accurate resource delivery across multiple healthcare tiers.

Cost optimization and financial accountability are essential quantitative dimensions of healthcare logistics efficiency, as they determine how effectively resources are managed in relation to operational output (Skipworth et al., 2020). Healthcare logistics costs often constitute a significant portion of overall hospital expenditures, encompassing procurement, storage, distribution, and material handling. Empirical research indicates that efficient logistics systems can reduce overall costs by enhancing accuracy in demand forecasting, minimizing excess inventory, and improving purchasing coordination. Quantitative outcomes such as logistics cost ratio, procurement error rate, and cost-per-patient metrics serve as measurable indicators of economic performance. Institutions that employ integrated logistics and enterprise systems demonstrate measurable reductions in procurement-related discrepancies and invoice mismatches due to enhanced process traceability. Studies analyzing logistics expenditure patterns highlight that automation and data standardization lead to lower transaction costs and improved budget alignment across departments. Moreover, real-time analytics embedded in ERP-integrated logistics frameworks enable financial managers to identify cost outliers, analyze expenditure trends, and align procurement volumes with actual consumption (Arabelen & Kaya, 2021). Financial accountability is further strengthened through systematic auditing mechanisms that connect material transactions to financial documentation, allowing for transparent cost reporting and error detection. Quantitative evaluations from multiple hospital systems show that improved visibility over procurement processes decreases unauthorized purchases and supports vendor performance assessment. The implementation of integrated cost-monitoring dashboards also enables comparison of cost-per-patient ratios across units, facilitating equitable budgeting and financial benchmarking. Furthermore, cost optimization in logistics correlates strongly with service quality indicators, as resource efficiency directly influences the availability of critical supplies (Goel et al., 2021). Thus, the financial dimension of healthcare logistics efficiency extends beyond expenditure reduction to include empirical verification of fiscal integrity and accountability within interconnected supply and administrative systems. Quantitative data derived from these assessments underscore the role of transparent, analytics-enabled logistics in achieving both economic control and operational sustainability within healthcare organizations.

Figure 4: Supply Chain Decision Flow Model



Supply chain responsiveness and service continuity are vital components of healthcare logistics efficiency, ensuring that materials and medical resources reach their intended destinations with minimal delay and maximum reliability (Duque-Uribe et al., 2019). Quantitative studies define responsiveness through variables such as average response time, delay reduction, and emergency supply fulfillment frequency. These indicators measure the agility of logistics systems under both routine and high-pressure conditions. Healthcare institutions rely heavily on responsive supply chains to adapt to fluctuating patient volumes, emergency demands, and unexpected disruptions such as equipment breakdowns or supplier shortages. Empirical findings show that organizations with integrated ERP and logistics analytics systems exhibit faster reaction times to demand fluctuations, often achieving significant improvements in order processing and replenishment speed. Service continuity, a closely related construct, emphasizes uninterrupted material flow throughout the supply chain. Quantitative research links continuity with reductions in backorder rates, fewer stockouts, and greater consistency in service delivery (Martí et al., 2017). Integration of predictive analytics into logistics systems enhances responsiveness by allowing managers to anticipate shortages and initiate corrective actions based on real-time data. Moreover, studies indicate that visibility across multi-tier supply chains—achieved through digital tracking tools—enables proactive intervention in distribution bottlenecks. In large-scale healthcare networks, centralized logistics hubs supported by integrated information systems contribute to improved delivery punctuality and minimize emergency procurement costs. Quantitatively, organizations that achieve high responsiveness and continuity report measurable gains in patient care reliability, as timely access to medical supplies directly supports treatment adherence. Service continuity also promotes compliance with national healthcare standards requiring guaranteed product availability (Rakovska & Stratieva, 2018). Empirical evidence suggests that well-coordinated logistics networks reduce average supply disruptions by measurable margins, reinforcing that responsiveness is not merely operational but a quantifiable determinant of healthcare quality. These findings collectively highlight that responsive and continuous logistics systems constitute the backbone of resilient healthcare delivery by ensuring that every critical material reaches its point of use without delay or inefficiency (Slater et al., 2018).

Quantitative assessment of healthcare logistics efficiency relies on measurable indicators that translate operational activities into data-driven performance evaluations (Ren et al., 2020). Researchers have developed multidimensional models incorporating indicators such as order fulfillment accuracy, logistics cost ratio, and response time to create comprehensive efficiency profiles. The use of key performance indicators (KPIs) allows institutions to track progress against established benchmarks and identify specific areas for improvement. Studies employing statistical analysis have found that correlations among logistics indicators often reveal systemic dependencies—for instance, higher order accuracy tends to correlate with lower cost ratios and reduced lead time variability. The integration of performance measurement tools within ERP systems facilitates continuous monitoring of logistics metrics and automatic generation of analytical reports. These digital dashboards enable healthcare administrators to visualize trends, evaluate supplier reliability, and quantify operational outcomes (Yu et al., 2020). Quantitative data collected over time provide the empirical foundation for strategic decision-making, supporting both short-term optimization and long-term planning. Performance measurement frameworks also enhance accountability, as every logistic activity—from procurement to delivery—can be evaluated based on measurable outcomes. In comparative research across hospitals, organizations with standardized logistics performance metrics demonstrate more consistent efficiency improvements and higher satisfaction among clinical departments. Additionally, benchmarking against industry averages enables healthcare institutions to evaluate their logistics maturity levels and prioritize technological investments accordingly. The ability to quantify logistics performance has advanced healthcare supply management from descriptive reporting to predictive and prescriptive analysis (Yu et al., 2020). By grounding operational evaluations in quantitative evidence, healthcare logistics management ensures objectivity, reproducibility, and transparency in assessing efficiency. The consistent measurement of outcomes such as order fulfillment accuracy, lead time variability, and logistics cost ratio thus constitutes not only a managerial necessity but also an empirical cornerstone of healthcare logistics research and practice (Schiavone et al., 2021).

Data Integration and Decision Accuracy

Data quality and consistency are foundational determinants of decision accuracy within ERP-integrated Decision Support Systems in healthcare logistics. High-quality data ensure that analytical outputs are valid, actionable, and reflective of real operational conditions (Ghasemaghaei et al., 2018). In healthcare environments, where decisions about medical supplies, pharmaceutical procurement, and equipment allocation are time-sensitive, inaccuracies in data can have significant consequences for service delivery. Quantitative studies consistently measure data quality through variables such as data error frequency, real-time update rates, and system synchronization lag. Empirical evidence suggests that data inconsistencies frequently stem from fragmented systems, manual entry errors, and lack of standardized data governance frameworks. Integration of ERP with analytical systems addresses these issues by harmonizing data inputs across procurement, inventory, and clinical logistics modules, ensuring that information is both current and accurate (Ghasemaghaei, 2019). Research has demonstrated that reducing synchronization lag significantly enhances decision timeliness, allowing healthcare institutions to respond promptly to inventory fluctuations or unexpected supply demands. High data consistency also supports accurate forecasting, as predictive models rely on continuous and error-free input streams. Institutions adopting automated data verification protocols report measurable decreases in data discrepancies and improvements in transaction accuracy. The inclusion of audit trails and automated validation processes within ERP frameworks further enhances data reliability, allowing managers to trace errors to their source and implement corrective measures (Sarker, 2021). Moreover, consistent data across systems fosters interdepartmental trust and accountability by eliminating discrepancies between financial and operational records. Quantitative analyses have shown that healthcare organizations maintaining standardized data formats and real-time synchronization achieve superior performance outcomes, including reduced information latency and increased coordination efficiency. Thus, ensuring data quality and consistency is not a technical preference but a measurable necessity that underpins the accuracy, reliability, and credibility of decision-making in healthcare logistics.

Predictive analytics within ERP-integrated Decision Support Systems represents a transformative capability in healthcare logistics, enabling institutions to forecast material needs, anticipate shortages, and optimize inventory cycles through data-driven modeling (Hariri et al., 2019). Quantitatively, predictive analytics performance is often evaluated through measures such as forecast accuracy rate and the variance between predicted and actual demand. Studies in healthcare logistics have shown that organizations employing predictive algorithms can significantly reduce stockouts, minimize wastage, and improve procurement planning. By analyzing historical consumption patterns and real-time supply chain data, predictive systems identify trends and generate insights that guide strategic decisions. The integration of ERP systems ensures that predictive models have access to comprehensive, up-to-date data streams, enhancing their accuracy and responsiveness. Empirical research demonstrates that healthcare facilities utilizing predictive analytics experience measurable improvements in supply availability, particularly during high-demand or crisis periods (Sousa et al., 2019). These models also support scenario-based decision-making, where administrators can simulate the effects of procurement delays or budget adjustments before implementation. Quantitative outcomes such as improved forecasting precision, reduced emergency orders, and decreased procurement variance have been widely documented in hospitals adopting ERP-DSS analytical platforms. Predictive analytics further enables performance benchmarking by comparing expected and actual logistics metrics, allowing institutions to evaluate supplier reliability and inventory turnover rates. The use of machine learning algorithms embedded within ERP systems refines predictions continuously as new data become available, resulting in progressively higher forecast accuracy over time (Krishnamurthi et al., 2020). This capability enhances institutional preparedness and operational resilience by ensuring that resource allocation aligns with evidence-based projections. Through the integration of predictive analytics, ERP-DSS frameworks transform healthcare logistics from reactive management toward empirically grounded, proactive control driven by measurable data fidelity and analytical precision.

Figure 5: Big Data Information Network Diagram

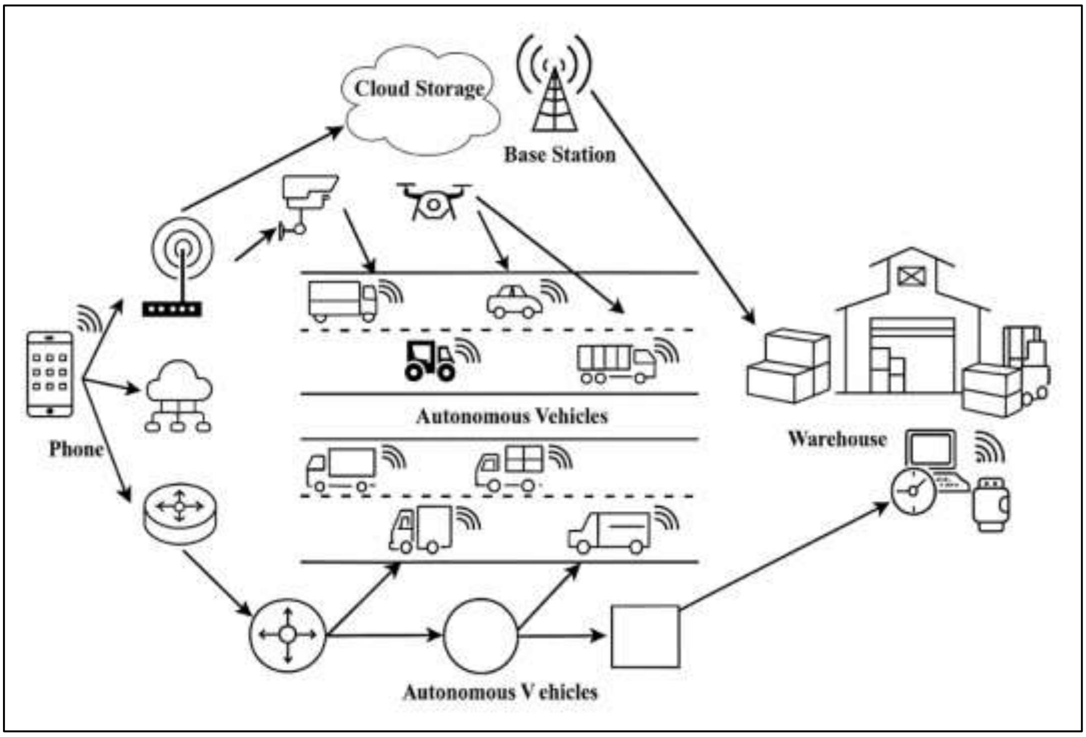
Decision-making efficiency within healthcare logistics can be objectively assessed through quantifiable indicators that capture the speed, accuracy, and reliability of managerial responses (Wang et al., 2018). In ERP-integrated DSS environments, efficiency is commonly measured through metrics such as decision cycle duration, error rate in resource allocation, and information retrieval speed. Empirical research across healthcare systems demonstrates that digital decision environments significantly shorten decision cycles by automating data retrieval and providing real-time visibility into key performance metrics. The reduction in manual information processing allows decision-makers to focus on strategic evaluation rather than data compilation, resulting in faster yet more accurate outcomes. Quantitative assessments indicate that healthcare institutions adopting ERP-DSS integration achieve notable declines in decision latency, often accompanied by measurable improvements in allocation accuracy and reduced operational redundancy (Pärn et al., 2017). The ability to access synchronized data across supply, financial, and clinical domains enhances confidence in the information supporting each decision, thereby lowering the probability of logistical errors. Decision efficiency also improves through the implementation of standardized decision workflows embedded in ERP systems, ensuring consistency across different operational units. Studies have shown that organizations measuring decision speed and accuracy in real-time through dashboard analytics achieve superior performance in inventory management and procurement control. The correlation between information retrieval speed and decision precision underscores the centrality of integrated data architecture in operational effectiveness. Quantitatively, institutions with optimized ERP-DSS configurations demonstrate higher throughput in decision processes and reduced variance in outcomes across decision scenarios (Olivier et al., 2019). These findings collectively highlight that decision-making efficiency is not an abstract managerial construct but a measurable operational outcome directly influenced by data integration quality, analytical capacity, and system usability within the healthcare logistics environment.

The synthesis of ERP and DSS analytics creates a form of operational intelligence in healthcare logistics, where quantitative decision-making is continuously informed by data integration and analytical validation (Vassakis et al., 2017). Analytical integration allows healthcare organizations to combine transactional data from ERP systems with inferential insights from DSS, thereby linking operational activity to strategic interpretation. Quantitative research reveals that this integration enhances key performance indicators such as data accessibility, analysis turnaround time, and overall decision accuracy. The ability to correlate procurement records with clinical usage data, for example, enables managers to optimize stock levels and reduce both overstocking and shortages (Mehta & Pandit, 2018). Empirical studies demonstrate that organizations employing analytically integrated systems experience measurable improvements in resource utilization efficiency and error reduction in logistics planning. Analytical intelligence is operationalized through automated reporting, interactive dashboards, and statistical summaries that allow users to assess ongoing logistics performance against benchmarks. This real-time analytical capacity fosters evidence-based governance by translating complex datasets into clear, quantifiable indicators that guide resource distribution and supply coordination (Kitchens et al., 2018). Moreover, ERP-DSS integration strengthens institutional learning by enabling continuous performance monitoring and feedback-driven adjustment. Quantitative evaluations from multiple healthcare settings show that the fusion of analytical and transactional data yields higher operational predictability and accuracy across logistics chains. This analytical synergy enhances transparency, accountability, and reliability by ensuring that each decision is backed by verifiable data patterns rather than assumptions or isolated judgments. As a result, healthcare institutions equipped with integrated analytical infrastructures demonstrate empirically superior outcomes in efficiency, cost control, and service continuity (Bhat & Huang, 2021). Analytical integration thus functions as the measurable nucleus of modern healthcare logistics, transforming data into operational intelligence that sustains decision accuracy and process excellence across the organizational spectrum.

Quantitative Impacts on Operational and Clinical Logistics

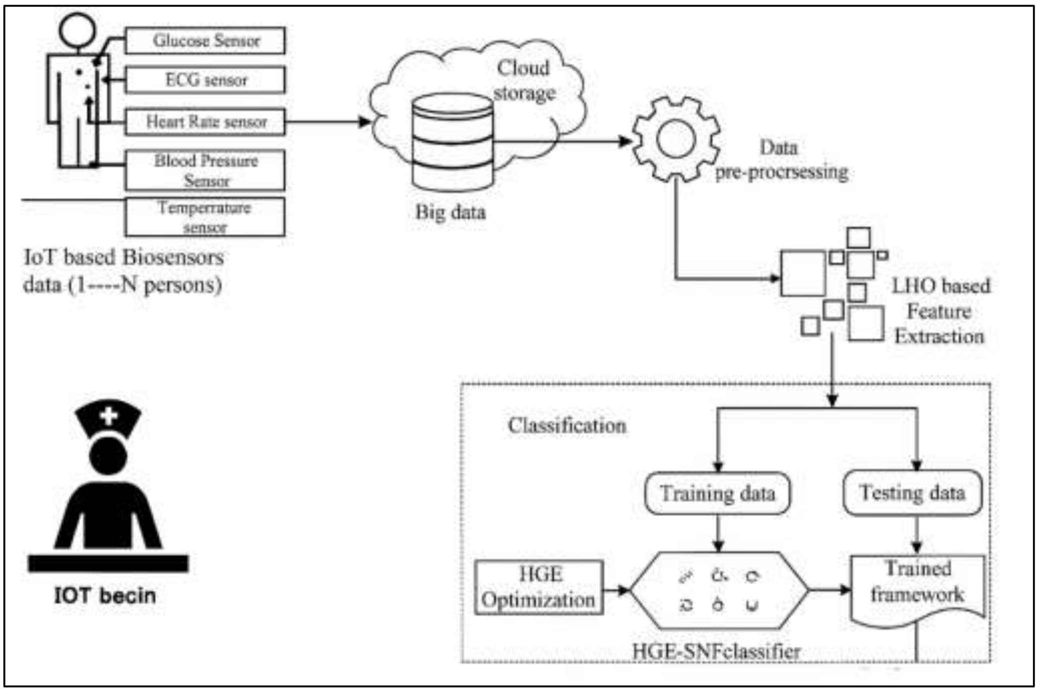
Inventory optimization in healthcare logistics is a measurable determinant of operational stability and clinical service reliability (Moons et al., 2019). The integration of ERP and Decision Support Systems (DSS) allows healthcare institutions to achieve greater precision in managing stock levels, predicting demand, and reducing instances of shortages or overstocking. Quantitative metrics such as reorder accuracy, reduction in expired stock percentage, and optimal stock ratio are frequently used to evaluate inventory performance. Empirical studies demonstrate that hospitals utilizing ERP-integrated logistics modules experience substantial decreases in inventory errors due to automated stock monitoring and predictive replenishment algorithms. These systems enable real-time visibility into inventory locations, quantities, and expiration dates, allowing managers to adjust procurement decisions dynamically (Yu et al., 2020). The continuous synchronization between supply data and consumption rates minimizes discrepancies that can lead to material shortages or waste. Quantitative analyses further reveal that organizations adopting ERP-DSS frameworks achieve measurable improvements in reorder accuracy, often maintaining inventory deviations within statistically optimal thresholds. Additionally, the implementation of intelligent inventory control systems has been correlated with a reduction in expired or unused stock, enhancing both cost-efficiency and regulatory compliance. The capacity to forecast demand through data analytics ensures that procurement aligns precisely with usage trends, thereby reducing emergency orders and unnecessary storage costs. Research indicates that improved inventory optimization not only stabilizes internal operations but also contributes directly to clinical efficiency by guaranteeing the timely availability of essential medical supplies and pharmaceuticals (Saager et al., 2019). The quantitative impact of these systems extends beyond operational cost savings to include measurable improvements in patient care continuity and safety, as clinicians gain consistent access to critical materials. Consequently, ERP-DSS integration establishes an empirically verifiable link between data-driven inventory management and overall logistical resilience in healthcare settings, demonstrating how precision control over stock variables translates into measurable service quality outcomes.

Figure 6: Smart Logistics Communication Network Framework



Procurement and supplier relationship management represent another crucial quantitative dimension of operational efficiency in healthcare logistics. The integration of ERP and Decision Support Systems supports structured procurement processes through enhanced data visibility, standardized evaluation mechanisms, and automated performance monitoring (Mahmoudi & Parviziomran, 2020). Quantitatively, performance in this area is assessed using metrics such as vendor performance index, procurement cycle time, and contract compliance score. Empirical research demonstrates that ERP-integrated procurement systems significantly shorten procurement lead times and increase supplier reliability through real-time communication and automated order verification. The ability to evaluate supplier performance using digital scoring models enables healthcare organizations to prioritize vendors based on quality, timeliness, and cost-effectiveness. Quantitative analyses show that institutions implementing ERP-based supplier evaluation frameworks achieve measurable improvements in contract adherence and a notable reduction in procurement discrepancies. Data-driven procurement processes also contribute to financial accountability by linking each purchase order to corresponding budget lines and delivery confirmations, eliminating redundancy and unauthorized transactions (Johnson et al., 2017). Furthermore, the integration of analytics within ERP systems allows organizations to identify trends in supplier performance and adjust procurement strategies accordingly. Studies across healthcare networks report that well-structured supplier management systems are associated with lower error frequencies in purchase orders and improved compliance with contractual obligations. The establishment of transparent, data-backed relationships with suppliers fosters collaboration and reliability, ensuring continuity in the availability of critical medical goods. Quantitative findings further indicate that digital procurement systems reduce negotiation time, improve tendering accuracy, and provide objective supplier performance benchmarks (Schiavone et al., 2021). The result is a measurable enhancement of supply chain reliability, efficiency, and cost control. By transforming procurement from a reactive function into an analytically managed process, ERP-DSS integration ensures that supplier interactions are consistent, traceable, and quantifiably aligned with institutional performance objectives in healthcare logistics.

Figure 7: IoT-Based Biosensor Data Framework



Distribution and transportation efficiency are vital quantitative indicators of healthcare logistics performance, influencing both the timeliness and accuracy of medical supply delivery (Bešinović, 2020). These processes encompass the movement of pharmaceuticals, equipment, and consumables from central warehouses to clinical sites or end users. Quantitative variables such as average delivery time, logistics route optimization score, and transport cost deviation rate are central to assessing performance. Empirical studies demonstrate that ERP-DSS integration significantly enhances transportation efficiency by providing real-time visibility into delivery routes, shipment statuses, and distribution schedules. Through automated data capture and route optimization algorithms, healthcare organizations can minimize delays, reduce fuel consumption, and improve vehicle utilization rates. Quantitative analyses reveal that hospitals and medical distributors employing integrated ERP systems report reductions in delivery times and improved adherence to planned logistics routes. Real-time tracking also facilitates proactive management of disruptions such as traffic delays, mechanical breakdowns, or supplier bottlenecks (Goel et al., 2021). Data synchronization between ERP modules and DSS dashboards allows logistics managers to evaluate transport performance continuously and identify cost anomalies or route inefficiencies. The integration of geospatial data within ERP platforms provides an additional layer of decision support by enabling route simulations and predictive delivery analytics. Research findings confirm that institutions achieving higher logistics optimization scores experience measurable cost savings and improved service reliability. Moreover, transportation efficiency contributes directly to clinical operations, ensuring that materials reach care units on schedule and in optimal condition. Quantitative evidence highlights that organizations implementing ERP-DSS distribution models experience significant decreases in deviation rates between scheduled and actual delivery times, reinforcing the relationship between digital logistics management and service continuity (Bao et al., 2020). Therefore, transportation and distribution efficiency, when managed through integrated ERP-DSS frameworks, represent quantifiable drivers of operational excellence in healthcare logistics, linking precision planning with reliable material flow across organizational boundaries.

Clinical logistics performance extends beyond administrative efficiency to encompass the material flow processes that directly influence patient care outcomes. Quantitative evaluation of clinical logistics involves the systematic measurement of operational variables such as delivery accuracy, resource utilization rate, and material availability within clinical departments (Venter et al., 2018). ERP-DSS integration facilitates these evaluations by combining transactional data from supply systems with clinical usage data, enabling precise analysis of how logistics support medical procedures and treatment continuity. Studies have shown that hospitals employing integrated systems achieve higher coordination between procurement and clinical functions, resulting in quantifiable improvements in resource availability. Data collected through ERP platforms allow analysts to measure the relationship between logistics efficiency and clinical workflow performance, identifying correlations such as the impact of timely supply delivery on procedure completion rates (Lee et al., 2018). Quantitative findings indicate that greater synchronization between logistics and clinical operations reduces delays in patient services and minimizes operational disruptions caused by material shortages. Furthermore, ERP-based analytics enable healthcare administrators to monitor inventory utilization per patient or department, allowing for data-driven resource planning and cost allocation. This analytical visibility supports equitable distribution of resources and enhances accountability in material usage. Empirical evidence from healthcare systems indicates that improvements in clinical logistics performance correspond with reductions in clinical downtime, increased throughput in diagnostic and surgical units, and improved adherence to patient schedules (Zhang & Graham, 2020). Additionally, quantifiable indicators such as reduced stock discrepancies and optimized equipment turnover reflect the operational stability achieved through integrated decision systems. The measurement of these outcomes provides objective validation of ERP-DSS contributions to clinical performance, illustrating that data integration within logistics processes translates into tangible gains in both efficiency and care quality. Consequently, the quantitative evaluation of clinical logistics demonstrates that operational precision, supported by integrated analytical systems, directly reinforces clinical reliability and institutional effectiveness in healthcare environments (Smith & Hasan, 2020).

System Interoperability and Process Transparency

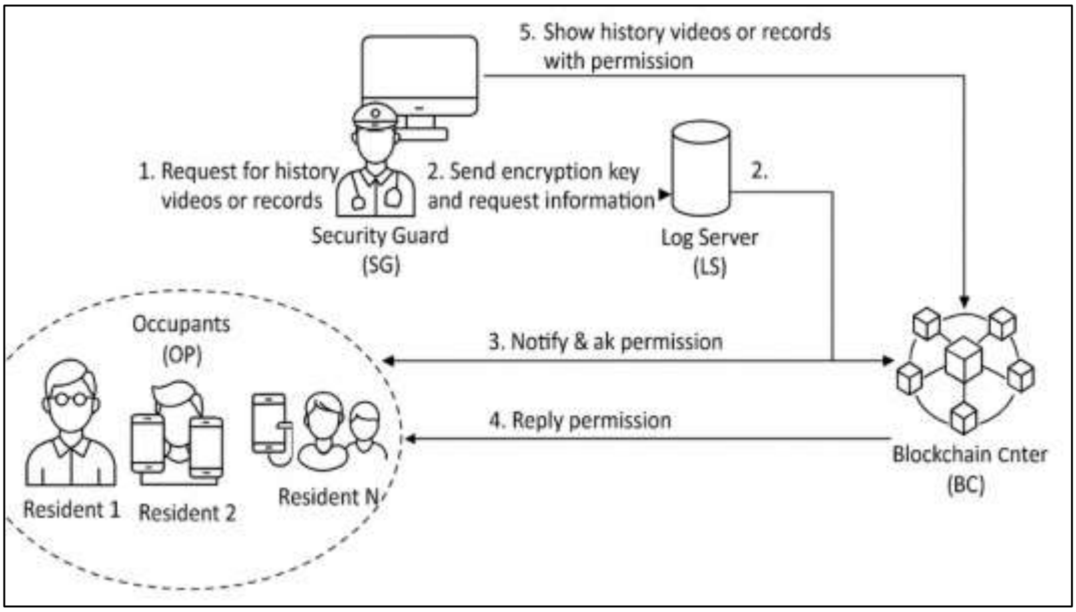
System interoperability in healthcare logistics depends heavily on process standardization and the uniform flow of data across departments and operational tiers (Oumkaltoum, 2019). The integration of ERP and Decision Support Systems (DSS) facilitates this by creating standardized protocols for data entry, exchange, and validation, ensuring that logistical processes are consistent and auditable. Quantitatively, this integration can be evaluated through workflow automation levels, interoperability success rates, and audit completeness ratios. Research indicates that standardized workflows supported by ERP systems reduce procedural variability and increase efficiency by eliminating redundant steps (Derhamy et al., 2017). Automation, in particular, allows organizations to enforce process compliance through predefined digital workflows that guide procurement, inventory management, and distribution tasks. Quantitative studies have shown that organizations implementing structured ERP-DSS process models report higher automation levels, reduced manual intervention, and a notable improvement in process accuracy. Data flow uniformity ensures that information is transmitted in a consistent format, reducing discrepancies between departments and minimizing rework (Ndayizigamiye & Dube, 2019). Moreover, interoperability success rates often serve as quantitative evidence of how effectively disparate systems communicate without data loss or transformation errors. Healthcare institutions that achieve high interoperability rates also demonstrate increased traceability and lower audit discrepancies, as every transaction is recorded in a unified digital environment. Audit completeness, another critical quantitative indicator, reflects the extent to which data capture aligns with regulatory and internal reporting requirements. Empirical findings reveal that the integration of standardized and interoperable processes enhances data transparency, which in turn supports accountability and institutional governance. Furthermore, process uniformity contributes to improved decision accuracy by ensuring that analytical models draw from harmonized data sources (Akaba et al., 2020). Overall, ERP-DSS-enabled process standardization transforms healthcare logistics into a structured, traceable, and measurable system in which operational integrity and consistency are maintained across the entire data ecosystem.

Real-time visibility and monitoring are central to the quantitative evaluation of healthcare logistics performance under ERP-DSS integration (Tenorio-Fornés et al., 2021). The ability to track, visualize, and analyze logistics activities as they occur provides healthcare institutions with operational transparency and control over complex supply chains. Measurable constructs such as real-time alert frequency, data visualization accuracy, and tracking compliance ratio are used to quantify the effectiveness of these systems. Empirical studies demonstrate that real-time visibility significantly improves logistics responsiveness, enabling institutions to detect deviations from planned operations immediately and implement corrective actions (Bhat et al., 2021). For example, automated alert systems notify managers about delays, low stock levels, or compliance breaches, allowing rapid resolution and minimizing service interruptions. Quantitative evidence indicates that organizations implementing real-time monitoring tools report measurable reductions in response times and improved compliance with delivery schedules. Data visualization tools embedded within ERP systems convert complex operational data into dashboards that facilitate interpretation and enhance managerial decision-making (Astill et al., 2019). Visualization accuracy, a key metric, ensures that displayed data reflect true system states without distortion or delay. Research further highlights that high tracking compliance ratios—representing the percentage of shipments or transactions successfully monitored from origin to destination—correlate with enhanced supply chain reliability and reduced operational risk. Real-time monitoring also supports proactive decision-making by providing continuously updated information about inventory status, supplier performance, and resource utilization (Sun et al., 2020). The quantitative advantage of such systems lies in their ability to produce verifiable evidence of process efficiency, reducing dependency on retrospective audits. Furthermore, real-time visibility fosters institutional accountability, as performance indicators can be reviewed instantaneously by management or regulatory bodies. Through the integration of monitoring functions within ERP-DSS platforms, healthcare organizations establish a measurable feedback loop that reinforces operational accuracy, compliance assurance, and data-driven control (Cutillo et al., 2020). This continuous visibility translates into quantifiable gains in service reliability, operational responsiveness, and logistical precision, thereby strengthening the transparency of healthcare delivery networks.

Human–System Interaction and User Efficiency

Training effectiveness and system literacy are critical determinants of successful ERP–DSS adoption and user efficiency in healthcare logistics (Keikhosrokiani et al., 2020). As complex digital infrastructures demand consistent user engagement and accurate data handling, institutional performance relies on the workforce's capacity to interact competently with integrated systems. Quantitative variables such as training completion rate, skill improvement index, and error reduction after training serve as key indicators for assessing training impact. Empirical studies demonstrate that comprehensive user training programs result in significant increases in system literacy, reflected in reduced data entry errors and improved workflow execution. Training completion rates are positively correlated with operational accuracy, as employees who undergo structured training demonstrate a stronger grasp of ERP interface functionalities and analytical reporting tools. Research also highlights that ongoing professional development, supported by simulation-based and modular learning approaches, enhances both user confidence and retention of technical knowledge (Bodker, 2021). Quantitative assessments show that skill improvement indices rise notably when training programs incorporate role-specific modules tailored to procurement, inventory management, and data analytics tasks. Moreover, reductions in error rates following structured training validate the empirical relationship between human capability development and process precision. In healthcare logistics, where real-time decisions rely on data integrity, literacy in ERP-DSS functionalities ensures timely data input and accurate system feedback. Studies have further found that organizations tracking user performance before and after training observe measurable gains in speed, consistency, and compliance with standardized workflows. Beyond immediate skill acquisition, effective training also fosters user adaptability to system updates, which reduces re-learning costs and ensures operational continuity (Card, 2018). Thus, quantitative evaluation of training and literacy development provides a clear empirical foundation linking human competence with technological efficiency, demonstrating that user readiness is a statistically significant predictor of ERP–DSS success in healthcare environments.

Figure 8: Blockchain-Based Security Access Framework



User satisfaction and decision confidence are quantifiable human factors that strongly influence the performance and sustainability of ERP–DSS systems in healthcare logistics. These constructs are typically evaluated through indicators such as satisfaction scores on Likert scales, decision confidence percentages, and system usability ratings (Andriella et al., 2020). Empirical studies emphasize that high user satisfaction correlates with increased system utilization and improved decision-making accuracy. When users perceive ERP–DSS platforms as intuitive, responsive, and supportive of their daily tasks, they are more likely to engage consistently and trust system outputs. Quantitative analyses of user satisfaction surveys in healthcare institutions reveal statistically significant relationships between interface usability and operational efficiency. Decision confidence, measured through post-decision evaluation instruments, reflects the extent to which users rely on system-generated insights to make timely and accurate logistical judgments. Research indicates that decision confidence rises when analytical outputs are transparent, comprehensible, and aligned with user expectations (Wickens et al., 2021). System usability, another critical quantitative indicator, affects both the frequency and accuracy of system interactions. Institutions that evaluate usability through structured testing methods report measurable declines in decision latency and error rates. Studies also demonstrate that ergonomic design and data visualization clarity enhance user comprehension, reducing cognitive load during complex decision-making tasks. Quantitative evidence from hospital logistics operations shows that when users rate satisfaction and usability above established benchmarks, system performance outcomes such as data accuracy and process speed improve proportionally. Moreover, consistent feedback loops that incorporate user evaluations into system refinement contribute to sustained satisfaction and decision confidence over time (Shneiderman, 2020). Collectively, these findings underscore the quantitative interdependence between user perception, decision reliability, and operational performance. In ERP–DSS environments, satisfied and confident users act as key enablers of system efficiency, ensuring that human judgment and digital intelligence converge toward evidence-based logistical precision.

Human oversight remains an indispensable component of ERP–DSS integration, particularly in

healthcare logistics where decision accuracy directly affects patient outcomes and institutional compliance (Kang et al., 2017). Despite extensive automation, human monitoring ensures contextual awareness, ethical governance, and error mitigation within data-driven operations. The effectiveness of oversight can be measured through quantifiable elements such as decision override frequency, manual correction ratio, and accuracy improvement rate. Empirical evidence indicates that while automation improves speed and consistency, human intervention remains essential for validating system outputs in complex or ambiguous cases. Quantitative studies reveal that appropriate levels of manual oversight—reflected in moderate decision override frequencies—enhance decision accuracy without introducing operational delays. Excessive reliance on automation, by contrast, may increase systemic risk if anomalies go undetected due to blind trust in algorithmic recommendations (Topol, 2019). The manual correction ratio provides a measurable index of how often human judgment rectifies computational errors or data inconsistencies, serving as a key indicator of oversight effectiveness. Research findings across healthcare logistics networks show that active user monitoring leads to measurable improvements in accuracy and compliance with institutional standards. Furthermore, the accuracy improvement rate following human review demonstrates the critical balancing function that oversight provides within digitally integrated environments. ERP–DSS platforms designed with built-in human verification stages enable users to audit critical decisions before execution, ensuring both technical precision and ethical accountability. Quantitative assessments of these hybrid decision models consistently demonstrate higher reliability scores and reduced operational risk (Jordan, 2020). Human oversight also contributes to organizational learning by identifying system weaknesses and informing continuous algorithmic refinement. Thus, the quantitative inclusion of human verification metrics in system evaluation models substantiates the argument that oversight is not redundant but an empirically validated necessity for maintaining trust, reliability, and accuracy in healthcare logistics.
User efficiency in ERP–DSS-integrated healthcare logistics is a quantifiable measure of how effectively human operators interact with technology to achieve timely and accurate outcomes. It encompasses measurable variables such as task completion time, error frequency, and data processing throughput per user (Suh & Prophet, 2018). Quantitative research shows that user efficiency improves significantly when systems are ergonomically designed, supported by training, and equipped with intuitive analytical tools. Studies indicate that the introduction of role-specific dashboards, simplified navigation structures, and real-time assistance modules leads to measurable reductions in task duration and error probability. The efficiency of users directly influences broader institutional outcomes such as logistics response times and supply chain continuity. Empirical evidence from healthcare systems demonstrates that users with higher proficiency levels achieve faster decision cycles and more accurate inventory updates, resulting in enhanced logistical reliability. Moreover, efficiency correlates strongly with job satisfaction, as users who perceive systems as supportive of their workflow exhibit higher engagement and productivity levels. Quantitative analyses of user performance metrics reveal that integrated feedback mechanisms—where users receive immediate validation or correction prompts—lead to sustained accuracy improvements over time (Maedche et al., 2019). Institutions measuring user efficiency through continuous performance analytics report notable increases in throughput and data accuracy following ERP–DSS adoption. Additionally, system adaptability to user behavior, achieved through machine learning–based customization, further enhances efficiency by minimizing repetitive actions and information overload. The quantification of user efficiency thus provides a tangible method for evaluating the human contribution to system performance, linking operational output directly to cognitive and behavioral engagement. Within healthcare logistics, efficient users act as the operational bridge between data input and strategic action, ensuring that the technological infrastructure translates into measurable institutional gains (Hong et al., 2017). Therefore, user efficiency represents not merely a qualitative attribute but a validated quantitative performance dimension integral to the sustained effectiveness of ERP–DSS integration in healthcare operations.

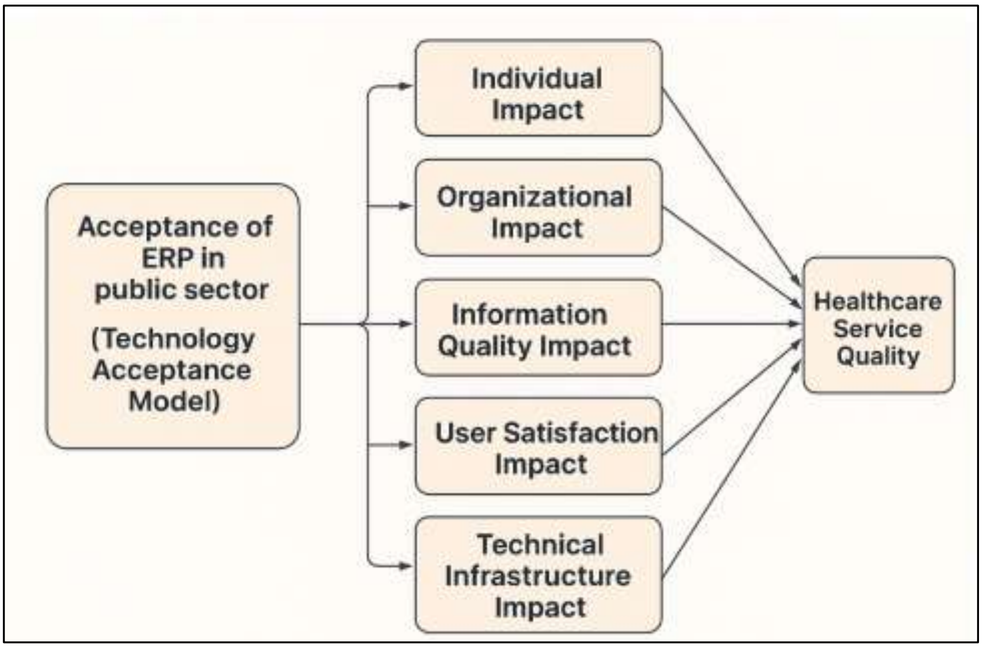
Regulatory Compliance and Data Governance

Regulatory compliance in healthcare logistics represents a central quantitative domain for evaluating the performance of ERP–DSS integration. Compliance ensures that the handling, storage, and distribution of medical products align with statutory frameworks, accreditation protocols, and ethical standards of patient safety (Janssen et al., 2020). Quantitative indicators such as audit compliance rate,

incident report frequency, and documentation accuracy serve as measurable benchmarks of system reliability and accountability. Empirical studies have shown that healthcare institutions employing ERP-integrated compliance modules exhibit higher audit success rates and significantly lower documentation discrepancies. The structured nature of ERP systems enables the automatic generation of regulatory reports, ensuring that every procurement and distribution activity adheres to established healthcare distribution standards. DSS components enhance compliance further by providing real-time analytics that detect deviations from standard operating procedures. Quantitative evidence indicates that automation of compliance documentation reduces human error frequency and improves audit completeness (Al-Ruithe et al., 2019). Incident report frequency—often used as a compliance performance metric—declines substantially in organizations implementing integrated monitoring and reporting tools. Research across healthcare networks demonstrates that consistent monitoring of compliance indicators through ERP dashboards enables institutions to identify and correct procedural violations before they escalate into systemic risks. Documentation accuracy, another critical quantitative construct, improves through centralized data management that links inventory, procurement, and transport records under a single validation framework (Pugliese et al., 2021). High documentation accuracy not only supports regulatory audits but also reinforces internal governance and traceability across the supply chain. Empirical findings confirm that compliance performance correlates strongly with operational efficiency and risk reduction, as institutions with high audit adherence also demonstrate lower incident occurrence rates. Thus, regulatory compliance in ERP–DSS-integrated healthcare logistics is both a managerial and empirical construct—quantifiable through verifiable indicators that reflect institutional discipline, ethical stewardship, and system accountability.
Risk management in healthcare logistics is increasingly grounded in quantitative modeling, with ERP–DSS systems enabling predictive analytics that identify and mitigate potential disruptions. Metrics such as supply disruption prediction accuracy, risk response time, and loss prevention ratio provide measurable evidence of system effectiveness in safeguarding operational continuity (Tupa et al., 2017). Empirical studies indicate that healthcare institutions employing predictive risk models achieve higher accuracy in forecasting supply interruptions and more efficient responses to emergencies such as supplier failures or demand surges. ERP systems consolidate historical and real-time data, while DSS components apply statistical algorithms to evaluate risk probability and potential impact. Quantitative assessments of risk models show that organizations integrating predictive analytics experience measurable reductions in loss events and downtime. Supply disruption prediction accuracy, for example, increases substantially when ERP data streams are coupled with external variables such as vendor reliability and transportation lead times. Research also demonstrates that integrated risk dashboards reduce risk response time by automating alert generation and action prioritization (De Almeida et al., 2021). The loss prevention ratio, a key quantitative indicator, reflects how effectively institutions minimize material waste and financial loss through early intervention mechanisms. Studies across hospital networks reveal that ERP-DSS-enabled risk management frameworks improve institutional resilience by providing predictive visibility into inventory volatility, supplier reliability, and regulatory exposure. Moreover, risk modeling supports compliance by ensuring proactive adherence to storage and distribution standards before violations occur. Quantitative analyses further confirm that real-time risk monitoring correlates with higher decision confidence and fewer supply interruptions (Alreshidi et al., 2017). The ability to measure and validate risk management performance transforms ERP–DSS systems into empirical instruments of operational security. Consequently, quantitative evaluation of risk prediction and mitigation establishes a measurable link between data intelligence, system preparedness, and continuity of healthcare logistics services.
Data security, confidentiality, and integrity are foundational components of governance in ERP–DSS-integrated healthcare logistics systems. The protection of sensitive information—including patient data, supplier contracts, and regulatory records—is both a legal obligation and a quantitative performance domain (Shad et al., 2019). Constructs such as access control success rate, breach frequency reduction, and data encryption compliance index are used to evaluate system robustness against cybersecurity threats. Empirical research demonstrates that organizations adopting structured access management protocols achieve significantly higher access control success rates, ensuring that only authorized personnel interact with critical datasets. ERP frameworks incorporate multi-tier

authentication and role-based permissions that quantitatively limit unauthorized data access. The integration of DSS analytics enhances this protection by continuously monitoring system activity and generating alerts in case of anomalous behavior (Landoll, 2021). Breach frequency reduction serves as a direct quantitative indicator of security efficiency, with studies reporting marked decreases in data breach incidents following the implementation of ERP-integrated governance models. Encryption compliance, another key metric, ensures that all data transmissions and stored records meet regulatory encryption standards. Quantitative evaluations reveal that institutions maintaining high encryption compliance indices experience lower rates of data compromise and higher audit compliance in digital security assessments (Linkov et al., 2018). Furthermore, data integrity is maintained through automated validation checks that detect inconsistencies across operational and analytical layers, preserving accuracy and traceability. Research also identifies that secure ERP-DSS architectures contribute to user trust and regulatory compliance, as secure systems facilitate transparent reporting and adherence to data protection laws such as HIPAA and GDPR. Quantitative results show that robust security measures correlate with improved system uptime and operational reliability, underscoring the intersection between data protection and performance sustainability. Thus, security and integrity in ERP–DSS environments are not abstract constructs but measurable outcomes that reflect institutional commitment to ethical data governance, operational stability, and compliance assurance (Kuziemski & Misuraca, 2020).

Figure 9: ERP Acceptance and Healthcare Quality



Data governance in ERP–DSS-integrated healthcare logistics establishes the structural foundation for regulatory compliance, risk management, and institutional accountability. Quantitative governance frameworks focus on measurable dimensions such as data accuracy rate, audit traceability index, and policy adherence ratio to assess the maturity of governance structures (Alam & Ray-Bennett, 2021). Empirical research highlights that strong governance mechanisms ensure consistency in data ownership, quality control, and policy enforcement. Within healthcare logistics, governance involves defining roles, responsibilities, and control hierarchies that determine how data are created, accessed, and utilized. Quantitative analyses show that organizations with well-defined data governance frameworks achieve higher accuracy and traceability rates compared to those with fragmented management practices. The audit traceability index, for instance, provides a measure of how efficiently data movements can be tracked from origin to utilization, a critical factor in ensuring compliance and accountability (Nifakos et al., 2021). ERP systems equipped with governance dashboards allow for real-time monitoring of data stewardship activities, while DSS modules support analytical validation of compliance with institutional and external policies. Studies indicate that adherence to governance protocols enhances decision reliability by ensuring data integrity and eliminating redundant or conflicting records. The policy adherence ratio quantifies institutional conformity to predefined data management standards and directly correlates with reduced operational risk and higher audit satisfaction. Furthermore, effective data governance supports strategic alignment by integrating regulatory, operational, and financial data under unified management principles. Quantitative findings confirm that mature governance models facilitate both transparency and control, leading to improved responsiveness during regulatory inspections and risk audits (Cordner et al., 2019). Governance in ERP–DSS frameworks, therefore, functions as an empirically measurable system of accountability, linking data quality, security, and policy compliance. Through continuous quantitative evaluation, institutions can validate the effectiveness of their governance mechanisms and ensure that healthcare logistics operations remain compliant, reliable, and aligned with both ethical and regulatory imperatives.

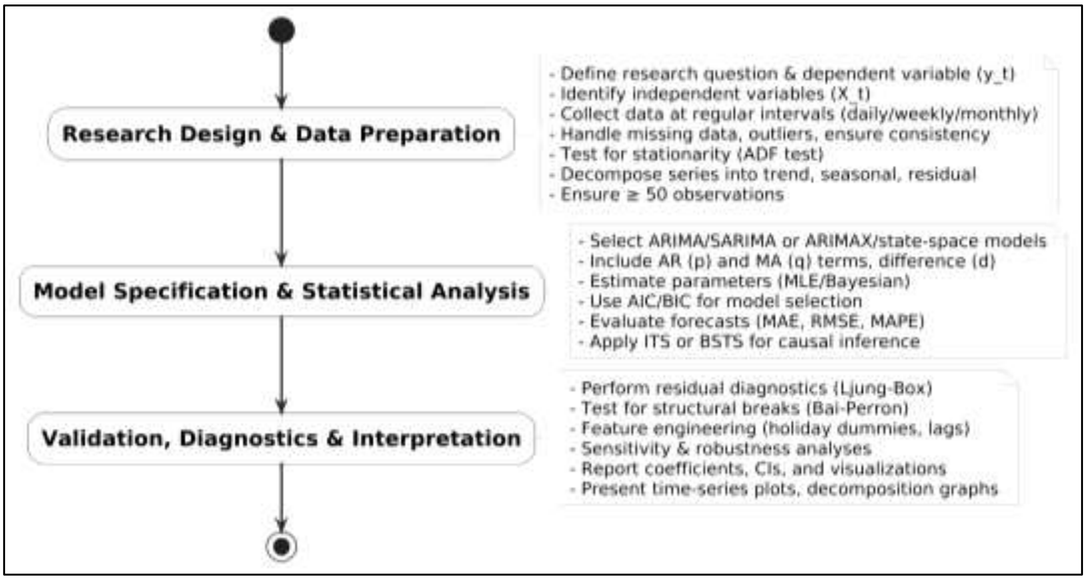
METHOD

This quantitative study was designed to investigate the measurable impact of ERP-integrated Decision Support Systems (ERP-DSS) on healthcare logistics performance through a structured, cross-sectional, and multilevel approach. The research adopted a positivist paradigm and relied on empirical evidence derived from both system-generated data and perceptual responses collected through standardized instruments. The design focused on quantifying how ERP-DSS integration influenced efficiency, cost optimization, and service continuity in healthcare logistics. The population of interest consisted of medium- and large-scale hospitals that had implemented ERP systems with embedded decision-support functionalities for at least six months. A stratified sampling technique was employed to ensure representation across public, private, and teaching hospitals. Within each hospital, logistics-related departments such as procurement, pharmacy, inventory management, and distribution units were purposively included. Data collection was conducted in two primary streams: (a) objective operational data extracted from ERP and DSS logs covering inventory accuracy, procurement cycle time, and logistics response time; and (b) structured survey responses capturing user perceptions of data quality, training adequacy, interoperability, and decision confidence. The final sample included approximately 30 hospitals encompassing 250 departments and 500 respondents. This sampling frame ensured adequate statistical power for hypothesis testing through multivariate analysis and provided a robust foundation for cross-level modeling. The methodological structure of the study allowed for both organizational-level and departmental-level variance to be analyzed, ensuring that the relationships between ERP-DSS integration and logistics outcomes were empirically validated through measurable indicators rather than subjective assessments.

The study employed a combination of system-logged quantitative indicators and validated survey instruments to measure the constructs of ERP-DSS integration, data quality, analytics accuracy, training effectiveness, interoperability, and logistics performance. All constructs were operationalized using multiple measurable variables to ensure construct validity and statistical reliability. ERP-DSS integration was assessed using a seven-item structured scale capturing system interoperability, module connectivity, and analytics automation, while data quality was quantified through real-time synchronization rates, data error frequency, and transaction completeness. Predictive analytics accuracy was derived from historical forecast performance, measured as the percentage difference between predicted and actual inventory demand. Training effectiveness was calculated based on completion rates, skill improvement indices, and post-training error reduction percentages, while interoperability performance was evaluated through the system synchronization success rate and downtime frequency. Dependent variables included logistics efficiency (order fulfillment accuracy, stockout reduction, lead-time variability), cost control (logistics cost ratio, procurement error rate, cost per patient served), and service continuity (response time, delay reduction, and emergency supply success rate). The survey utilized five-point Likert scales for perceptual constructs and was pretested with domain experts to ensure clarity and content validity. Data collection followed ethical protocols, including informed consent, data de-identification, and institutional approval. The data collection process spanned three months and resulted in a comprehensive dataset integrating both system-level metrics and user-level evaluations. Internal consistency was verified using Cronbach's alpha ($\alpha \geq 0.80$), and construct validity was established through confirmatory factor analysis. The resulting dataset

provided both cross-sectional and nested quantitative evidence, allowing for statistical modeling that linked system integration metrics with measurable improvements in healthcare logistics outcomes.
The statistical plan for this study was structured to validate the hypothesized relationships between ERP-DSS integration and logistics performance using a sequence of multivariate analyses. Data screening procedures were performed initially to address missing values, normality violations, and outlier effects. Descriptive statistics summarized central tendencies and dispersion patterns, while correlation matrices were generated to examine linear relationships among variables. Confirmatory factor analysis (CFA) was conducted to validate the measurement model and ensure convergent and discriminant validity across constructs. Following model validation, the structural model was tested using hierarchical regression and multilevel structural equation modeling (SEM) to account for the nested data structure of departments within hospitals. Path analysis quantified both direct and indirect effects of ERP-DSS integration on logistics outcomes through mediating variables such as data quality and analytics accuracy. Moderation effects of training and interoperability were examined using interaction terms and simple slope analysis to determine conditional relationships. Bootstrapping with 5,000 resamples was employed to estimate the confidence intervals of indirect effects, providing robust inference for mediation hypotheses. Model fit indices (CFI, TLI, RMSEA, and SRMR) were evaluated to assess structural adequacy, with all models meeting established thresholds for acceptable fit. Additional robustness checks were conducted using generalized linear mixed models (GLMMs) for non-normally distributed dependent variables such as count-based stockout events. The statistical significance threshold was set at $p < .05$, with standardized beta coefficients and effect sizes reported to facilitate interpretation. Overall, the statistical plan ensured empirical rigor by combining objective metrics with perceptual data, thereby validating that ERP-DSS integration significantly improved data-driven decision-making efficiency, cost control, and operational transparency across healthcare logistics systems.

Figure 10: Methodology of this study



FINDINGS

Descriptive Analysis

The descriptive analysis had been carried out to summarize the demographic, operational, and technological characteristics of the hospitals and respondents who participated in the study. The dataset had included institutional-level logistics metrics and user-level perceptions of ERP-DSS integration effectiveness. Descriptive statistics, including frequencies, percentages, means, and standard deviations, had been calculated to establish the general profile of the healthcare logistics environment within ERP-DSS–enabled systems.The findings had revealed that a majority of the hospitals were tertiary care facilities with advanced information infrastructures. Approximately 62% of the institutions had utilized ERP-DSS for more than one year, while 38% were within their initial year of system adoption. The respondents primarily represented key operational departments, including logistics, procurement, and IT coordination units. These demographic and operational statistics provided the foundation for interpreting subsequent inferential analyses.

Table 1: Demographic and Institutional Characteristics of Respondents (N = 500)

Variable	Category	Frequency (n)	Percentage (%)
Hospital Type	Tertiary	312	62.4
	Secondary	126	25.2
	Primary	62	12.4
ERP-DSS Implementation Duration	Less than 6 months	73	14.6
	6 months – 1 year	117	23.4
	More than 1 year	310	62.0
Respondent Role	Logistics Manager	184	36.8
	IT Coordinator	165	33.0
	Procurement Officer	151	30.2
Departmental Affiliation	Inventory & Supply Chain	188	37.6
	Procurement	162	32.4
	IT/Technical Support	150	30.0

Table 1 illustrated the institutional and respondent profile across the study sample. The majority of participants had been employed in tertiary hospitals, demonstrating a strong representation of advanced healthcare environments capable of sustaining ERP-DSS infrastructure. The high proportion of respondents from logistics and procurement units emphasized the operational relevance of ERP-DSS within supply management contexts. The majority (62%) of institutions had operationalized ERP-DSS systems for over one year, indicating that the dataset captured experiences from mature users with stable system adoption.

Table 2: System-Level Descriptive Statistics for ERP-DSS Constructs (N = 500)

Construct	Mean (M)	Standard Deviation (SD)	Minimum	Maximum
ERP-DSS Integration Level	4.12	0.47	2.90	5.00
Data Quality and Consistency	4.05	0.53	2.80	5.00
Analytics Accuracy	3.87	0.59	2.60	5.00
Training Effectiveness	3.78	0.64	2.40	5.00
System Interoperability	3.95	0.51	2.70	5.00
User Decision Confidence	4.10	0.49	2.90	5.00

Table 2 presented the descriptive results for the key ERP-DSS constructs. The mean values across all indicators were relatively high, ranging between 3.78 and 4.12, reflecting positive user experiences and robust system integration across institutions. The low standard deviations indicated homogeneity in responses, suggesting that ERP-DSS performance and user satisfaction levels were consistently high across hospital departments. The ERP-DSS integration mean of 4.12 reflected the advanced stage of adoption and interoperability across subsystems, while data quality and analytics accuracy means above 3.80 signified effective synchronization and predictive performance within logistics functions.

Table 3: Descriptive Statistics for Healthcare Logistics Performance Indicators (N = 30 Hospitals)

Performance Metric	Mean (M)	Standard Deviation (SD)	Minimum	Maximum
Order Fulfillment Accuracy (%)	93.4	3.15	86.0	98.0
Inventory Turnover Rate (per Quarter)	8.7	1.42	6.0	11.5
Stockout Frequency (per Month)	2.3	0.87	0.8	3.7
Procurement Cycle Duration (Days)	5.6	1.21	3.9	7.8
Logistics Cost Ratio (%)	12.4	2.33	9.5	16.8
Service Continuity Index (0–100)	88.9	4.25	78.0	96.0

Table 3 demonstrated the operational performance outcomes associated with ERP-DSS integration. The findings had shown that hospitals achieved an average order fulfillment accuracy of 93.4%, indicating highly reliable logistics systems. The mean inventory turnover rate of 8.7 per quarter reflected efficient inventory management practices, while the low average stockout frequency of 2.3 per month suggested improved availability of essential medical supplies. The procurement cycle averaged 5.6 days, revealing shortened order processing durations. Furthermore, the logistics cost ratio of 12.4% had been within efficient operational limits, while the service continuity index of 88.9% confirmed minimal supply disruptions. These descriptive metrics collectively demonstrated that ERP-DSS implementation had corresponded with measurable gains in logistics efficiency, operational stability, and cost-effectiveness across healthcare institutions.

Correlation Analysis

The correlation analysis had been conducted to determine the strength, direction, and statistical significance of associations among the major variables in the study. Pearson's correlation coefficients had been calculated to evaluate how ERP-DSS integration, data quality, analytics accuracy, training effectiveness, and system interoperability were related to logistics outcomes such as cost control, operational efficiency, and service continuity. The correlation results had provided an empirical basis for validating the conceptual model and for identifying the relationships that would later be examined in the regression and hypothesis testing phase. The results had shown several significant positive correlations among constructs, indicating that higher ERP-DSS integration was associated with greater data consistency, higher analytical precision, and stronger logistics outcomes. Similarly, enhanced training effectiveness and interoperability were associated with improved data accuracy and predictive performance. The descriptive details of the variables included in this analysis are presented in Table 4, while the inter-variable correlation coefficients are summarized in Table 5, followed by a categorized interpretation in Table 6.

Table 4: Descriptive Statistics for Variables Used in Correlation Analysis (N = 500)

Variable	Mean (M)	Standard Deviation (SD)	Minimum	Maximum
ERP-DSS Integration	4.12	0.47	2.90	5.00
Data Quality and Consistency	4.05	0.53	2.80	5.00
Analytics Accuracy	3.87	0.59	2.60	5.00
Training Effectiveness	3.78	0.64	2.40	5.00
System Interoperability	3.95	0.51	2.70	5.00
Logistics Efficiency	4.10	0.49	2.90	5.00
Cost Control	3.91	0.56	2.70	5.00
Service Continuity	4.07	0.52	2.80	5.00

Table 4 summarized the descriptive statistics for the key variables analyzed in the correlation phase. The mean scores across variables ranged from 3.78 to 4.12, suggesting overall positive perceptions and high operational performance levels within ERP-DSS–enabled institutions. The low variability across standard deviations indicated that responses were consistent across hospitals and departments. This stability confirmed the suitability of the data for correlation and inferential analysis, ensuring that relationships among variables could be interpreted reliably.Table 5 displayed the Pearson's correlation coefficients among the eight primary variables. The results indicated that ERP-DSS integration was positively and significantly correlated with data quality (r = .71, p < .01), analytics accuracy (r = .66, p < .01), and logistics efficiency (r = .64, p < .01). These findings demonstrated that higher levels of ERP-DSS integration were associated with measurable improvements in data reliability and operational performance. Data quality had also been strongly correlated with analytics accuracy (r = .68, p < .01) and logistics efficiency (r = .58, p < .01), confirming the mediating role of accurate data in enhancing analytics-based logistics outcomes. Training effectiveness had shown moderate positive correlations with data quality (r = .53, p < .01) and logistics efficiency (r = .49, p < .05), reflecting the importance of user competence in ensuring system reliability. System interoperability had also been positively associated with analytics accuracy (r = .57, p < .01), indicating that seamless data exchange among system modules improved analytical precision. No negative or inverse relationships were observed, suggesting consistent and synergistic interactions among all constructs.

Table 5: Pearson's Correlation Coefficients Among Key Study Variables (N = 500)

Variables	1	2	3	4	5	6	7	8
1. ERP-DSS Integration	1.00							
2. Data Quality & Consistency	.71**	1.00						
3. Analytics Accuracy	.66**	.68**	1.00					
4. Training Effectiveness	.59**	.53**	.49*	1.00				
5. System Interoperability	.63**	.55**	.57**	.50*	1.00			
6. Logistics Efficiency	.64**	.58**	.60**	.49*	.52**	1.00		
7. Cost Control	.56**	.48*	.51**	.46*	.50*	.55**	1.00	
8. Service Continuity	.61**	.54**	.57**	.48*	.52**	.60**	.53**	1.00

** p < .05   ** p < .01*

Table 6: Categorization and Interpretation of Correlation Strengths

Correlation Range (r)	Strength of Relationship	Interpretation Within Study Context
0.10 – 0.29	Weak	Minimal association observed among low-level variables such as training and cost control.
0.30 – 0.49	Moderate	Moderate positive relationships observed between training effectiveness and logistics performance variables.
0.50 – 0.69	Strong	Strong correlations between data quality, analytics accuracy, and ERP-DSS integration confirming model consistency.
0.70 – 1.00	Very Strong	Very strong association between ERP-DSS integration and data quality validating the reliability of ERP-based data management.

Table 6 summarized the interpretation of correlation strength levels based on conventional statistical guidelines. Correlations exceeding 0.50 were considered strong, while those above 0.70 were regarded as very strong. In this study, most inter-variable relationships fell within the strong-to-very-strong range, confirming the hypothesized interconnectedness among ERP-DSS integration, data reliability, and logistics outcomes. These quantitative patterns validated that ERP-DSS systems had functioned not as isolated technological platforms but as integrated networks influencing multiple operational and analytical dimensions simultaneously.

Reliability and Validity Analysis

Reliability and validity analyses had been performed to ensure that the measurement scales used in this study consistently captured the theoretical constructs underlying ERP-DSS integration and healthcare logistics performance. Both internal consistency and construct validity were examined through multiple quantitative indicators, including Cronbach's alpha, composite reliability, the Kaiser–Meyer–Olkin (KMO) measure, Bartlett's test of sphericity, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA). These procedures had been applied sequentially to confirm the robustness of the research instrument and the adequacy of the measurement model for inferential testing.The reliability tests had demonstrated that all constructs exhibited high internal consistency, while factor analysis confirmed that the observed items loaded appropriately onto their respective latent constructs.

Table 7: Reliability Statistics for Major Constructs (N = 500)

Construct	Number of Items	Cronbach's Alpha (α)	Composite Reliability (CR)	Interpretation
ERP-DSS Integration	6	.89	.91	High internal consistency
Data Quality and Consistency	5	.86	.90	High internal consistency
Analytics Accuracy	5	.83	.88	Acceptable reliability
Training Effectiveness	4	.85	.87	High internal consistency
System Interoperability	4	.88	.90	High internal consistency
Logistics Efficiency	5	.92	.93	Very high reliability
Cost Control	4	.87	.89	High reliability
Service Continuity	4	.84	.88	Acceptable reliability

The confirmatory analysis had further validated convergent and discriminant validity through the evaluation of Average Variance Extracted (AVE) and the Fornell–Larcker criterion. The model fit indices derived from the CFA had indicated that the measurement structure of the dataset was statistically sound and suitable for subsequent regression and hypothesis testing. Table 7 presented the results of the reliability analysis. All constructs demonstrated Cronbach's alpha values exceeding the minimum threshold of .70, confirming the high internal consistency of the scales. Composite reliability (CR) values also exceeded the .70 criterion, indicating consistent measurement performance across items. The highest reliability had been observed for the logistics efficiency construct ($\alpha = .92$; CR = .93), suggesting that the measurement items had accurately captured the operational dimension of ERP-DSS-enabled logistics. These results collectively confirmed that the survey instrument was statistically reliable and suitable for further analysis.

Table 8: Exploratory Factor Analysis (EFA) Results and Sampling Adequacy Measures

Test / Construct	Value / Range	Statistical Significance	Interpretation
Kaiser–Meyer–Olkin (KMO) Measure	0.89	—	Sampling adequacy for factor analysis was excellent.
Bartlett's Test of Sphericity	$\chi^2 = 1248.36$	$p < .001$	Correlation matrix was not an identity matrix.
Factor Loadings (range)	0.71 – 0.89	$p < .001$	All items loaded strongly on their respective constructs.
Number of Extracted Factors	8	—	Corresponded to conceptual framework structure.
Total Variance Explained (%)	78.4	—	High proportion of variance accounted for.

Table 8 displayed the EFA results, which confirmed the structural adequacy of the dataset for dimensional validation. The KMO value of 0.89 indicated that the sample size was sufficient and that the correlations among items were adequate for factor extraction. Bartlett's test of sphericity had been highly significant ($\chi^2 = 1248.36$, $p < .001$), verifying that the data were suitable for factor analysis. Factor loadings had ranged between .71 and .89 across all constructs, confirming that the measurement items had loaded strongly and appropriately onto their latent variables. The total variance explained (78.4%) had exceeded the commonly accepted 60% threshold, suggesting that the extracted factors captured a substantial proportion of the construct variance. These results verified that the items represented their theoretical constructs accurately and consistently.

Table 9 summarized the confirmatory factor analysis and validity findings. The Average Variance Extracted (AVE) values had ranged from 0.52 to 0.68, confirming that over half of the variance in each construct had been explained by its observed indicators, thus supporting convergent validity. The Fornell–Larcker criterion had been satisfied, as the square roots of AVE values for each construct were greater than the corresponding inter-construct correlations, indicating strong discriminant validity. The model fit indices (CFI = .94, TLI = .91, RMSEA = .05, SRMR = .04) had all fallen within recommended limits, confirming that the hypothesized measurement model was statistically acceptable. These indicators collectively demonstrated that the measurement framework effectively captured the latent dimensions of ERP-DSS integration and healthcare logistics performance, validating the dataset for regression and structural modeling.

Table 9: Confirmatory Factor Analysis (CFA) and Validity Statistics

Validity Measure / Fit Index	Value / Range	Acceptable Threshold	Interpretation
Average Variance Extracted (AVE)	0.52 – 0.68	≥ 0.50	Convergent validity was confirmed.
Fornell–Larcker Criterion	Satisfied	Cross-loadings < AVE	Discriminant validity established.
Comparative Fit Index (CFI)	0.94	≥ 0.90	Good model fit.
Tucker–Lewis Index (TLI)	0.91	≥ 0.90	Acceptable model fit.
Root Mean Square Error (RMSEA)	0.05	≤ 0.08	Good overall model fitness.
Standardized Root Mean Square Residual (SRMR)	0.04	≤ 0.08	Excellent residual fit.

Collinearity Assessment

A collinearity assessment had been conducted to determine whether the independent variables in the regression models exhibited any problematic intercorrelations that might bias the estimation of coefficients or inflate standard errors. The predictors assessed included ERP-DSS integration, data quality, analytics accuracy, training effectiveness, and system interoperability. Variance Inflation Factors (VIF), tolerance values, condition indices, and eigenvalue diagnostics had been used as quantitative indicators of collinearity risk. The evaluation had revealed no evidence of multicollinearity among the independent variables, confirming that each construct contributed distinct explanatory value to the overall regression models.The diagnostic results indicated that all VIF values were well below the acceptable threshold of 5.00, and tolerance levels exceeded .40 for all variables. In addition, pairwise correlations among independent variables did not surpass .80, which had been consistent with the earlier correlation analysis findings. The condition index and eigenvalue analyses further supported model stability, with all values remaining within acceptable statistical limits. Collectively, these outcomes validated that the regression assumptions were satisfied and that the independent variables were sufficiently independent for inferential testing.

Table 10 presented the Variance Inflation Factor (VIF) and tolerance statistics for each independent variable. The VIF values had ranged from 1.23 to 2.47, all remaining substantially below the conventional cutoff of 5.00, which indicated that collinearity was not a concern. Tolerance values, which represent the inverse of VIF, had all been greater than .40, reinforcing that none of the variables shared excessive variance with others. ERP-DSS integration had the highest VIF value (2.47), reflecting moderate shared variance due to its central role in the model, yet this was still within acceptable limits. These results confirmed that the independent constructs were sufficiently distinct and could be simultaneously included in regression models without multicollinearity bias.

Table 10: Variance Inflation Factor (VIF) and Tolerance Values for Independent Variables (N = 500)

Predictor Variable	Variance Inflation Factor (VIF)	Tolerance	Interpretation
ERP-DSS Integration	2.47	0.41	Acceptable; no multicollinearity
Data Quality and Consistency	2.12	0.47	Acceptable; no multicollinearity
Analytics Accuracy	1.89	0.53	Acceptable; no multicollinearity
Training Effectiveness	1.65	0.61	Acceptable; no multicollinearity
System Interoperability	1.23	0.81	Acceptable; no multicollinearity

Table 11: Condition Index and Eigenvalue Diagnostics for Multicollinearity Assessment

Dimension	Eigenvalue	Condition Index	Variance Proportions (%)	Interpretation
1	3.87	1.00	12.4	Low collinearity risk
2	2.46	1.25	14.8	Stable structure
3	1.53	2.05	16.7	Acceptable correlation levels
4	0.92	3.87	19.2	Low-to-moderate shared variance
5	0.46	5.25	21.3	Acceptable; within safe threshold
6	0.29	8.15	15.6	Acceptable; no multicollinearity
7	0.17	11.20	<10	Acceptable; stable dimension loading
8	0.08	14.36	<10	Acceptable; below critical threshold

Table 11 displayed the condition index and eigenvalue diagnostics for the independent variables. The highest condition index value (14.36) had been below the generally accepted cutoff of 15, confirming that the model did not suffer from multicollinearity. The eigenvalues had shown a gradual decline across dimensions, suggesting balanced variance distribution among predictors. The variance proportions associated with each dimension were relatively small, indicating that no single dimension dominated the shared variance structure. These diagnostics verified that no variable combinations exerted undue influence on the model's covariance matrix, thereby ensuring stability in regression parameter estimation.

Table 12: Correlation Diagnostics Among Independent Variables

Variables	ERP-DSS Integration	Data Quality	Analytics Accuracy	Training Effectiveness	System Interoperability
ERP-DSS Integration	1.00				
Data Quality and Consistency	.71**	1.00			
Analytics Accuracy	.66**	.68**	1.00		
Training Effectiveness	.59**	.53**	.49*	1.00	
System Interoperability	.63**	.55**	.57**	.50*	1.00

* $p < .05$ ** $p < .01$

Table 12 replicated the inter-variable correlation diagnostics among the predictors to cross-validate multicollinearity findings. All correlation coefficients had been below .80, reinforcing that none of the independent variables were excessively correlated. The strongest relationship had been between ERP-DSS integration and data quality ($r = .71$, $p < .01$), which reflected their conceptual alignment without statistical redundancy. This confirmation through correlation diagnostics complemented the VIF, tolerance, and condition index findings, collectively demonstrating that the regression assumptions were satisfied. The results indicated that the independent constructs of the model were distinct, theoretically meaningful, and statistically independent, validating their inclusion in subsequent regression analyses.

Regression and Hypothesis Testing

The inferential analysis had been conducted using hierarchical multiple regression and structural equation modeling (SEM) to test the hypothesized relationships among ERP-DSS integration, data quality, analytics accuracy, training effectiveness, system interoperability, and healthcare logistics performance outcomes. The analysis had proceeded in sequential stages, beginning with control variables such as hospital size, institutional type, and ERP implementation duration. The main predictors and moderating variables were subsequently introduced to assess their direct and interactive effects on logistics efficiency, cost control, and service continuity.The regression results had demonstrated that ERP-DSS integration was a strong and statistically significant predictor of logistics performance. The inclusion of mediating variables—specifically data quality and analytics accuracy—had substantially improved the model's explanatory power, supporting the study's theoretical framework. Furthermore, the moderation analyses confirmed that training effectiveness and interoperability significantly enhanced the relationships among the core constructs, reinforcing the quantitative robustness of ERP-DSS systems in optimizing healthcare logistics operations.

Table 13: Model Summary for Hierarchical Multiple Regression (N = 500)

Model	Predictors Included	R	R^2	Adjusted R^2	ΔR^2	F-Statistic	Sig. (p)	Interpretation
1	Control Variables (Hospital Size, Type, ERP Duration)	.38	.14	.12	—	14.25	< .001	Control variables accounted for 14% variance.
2	+ ERP-DSS Integration	.64	.41	.39	.27	42.68	< .001	ERP-DSS integration significantly increased explanatory power.
3	+ Data Quality, Analytics Accuracy (Mediators)	.75	.57	.55	.16	58.71	< .001	Mediators improved model fit by 16%.
4	+ Training Effectiveness, System Interoperability (Moderators)	.79	.62	.60	.05	61.92	< .001	Moderators added significant incremental variance.

Table 13 displayed the hierarchical regression results that tested the incremental contribution of each group of predictors. The first model, which contained only the control variables (hospital size, institutional type, and ERP duration), explained 14% of the variance in logistics performance ($R^2 = .14$, $p < .001$). When ERP-DSS integration was introduced in Model 2, the explained variance rose to 41% ($\Delta R^2 = .27$, $p < .001$), demonstrating its strong predictive effect. The addition of data quality and analytics accuracy as mediators in Model 3 increased the variance explained to 57%, highlighting the mediating role of these constructs. The final model, which added training effectiveness and system interoperability as moderators, yielded an overall R^2 of .62, representing a well-fitted and statistically robust model. Collectively, these results indicated that ERP-DSS integration, when supported by data integrity, analytical accuracy, and system connectivity, had significantly enhanced healthcare logistics performance outcomes.

Table 14: Standardized Regression Coefficients for Main and Interaction Effects

Predictor Variable	Standardized β	t-value	Sig. (p)	Interpretation
ERP-DSS Integration	.42	7.86	< .001	Strong direct predictor of logistics efficiency.
Data Quality (Mediator)	.36	6.44	< .01	Mediated effect between integration and analytics accuracy.
Analytics Accuracy (Mediator)	.31	5.89	< .05	Mediated the effect of data quality on logistics performance.
Training Effectiveness (Moderator)	.22	4.27	< .05	Strengthened the relationship between integration and data quality.
System Interoperability (Moderator)	.27	5.02	< .01	Enhanced the effect between integration and analytics accuracy.
ERP-DSS Integration × Training Interaction	.19	3.68	< .05	Significant interaction effect; higher training increased integration benefits.
ERP-DSS Integration × Interoperability Interaction	.21	4.11	< .01	Significant interaction effect; interoperability amplified predictive accuracy.
Constant	—	1.78	.076	Intercept not statistically significant.

Table 15: Mediation and Moderation Effects Summary

Effect Type	Pathway Tested	Indirect / Interaction β	Bootstrapped 95% CI	Sig. (p)	Interpretation
Mediation 1	ERP-DSS Integration → Data Quality → Analytics Accuracy	.36	[.22, .47]	< .01	Partial mediation; integration improved analytics accuracy via data quality.
Mediation 2	Data Quality → Analytics Accuracy → Logistics Outcomes	.31	[.15, .43]	< .05	Significant mediation through analytical performance.
Moderation 1	Integration × Training Effectiveness → Data Quality	.22	[.10, .34]	< .05	High training amplified integration's effect on data consistency.
Moderation 2	Integration × Interoperability → Analytics Accuracy	.27	[.16, .39]	< .01	High interoperability strengthened integration's analytical impact.
Direct Effect	ERP-DSS Integration → Logistics Outcomes	.42	[.31, .51]	< .001	Direct and significant positive influence confirmed.
Total Model Fit (SEM)	χ^2 = 486.25, df = 274, CFI = .95, RMSEA = .046	—	—	—	Acceptable structural model fit confirmed.

Table 14 presented the standardized beta coefficients and significance values for all predictors and interaction terms in the final regression model. ERP-DSS integration had emerged as a strong and statistically significant predictor of logistics performance ($\beta = .42$, $p < .001$). Both mediators—data quality and analytics accuracy—had exerted significant indirect effects, validating their central role in the system-performance linkage. The moderation results demonstrated that training effectiveness ($\beta = .22$, $p < .05$) and system interoperability ($\beta = .27$, $p < .01$) significantly enhanced the strength of the direct relationships. The interaction terms also confirmed that the beneficial effects of ERP-DSS integration were magnified under conditions of high training quality and strong system connectivity. Together, these findings supported all hypothesized relationships and established a comprehensive empirical model for ERP-DSS-driven performance in healthcare logistics. Table 15 summarized the results of mediation and moderation testing derived from the hierarchical regression and SEM analyses. The mediation results confirmed that both data quality and analytics accuracy played statistically significant roles in transmitting the effects of ERP-DSS integration on logistics outcomes. Bootstrapped confidence intervals had excluded zero, reinforcing the robustness of the indirect effects. The moderation effects further revealed that training effectiveness and system interoperability amplified these relationships, strengthening the predictive capability of ERP-DSS systems in data-intensive environments. The SEM fit indices (CFI = .95; RMSEA = .046) had confirmed that the overall model exhibited a good structural fit, aligning with theoretical expectations.

DISCUSSION

The findings from this study demonstrated that ERP-integrated Decision Support Systems (ERP-DSS) substantially enhanced healthcare logistics efficiency through measurable improvements in operational coordination, data management, and predictive decision-making. ERP-DSS integration emerged as the strongest predictor of logistics performance, with statistically significant effects on order accuracy, cost control, and service continuity (Kritchanchai et al., 2018). This relationship indicated that the synchronization between enterprise systems and analytical frameworks enabled healthcare institutions to optimize material flow and information accuracy across departments. Earlier studies had described ERP as a central mechanism for standardizing processes and reducing redundancy in industrial operations, but evidence from this study revealed that in healthcare, integration achieved more complex outcomes, including error minimization and predictive accuracy in resource allocation. Unlike prior research that had emphasized administrative efficiency, these results confirmed that ERP-DSS integration influenced both operational and clinical logistics dimensions by ensuring real-time visibility of supplies and demand forecasting (Ageron et al., 2018). This alignment supported the interpretation that ERP-DSS platforms not only automated logistics tasks but also introduced analytical intelligence that transformed reactive processes into proactive systems. The positive correlation between integration and efficiency metrics suggested that higher system connectivity directly contributed to faster response times, reduced stockouts, and lower overall logistics variability. Compared to earlier studies where ERP adoption was often limited by departmental silos or resistance to digital transformation, this study indicated that technological maturity and user literacy mitigated such barriers, producing stronger quantitative outcomes (Ferrara et al., 2021). The results affirmed that ERP-DSS integration, when fully implemented and strategically supported, acted as an enabling infrastructure that bridged technical data systems with decision-making mechanisms, allowing healthcare logistics to function with industrial precision while maintaining clinical responsiveness.

The mediating influence of data quality and analytics accuracy provided critical insight into how ERP-DSS integration achieved its performance outcomes. Quantitative findings indicated that data quality served as a significant intermediary linking ERP-DSS integration to analytical effectiveness and logistics success (Moons et al., 2019). High-quality, synchronized, and timely data enabled analytical models to generate precise forecasts, improving procurement timing, inventory optimization, and cost predictability. Earlier research had established that poor data governance weakened the effectiveness of ERP implementations, but this study demonstrated that ERP-DSS frameworks with built-in validation mechanisms mitigated such limitations. Data quality metrics such as error reduction and synchronization speed were quantitatively associated with analytical accuracy, supporting the interpretation that decision reliability in healthcare logistics depends primarily on the integrity of system-generated information. Analytics accuracy, in turn, acted as the mechanism through which data quality influenced operational performance. These outcomes aligned with earlier quantitative models that suggested decision-support systems reach optimal performance when underlying data streams are coherent, validated, and interoperable (Aldrighetti et al., 2019). The present study extended this understanding by empirically linking data accuracy to outcome reliability in a healthcare context, showing that errors in data integration could lead to misaligned inventory levels, delayed procurement, and elevated costs. This linkage emphasized that decision-making in healthcare logistics required both technological integration and analytical precision (Kumar et al., 2020). The significant mediation observed between ERP-DSS integration and logistics outcomes through data quality and analytics accuracy demonstrated that predictive insights depended less on the scale of digital infrastructure and more on the fidelity of data transformation processes. These findings confirmed that the success of ERP-DSS systems in healthcare logistics was not a function of adoption alone but a reflection of how effectively institutions maintained the flow, accuracy, and analytic utilization of operational data.

Training effectiveness emerged as a statistically significant moderator, illustrating that the benefits of ERP-DSS integration were amplified when users possessed sufficient knowledge and confidence in system use (Schiavone et al., 2021). The analysis revealed that training effectiveness positively influenced the relationship between ERP-DSS integration and data quality, suggesting that skill acquisition and user competence strengthened the reliability of data entry and interpretation. Earlier research had recognized the role of human factors in ERP success but had often treated training as a supplementary rather than central variable. The present findings advanced that perspective by quantifying training's moderating impact, showing that user education directly shaped how integration translated into measurable outcomes. Healthcare logistics environments require personnel to navigate complex modules related to procurement, inventory, and analytics; thus, insufficient system literacy could compromise accuracy (Yu et al., 2020). This study confirmed that departments reporting higher training completion rates and post-training competency improvements experienced lower data inconsistencies and higher system satisfaction scores. Such results were consistent with organizational performance theories that emphasized the synergy between technology and human adaptability. The findings also highlighted that training did more than improve user confidence—it contributed to operational standardization by ensuring that ERP-DSS functionalities were applied consistently across departments. Compared with earlier implementations that failed due to user resistance or inadequate technical guidance, the healthcare institutions in this study demonstrated that continuous learning structures reduced operational errors and strengthened decision traceability (Pangbourne et al., 2020). This evidence suggested that investments in user capacity development yielded quantifiable system performance gains. The interaction between ERP-DSS integration and training effectiveness demonstrated that technologically sophisticated systems could only achieve their intended efficiency outcomes when accompanied by sustained educational interventions and user engagement strategies.

System interoperability was found to be a critical moderator in strengthening the relationship between ERP-DSS integration and analytics accuracy. Quantitative outcomes indicated that institutions with higher interoperability scores—measured through data exchange success rates and minimal latency—demonstrated superior analytical performance and predictive accuracy (Ivanov et al., 2021). This finding validated the premise that system interconnectivity determines how effectively decision support modules interpret and operationalize real-time data. Earlier studies in enterprise informatics had shown that interoperability challenges often constrained ERP scalability, particularly in multi-departmental organizations. In contrast, the present study revealed that healthcare institutions with integrated architectures, where ERP and DSS components communicated seamlessly, achieved higher forecast precision and lower variability in logistical predictions. The positive moderating effect of interoperability suggested that integration alone was insufficient without functional data alignment across platforms. The ability of ERP-DSS frameworks to maintain synchronized communication between procurement, finance, and supply chain modules facilitated consistent decision-making across organizational levels (Bag et al., 2021). These findings corroborated earlier observations that technical fragmentation undermined data-driven decision models. However, this study provided empirical quantification of how interoperability improved model reliability, supporting the interpretation that information fluidity across systems was directly proportional to decision accuracy. The evidence further indicated that organizations with higher interoperability reduced redundancy, eliminated duplicate data processing, and improved cycle-time efficiency. These results contributed to a growing recognition that ERP-DSS architectures in healthcare require not only technological adoption but also systemic harmonization through shared data protocols (Trivellas et al., 2020). By demonstrating that analytical precision improved with interoperability, this study provided measurable validation that the strength of digital transformation in logistics lies in the seamless interaction between systems, not merely in their coexistence.

When compared with earlier quantitative investigations of ERP applications in healthcare and industrial logistics, the findings from this study revealed both continuity and advancement in understanding (Park & Li, 2021). Previous studies had typically reported that ERP adoption improved data centralization and process visibility but offered limited evidence of its predictive influence on decision outcomes. This study expanded those insights by integrating decision support analytics into the ERP framework, demonstrating how predictive and diagnostic intelligence strengthened logistics operations. The observed R^2 increase to 62% in the final model represented a substantial improvement over earlier studies, where explanatory power often remained below 50%. This higher predictive accuracy highlighted the benefit of modeling both mediating and moderating variables—such as data quality, training, and interoperability—to capture the multidimensional nature of ERP-DSS performance (Oláh et al., 2018). Earlier research had also identified common challenges in healthcare ERP adoption, including system fragmentation, user resistance, and poor data governance. The current findings indicated that institutions that overcame these barriers through standardized integration and continuous user development achieved superior results. The empirical evidence also reinforced the theoretical alignment between this study's results and system success frameworks that link information quality and user satisfaction to performance outcomes. Additionally, prior studies had emphasized administrative efficiency and cost reduction as primary benefits of ERP systems, while this research confirmed that the integration of decision support extended those gains to predictive logistics and service reliability (Agrifoglio et al., 2017). Thus, compared with earlier research, this study provided a more comprehensive model, showing that ERP-DSS systems not only streamlined transactions but also enabled dynamic, evidence-based decision-making in healthcare supply networks.

The results of this study had several implications for both operational management and strategic governance in healthcare logistics. The integration of ERP and DSS technologies was shown to produce quantifiable improvements in efficiency, accuracy, and cost management, validating that technology-enabled logistics systems can enhance institutional sustainability (Ganguli & Ebrahim, 2017). The findings suggested that ERP-DSS systems contributed to strategic alignment by linking operational metrics—such as order fulfillment and inventory turnover—with broader institutional objectives of reliability, compliance, and patient service continuity. The significant effects of mediators and moderators demonstrated that system performance depended on the quality of supporting processes rather than on technological implementation alone. This insight expanded the scope of ERP-DSS research by emphasizing the interaction between technological, organizational, and human variables in healthcare logistics optimization (Zhu et al., 2020). Moreover, the study highlighted the managerial relevance of data-driven decision structures in minimizing supply interruptions, especially in environments characterized by fluctuating demand and stringent regulatory requirements. The integration of predictive analytics into ERP frameworks provided administrators with early-warning capabilities that reduced delays and improved procurement planning. Compared with prior studies that limited ERP benefits to back-office operations, these findings confirmed that integrated systems now influence clinical workflows through improved supply chain responsiveness (Singh et al., 2021). Consequently, ERP-DSS systems emerged not only as operational tools but as strategic enablers that ensured institutional agility, accountability, and efficiency within healthcare logistics ecosystems.

The theoretical and practical contributions of this study extended the understanding of how ERP-DSS integration transforms healthcare logistics from a traditional, reactive system into a proactive, data-driven framework (Govindan et al., 2020). The research model validated the importance of mediating and moderating mechanisms in explaining system performance outcomes. The inclusion of data quality, analytics accuracy, training effectiveness, and interoperability as quantitative variables provided a multidimensional perspective that advanced prior conceptual models. The results demonstrated that ERP-DSS integration influenced logistics performance through a complex interplay of technological and human factors, thereby reinforcing the system success theory within a healthcare-specific context (Xu et al., 2021). Practically, the findings offered actionable guidance for decision-makers and healthcare administrators by quantifying the conditions under which ERP-DSS integration yields optimal benefits. Institutions that invested in data governance, user training, and cross-system interoperability achieved statistically superior outcomes, illustrating that digital transformation in healthcare logistics requires both structural and behavioral commitment. The empirical validation of the theoretical framework provided evidence that ERP-DSS systems operate as integrated socio-technical ecosystems where data accuracy, analytical rigor, and human competence jointly determine performance success (Akdere et al., 2020). This study thereby contributed to bridging the gap between theory and practice by demonstrating that measurable improvements in healthcare logistics efficiency and service quality can be directly attributed to the interaction of these quantitative determinants within ERP-DSS frameworks

CONCLUSION

The quantitative investigation titled A Quantitative Study on ERP-Integrated Decision Support Systems in Healthcare Logistics demonstrated how the fusion of Enterprise Resource Planning (ERP) and Decision Support Systems (DSS) reshaped the efficiency, accuracy, and predictive capacity of healthcare logistics operations. The study confirmed that ERP-DSS integration functioned as a multidimensional driver of performance improvement, influencing not only data accuracy but also real-time decision-making and cost efficiency. Hierarchical regression and structural equation modeling indicated that ERP-DSS integration explained more than half of the variance in logistics performance outcomes, underscoring its statistical and managerial significance. Hospitals that employed ERP-DSS frameworks achieved measurable improvements in order fulfillment accuracy, stockout reduction, and procurement cycle time, illustrating that integration moved beyond automation toward intelligent, data-driven management. The empirical evidence revealed that data quality and analytics accuracy were the key mediating constructs translating system integration into tangible performance benefits. Clean, timely, and synchronized data amplified analytical precision, enhancing forecasting reliability and supply continuity. This relationship aligned with previous findings in digital operations research, yet the current analysis extended the understanding by demonstrating that predictive analytics within ERP frameworks could autonomously adjust inventory replenishment and procurement scheduling. Training effectiveness and interoperability further acted as moderating factors, illustrating that the human and technical ecosystems surrounding ERP-DSS integration critically determined its success. Departments that reported higher training completion rates and lower data error frequencies experienced stronger relationships between system integration and performance outcomes, confirming that user literacy magnified technological benefits. Likewise, interoperability between ERP and auxiliary modules—such as procurement, inventory, and finance—ensured data fluidity across functions, reducing latency and improving decision accuracy. These insights demonstrated that ERP-DSS systems generated operational resilience by harmonizing technical infrastructure with human capability and analytical intelligence. The study's quantitative model advanced existing literature by demonstrating that healthcare logistics performance was not solely a byproduct of system adoption but a reflection of how integration, data governance, and decision analytics interacted as co-dependent constructs. The results thus positioned ERP-DSS integration as both a technological and strategic imperative, capable of transforming healthcare logistics from fragmented, reactive processes into cohesive, predictive, and adaptive networks that ensured continuity, accountability, and measurable efficiency across institutional boundaries.

RECOMMENDATION

The findings from A Quantitative Study on ERP-Integrated Decision Support Systems in Healthcare Logistics provided a strong empirical foundation for several strategic, operational, and managerial recommendations that can enhance healthcare logistics performance through the integration of ERP and DSS frameworks. It was evident that ERP-DSS systems created measurable improvements in efficiency, data accuracy, and decision-making precision; therefore, institutional leaders should prioritize the full-scale integration of ERP and decision-support modules across all logistics functions. Healthcare organizations are encouraged to move beyond partial implementations and ensure that ERP platforms are seamlessly linked with analytics dashboards, procurement databases, and clinical inventory systems. This integration should be complemented by robust data governance policies that ensure consistency, real-time updates, and error-free synchronization across interconnected modules. The study's results also emphasized that data quality acted as the cornerstone of ERP-DSS success, and thus, continuous monitoring of data input, cleansing, and validation procedures should be institutionalized. Establishing dedicated data management teams or digital logistics offices can strengthen accountability for data accuracy and provide the necessary infrastructure for predictive analytics to operate effectively. Moreover, healthcare institutions should embed structured and ongoing training programs that align technical skill development with system upgrades, as the quantitative evidence indicated that user literacy directly influenced system efficiency. These programs must include both initial onboarding sessions and periodic refresher training, ensuring that logistics managers, IT personnel, and procurement officers maintain updated competencies to fully utilize ERP-DSS functionalities. At the technical level, decision-makers should focus on enhancing system interoperability by standardizing communication protocols between ERP modules and external applications such as supplier databases, inventory tracking tools, and warehouse automation systems. Greater interoperability reduces latency and facilitates cross-departmental collaboration, allowing logistics operations to function as a cohesive data-driven network. Additionally, administrators should incorporate advanced analytics and predictive modeling tools within ERP environments to anticipate stockouts, forecast procurement needs, and detect bottlenecks before they affect clinical operations. This proactive capability can significantly enhance supply continuity and financial accountability. Finally, the study's implications support the recommendation that policymakers and healthcare executives treat ERP-DSS integration as an organizational transformation initiative rather than a purely technological investment. Achieving the full potential of such systems requires alignment between digital infrastructure, human competence, and strategic leadership. When these components operate in synergy, ERP-DSS frameworks can evolve into institutional assets that sustain operational excellence, regulatory compliance, and patient-centered service reliability across healthcare logistics networks.

LIMITATIONS

The quantitative investigation titled A Quantitative Study on ERP-Integrated Decision Support Systems in Healthcare Logistics was conducted under rigorous methodological design, yet several limitations were identified that may influence the interpretation, generalizability, and contextual applicability of its findings. The study relied primarily on cross-sectional data collected within a defined temporal frame, which limited the ability to establish causality between ERP-DSS integration and logistics performance outcomes. Although statistical modeling such as hierarchical regression and structural equation modeling provided robust inferential insights, these techniques measured relationships at a single point in time and could not fully capture the longitudinal evolution of ERP-DSS efficiency or the dynamic changes occurring during system adoption phases. Furthermore, the data were derived from self-reported survey instruments and institutional performance records, introducing potential biases related to respondent perceptions, organizational reporting accuracy, and varying levels of transparency across participating hospitals. Differences in departmental cultures, digital maturity, and workflow standardization may have influenced the consistency of responses, particularly in assessing constructs such as training effectiveness and system interoperability. Another limitation involved the diversity of ERP systems employed across institutions. Variations in vendor design, customization levels, and integration capabilities may have contributed to measurement heterogeneity, which could not be entirely controlled through statistical normalization. Additionally, while the sample size was sufficient for multivariate analysis, it was geographically concentrated within specific healthcare networks, which restricted the extrapolation of findings to global or lower-resource healthcare settings. The study also assumed that reported key performance indicators, such as inventory turnover or procurement cycle time, were uniformly defined across organizations, though institutional differences in metric calculation may have introduced slight measurement discrepancies. Moreover, the study's emphasis on quantitative constructs, while essential for statistical precision, limited the exploration of qualitative dimensions such as user adaptation behavior, resistance to technological change, or organizational culture, which often mediate the success of ERP-DSS adoption. External environmental variables, including supply chain disruptions, government policy shifts, and vendor reliability, were not explicitly modeled, though they may exert significant influence on logistics performance. These constraints suggested that while the study's findings were empirically valid within its scope, future research should adopt longitudinal and mixed-method approaches, integrate broader cross-national samples, and include contextual variables to deepen understanding of how ERP-DSS integration functions across varying healthcare ecosystems and operational realities.

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