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Hospital Supply Chain Management: Research Gaps and Decision Support Opportunities

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Abstract

This paper presents a systematic literature review on hospital supply chain management (HSCM), with the aim of identifying research gaps to guide future studies and support the development of decision support systems (DSS) that enhance healthcare supply chain performance. Using the PRISMA 2020 methodology, 117 articles were initially retrieved from the Web of Science database, of which 53 articles were based on real data and retained for analysis. The review classified research across three key dimensions: type of data, methodological approach, and supply chain function. Results show that inventory management is the least studied function, addressed in in only 6 articles (11.3%) of articles, despite its importance in reducing shortages and waste. From a methodological perspective, traditional approaches (13.2%) and pure ML/AI (30.2%) were underutilized, while hybrid methods dominate (56.6%). These findings highlight two underexplored areas. That is, there is limited use of traditional and AI/ML approaches and insufficient focus on inventory management within HSCM. Addressing these gaps will be vital for developing robust DSS solutions capable of strengthening forecasting, enhancing operational resilience, and improving overall efficiency. Future research should therefore place greater emphasis on inventory management and expand the application of AI/ML methodologies in HSCM.

Keywords
Hospital supply chain Management, Real data, Systematic literature review, PRISMA

1. Introduction
The healthcare supply chain, and hospital supply chains in particular, plays a critical role in ensuring that medical products, equipment, and services are delivered at the right place and time to support patient care. Effective hospital supply chain management (HSCM) is essential for improving treatment outcomes, minimizing costs, and maintaining resilience during emergencies and disruptions (Fallahnezhad et al. 2024). A well-functioning supply chain also reduces shortages and waste, while enabling hospitals to respond to sudden surges in demand during pandemics or disaster situations (Sarangi and Ghosh 2024). Despite these benefits, HSCM is often constrained by fluctuating demand, supplier delays, regulatory restrictions, and product expiration, which complicate planning and coordination.

To address these challenges, this study conducts a systematic literature review (SLR) on HSCM. The review adopts the PRISMA 2020 guidelines (Page et al. 2021) to ensure methodological rigor and transparency. It also employs a structured Boolean search strategy in the Web of Science database. The selected studies are analyzed across three key dimensions: (i) data type (real, simulated, or hybrid), (ii) supply chain function (procurement and planning, delivery and logistics, or inventory management), and (iii) methodological approach (ML/AI, traditional, or hybrid).

Despite the growing attention to HSCM, prior reviews have often taken a broad perspective on healthcare systems or relied extensively on simulated data, which limits their applicability to real hospital contexts. Furthermore, certain critical functions, particularly inventory management, remain underexplored, while the adoption of advanced methods such as AI and machine learning (ML) has yet to be systematically examined. These gaps hinder the development of practical solutions and decision support tools that can strengthen healthcare supply chain performance.

The objective of this study is therefore to build a comprehensive understanding of HSCM with a particular focus on real data-based research. By classifying existing studies across the above-mentioned dimensions, the review seeks to uncover limitations in current research and highlight areas that constrain the advancement of practical HSCM solutions. In doing so, the study aims to guide future research toward the development of robust, data-driven decision support systems (DSS) capable of enhancing forecasting accuracy, improving operational resilience, and strengthening overall efficiency in HSCM.

2. Methodology

2.1 Study Design and Database Selection

This research is designed as a SLR with the purpose of classifying and analyzing hospital supply chain studies. To ensure rigor and transparency, the review follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which provide a structured approach for identifying, screening, and reporting literature in a clear and replicable manner (Page et al. 2021). The PRISMA framework ensures that the selection process is systematic, avoids bias, and allows for reproducibility of results.

The primary and only database chosen for this review is Web of Science, as it provides high-quality, peer-reviewed academic journal articles across multiple disciplines. Web of Science is also widely recognized in healthcare and supply chain research, making it a reliable source for collecting relevant articles.

2.2 Initial Search Strategy, Screening, and Classification

To identify the relevant body of literature, a Boolean search string was constructed to capture studies on Al, ML, data-driven methods, and hospital supply chain. The “healthcare” word was also used to ensure full review of the available literature. The Boolean search used was:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks" OR "data analytics" OR "predictive analytics") AND ("healthcare" OR "hospital") AND ("supply chain" OR "logistics" OR "inventory" OR "procurement" OR "planning")

This search retrieved a total of 117 articles, which were first screened by language and type of study. They were then classified according to the type of data used (real, simulated, or hybrid). The results of this classification are summarized in Table 1.

Table 1. Initial Screening Results

Category	Number of Articles
Total articles	117
Excluded (non-English)	1
Literature review papers	17
Simulated/hypothetical data only	31
Hybrid (real + simulated)	15
Real data studies	53

It is clear from this classification that only a portion of the articles used real-world data, while many relied solely on simulations or hypothetical scenarios.

2.3 Refined Search Strategy

To ensure alignment with the objective of focusing exclusively on studies using real data, the Boolean search was refined by adding the filter **“**real data.**”** The final Boolean string was:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural networks" OR "data analytics" OR "predictive analytics") AND ("healthcare" OR "hospital") AND ("supply chain" OR "logistics" OR "inventory" OR "procurement" OR "planning") AND ("real data")

The following inclusion criteria was applied (Table 2). This refinement ensured that only studies that explicitly employed real-world data were retained for analysis, reducing the pool to 56 articles.

Table 2. Inclusion Criteria

Criteria	Description
Keywords	Boolean string (AI, ML, healthcare, supply chain, logistics, inventory, procurement, planning, real data)
Timeframe	2015–2025 (last 10 years)
Language	English only
Type of Articles	Journal articles and review articles
Data Scope	Only studies using real data included simulated-only and hybrid studies excluded

3. Literature Review

Building on the motivation outlined in the introduction, this section synthesizes existing research on HSCM. The aim is not only to review methodological approaches and applications but also to highlight underexplored areas that limit the development of practical, data-driven solutions. Following the classification framework, the review is organized around three core supply chain functions: procurement and planning, delivery and logistics, and inventory management. Within each, studies are examined in terms of their data type, methodological approach (traditional, AI/ML, or hybrid), and practical implications for hospital supply chains. This structure allows for a systematic comparison across functions while identifying methodological trends and gaps that can inform future decision support systems (DSS) in healthcare supply chains.

3.1 Procurement/Planning

Hospital procurement and planning have gradually shifted from traditional forecasting toward data-driven and automated approaches supported by machine learning (ML) and deep learning (DL). This trend became especially visible during the COVID-19 pandemic. For example, the Earth Cognitive System for COVID-19 (ECO4CO) integrated geospatial, social media, and satellite data to predict regional risks, emergency visits, and medical supply requirements with an accuracy of nearly 85% (Atek et al. 2023). By using multiple data streams rather than relying only on historical records, the platform enabled authorities to anticipate demand surges and adjust procurement strategies more proactively. In a non-crisis context, Piccialli et al. (2021) proposed a Long Short-Term Memory (LSTM) Autoencoder combined with Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) to forecast seven day hospital bookings. The integration of linear regression with advanced predictive algorithms enhanced the model's ability to detect both regular seasonal trends and sudden fluctuations in patient demand, outperforming traditional forecasting methods.

Classical statistical models remain useful when demand is stable and historical records are long. However, their performance drops when data are limited or consumption patterns fluctuate. In Rwanda, an LSTM model achieved a coefficient of determination (R^2) of 0.91 and a root mean square error (RMSE) close to 2 recognizing irregular shifts in the demand, while the traditional Autoregressive Integrated Moving Average (ARIMA) model recorded an R^2 of only 0.24 and an RMSE above 8 (Mbonyinshuti et al. 2024). A similar pattern appeared in a Canadian study on platelet usage. With eight years of data, ARIMA and Prophet performed comparably to multivariable ML models such as LASSO, RF, and LSTM. However, when the dataset was reduced to two years, ARIMA and Prophet errors increased sharply, while ML models maintained accuracy by incorporating additional signals like patient admissions and laboratory activity (Motamedi et al. 2024). Forecasting hospital length of stay also supports procurement decisions, since bed occupancy directly affects daily supply needs; recent AI models have shown strong accuracy in predicting stay durations (Alnsour et al. 2023). Likewise, predictive analytics used in clinical risk modeling, such as disease detection frameworks, demonstrate how data-driven tools can strengthen broader planning and procurement strategies (Chen et al. 2024). Overall, the evidence suggests that model selection should match data conditions: classical models work when demand is stable, but ML and DL methods provide higher adaptability and precision in volatile or data-scarce environments.

Recent evidence shows that predictive analytics is increasingly shaping hospital procurement and planning, but its adoption is advancing faster than the development of proper validation and governance practices. In the United States, most hospitals now use predictive tools, yet fewer than two-thirds formally assess model accuracy and less than half evaluate bias (Nong et al. 2025). This gap raises concerns because procurement decisions, including supplier selection, stock prioritization, and budget allocation, may rely on unverified forecasts, risking inefficient or inequitable resource distribution. In settings where hospital records are incomplete or inconsistent, predictive methods have helped compensate for missing data. In Ghana, K-Nearest Neighbor (KNN) and Extreme Learning Machine (ELM) models successfully forecasted and reconstructed blood demand under irregular or sparse data conditions, supporting procurement for hospitals with limited digital infrastructure (Twumasi & Twumasi 2022). Similarly, Xu and Chan (2019) showed that Baidu search trends act as early indicators of shifts in medical device demand, allowing procurement teams to anticipate market changes and reduce both shortages and excess inventory.

For pharmaceuticals and consumables, tree-based ML models have demonstrated clear improvements in forecasting accuracy. RF and Decision Tree algorithms improved prediction performance by 10–41% compared with traditional statistical methods (Yani & Aamer 2023). Higher accuracy strengthens procurement by improving demand visibility, enabling earlier purchasing decisions, and reducing reliance on emergency orders. These models also help hospitals coordinate suppliers more effectively and maintain balanced inventory levels. Broader Healthcare 4.0 research links artificial intelligence (AI), big data analytics, and blockchain to increased supply chain resilience and adaptability under uncertain conditions (Saha & Rathore 2024; Chatterjee et al. 2023). Together, these findings demonstrate that predictive analytics enhances both forecasting performance and procurement planning.

The strongest procurement results occur when forecasting is directly linked to optimization or structured ordering policies. In Canada, Li et al. (2021) showed that integrating demand forecasts with clear reorder rules improved red cell inventory management by reducing emergency replenishments, minimizing waste, and stabilizing supply. The key benefit came from aligning daily predictions with predefined reorder thresholds, allowing hospitals to maintain optimal stock levels without overstocking or shortages. Similarly, Song et al. (2019) combined disease occurrence rates with an optimization framework to support emergency drug procurement. Their approach achieved about an 8% prediction error and a 99% recovery rate, demonstrating how linking accurate forecasting with purchasing and allocation rules can prevent shortages and improve distribution efficiency during emergencies. In parallel, Bi (2015) introduced a fuzzy optimization model that outperformed conventional methods by accounting for uncertain, time-sensitive, and seasonal demand patterns. Collectively, these studies highlight that forecasting achieves meaningful impact when paired with optimization techniques that guide actual procurement decisions.

DL models show strong performance during unpredictable or crisis-driven supply needs. A stacked LSTM model accurately forecasted ICU bed and ventilator demand with error rates of only 3-5%, supporting faster emergency procurement (Koç and Türkoğlu 2021). Hybrid LSTM and Support Vector Regression (SVR) models have also captured fluctuating demand in humanitarian settings more effectively than traditional methods (Hasni et al. 2024). Studies on Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and neuro-fuzzy systems showed strong accuracy in predicting hospital asset use, even when data were limited, helping teams prepare for sudden surges (Jebbor et al. 2021). During pandemic transport disruptions, sequence based models predicted shipment delays with high accuracy, allowing procurement teams to adjust orders early and avoid shortages (Bassiouni et al. 2023). Overall, DL improves prediction reliability during volatile conditions and helps procurement teams act before shortages occur.

Recent procurement research has expanded from forecasting to broader supplier and system planning. Using the SCOR 4.0 framework with Gradient Boosting, hospitals were able to evaluate and rank suppliers more clearly, improving visibility into weaknesses and helping teams choose reliable alternatives during disruptions (Khan et al. 2023). Knowledge graph models have offered similar advantages. Eberhardt et al. (2025) showed that shortages often arise from interconnected factors such as supplier performance, medicine availability, and regulatory issues. Understanding these links allows procurement teams to adjust contracts or diversify sourcing instead of relying on higher safety stocks that increase cost without preventing future shortages. Sustainability oriented procurement has also been explored through network Data Envelopment Analysis combined with DL, which ranks suppliers based on resource use and undesirable outputs, giving hospitals a data-driven basis for awarding contracts under environmental constraints (Azadi et al. 2023).

Seasonal studies also highlight the value of predictive data systems in healthcare logistics. Kabrah (2022) examined hospital operations in Makkah during Hajj and Umrah, when demand for blood and medical supplies rises sharply. The study recommended AI-based systems that track donor activity and inventory levels in real time, helping hospitals prepare for predictable surges and offering a model that can be adapted to other seasonal peaks such as flu periods. Cold-chain planning research supports the same idea. Kochakkashani et al. (2024) used a Mixed Integer Nonlinear Programming model to plan vaccine and pharmaceutical orders that maintain temperature and reliability standards. At a wider scale, hybrid scenario based and robust optimization frameworks have combined demand forecasts with supply risk assessments to strengthen disaster logistics and pharmaceutical planning, allowing hospitals to maintain service continuity while controlling cost (Amani et al. 2025; Jafarian et al. 2025).

Overall, three lessons emerge. First, model selection should match data conditions. Classical methods work for stable demand, while ML and DL are more reliable when patterns are volatile or data are limited. Second, procurement improves when forecasts are tied to clear ordering rules or optimization methods that balance cost and service needs. Third, resilience requires diversified suppliers, transparent evaluation, and real time monitoring so hospitals can adjust orders quickly during disruptions (Zerine et al. 2025). These findings show that data-driven approaches are reshaping procurement and enabling more accurate and adaptable decisions.

3.2 Delivery and Logistics

Hospital supply chain delivery and logistics have undergone a significant transformation, evolving from conventional planning approaches to sophisticated data-driven techniques using machine learning (ML), artificial intelligence (AI), and hybrid optimization models. During the COVID-19 pandemic, supply chains faced severe disruptions, highlighting the limitations of traditional methods that depend heavily on historical data and fail to capture sudden demand fluctuations. Studies in the U.S. healthcare sector showed that conventional models were capable of managing predictable demand but struggled to maintain continuity during crises (Zamiela et al., 2022). These findings emphasized the importance of agile and predictive frameworks that integrate multiple data sources and anticipate disruptions.

In non-crisis environments, traditional forecasting models such as vendor-managed inventory strategies or network optimization approaches remain effective when demand is stable and predictable. Lotfi et al. (2024) demonstrated that combining vendor-managed and consignment stock policies enhanced supply reliability and reduced emergency replenishments in healthcare networks. Similarly, Kamali et al. (2024) optimized integrated healthcare supply chain network design, balancing cost reduction with timely delivery. Yet, these classical methods tend to underperform when demand volatility increases, underscoring the role of hybrid and AI-enhanced models.

ML and AI techniques have shown strong potential in improving efficiency and resilience in healthcare supply chains. Wang et al. (2023) developed a data-driven decision-making model for risk assessment in cardiovascular health, illustrating how predictive analytics can optimize medical logistics planning. Farič et al. (2023) demonstrated that AI-based diagnostic decision support systems in radiology not only improve clinical decision-making but also enable better supply planning by forecasting consumable requirements in real time. These applications highlight the ability of ML and AI to generate actionable insights beyond historical trends, strengthening operational responsiveness.

Hybrid frameworks that integrate AI with optimization, simulation, or blockchain technologies have become increasingly central to healthcare logistics. Ghazvinian et al. (2025) applied machine learning-based multi-objective optimization to enhance drug distribution efficiency and reduce freight costs in HIV treatment programs. Similarly, Elmir et al. (2023) used neural network forecasting for blood bank management, ensuring consistent inventory under uncertain demand. Blockchain-enabled models have also demonstrated promise. Nair et al. (2025) combined blockchain technology with LSTM predictive models to improve vaccine distribution traceability and supply chain resilience. Collectively, these hybrid systems improved reliability, responsiveness, and transparency in healthcare supply operations.

Empirical research further suggests that predictive analytics alone is insufficient for effective logistics management; stronger outcomes occur when prediction is combined with structured optimization and decision-making systems. Goodarzian and Ghasemi (2025) developed a simulation-optimization model that integrates predictive demand forecasts with sustainable delivery planning, minimizing stockouts while avoiding overstocking. Goodarzian et al. (2024) extended this work by coupling fuzzy logic with optimization to address uncertainty in medical waste logistics, improving decision accuracy and coordination across hospital networks. Kumar et al. (2024) also emphasized that hybrid ML-optimization models strengthen supply chain reliability by learning from operational variability.

Resilience remains a key objective in advanced supply chain design. Kar et al. (2024) argued that human-centric, intelligent operations under the Industry 5.0 paradigm foster adaptive, self-learning healthcare systems capable of real-time response to disruptions. Park et al. (2023) showed that process mining and machine learning can dynamically identify inefficiencies in healthcare logistics, improving transparency and delivery coordination. Ziaee et al. (2023) demonstrated that big data analytics enhance visibility in pharmaceutical supply chains, enabling quicker recovery from delays and fluctuations.

Overall, several lessons emerge for hospital delivery and logistics management. First, model selection should reflect the data environment, traditional models work best under stable demand, while ML, AI, and hybrid systems perform better in uncertain conditions. Second, predictive insights achieve the greatest value when coupled with structured optimization or risk-based planning frameworks that guide procurement and replenishment decisions. Third, resilience depends not only on accurate forecasting but also on diversification, real-time monitoring, and adaptive decision support to maintain continuity during disruptions (Kar et al., 2024; Nair et al., 2025; Goodarzian & Ghasemi, 2025). Collectively, these studies illustrate how data-driven, intelligent methods are transforming hospital logistics into more adaptive, efficient, and resilient systems.

3.3 Inventory Management

The management of medical inventories is a critical pillar of hospital logistics, directly affecting service continuity, patient safety, and operational efficiency. Over the past decade, research has evolved from traditional statistical forecasting toward hybrid frameworks combining predictive analytics, machine learning (ML), and optimization techniques. The primary goal has been to balance demand responsiveness with cost containment while minimizing shortages and waste. These studies illustrate a shift from static, experience-driven decisions to intelligent, data-informed systems capable of adapting to dynamic and uncertain environments.

Early applications of hybrid analytics in hospitals demonstrated the potential of combining ML with stochastic optimization to refine replenishment. Galli et al. (2020) proposed a framework using historical drug administration and real-time ward data to determine optimal inventory levels, embedding simulation-based optimization within predictive analytics. This patient-centric approach reduced emergency replenishments and ensured service continuity, establishing a precedent for smart, hybrid optimization in clinical supply management.

Building on classical methods, Wang et al. (2025) applied a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast platelet demand in Chinese blood banks. Despite being purely statistical, SARIMA captured seasonal fluctuations and improved resource allocation, demonstrating the continued relevance of interpretable models in data-limited environments.

AI-driven systems have further advanced inventory management. AlZu’bi et al. (2022) developed a model integrating real-time data with predictive algorithms to schedule blood donations and maintain stable inventory. The system minimized supply-demand mismatches, reduced expiration waste, and supported continuous replenishment, highlighting how predictive intelligence can enable holistic decision-making.

Fernandez et al. (2020) employed a Linear Time-Varying (LTV) framework in a Decision Support System (DSS) for hospital drug inventory, forecasting consumption across multiple horizons and estimating stockout risks. Tested in a Spanish hospital, it reduced emergency shortages and improved pharmacy decision-making, demonstrating the practical impact of embedding predictive models into daily workflows.

More complex hybrid frameworks have emerged, combining ML with optimization for end-to-end control. Haoudi et al. (2023) developed an insulin distribution system comparing RF, multiple regression, and neural networks; RF, integrated with an optimization module, improved forecasting accuracy, reduced shortages, and enhanced distribution planning. Feng et al. (2025) applied a Temporal Fusion Transformer (TFT) to pharmaceutical sales, achieving a 23.6% increase in forecast accuracy and reducing stockouts and costs by over 25%, illustrating the power of advanced temporal modeling in large-scale inventory systems.

Overall, these studies reflect an evolution from statistical and rule-based methods to intelligent, adaptive systems capable of managing complexity and uncertainty. While traditional models remain valuable benchmarks, hybrid ML-optimization approaches are more effective in practice. The convergence of predictive forecasting, prescriptive analytics, and decision support frameworks has shifted hospitals from reactive inventory management to proactive, data-driven control. Challenges remain in data integration, interoperability, and transparency, which will determine the scalability and sustainability of such systems. The next frontier lies in unifying hybrid models within integrated hospital platforms capable of real-time learning and autonomous decision-making.

4. Results

4.1 PRISMA Flow Results

The article selection process described in the previous section, yielded the final set of studies that met all inclusion criteria. The details of identification, screening, and inclusion are summarized in the PRISMA flow diagram (Figure 1).

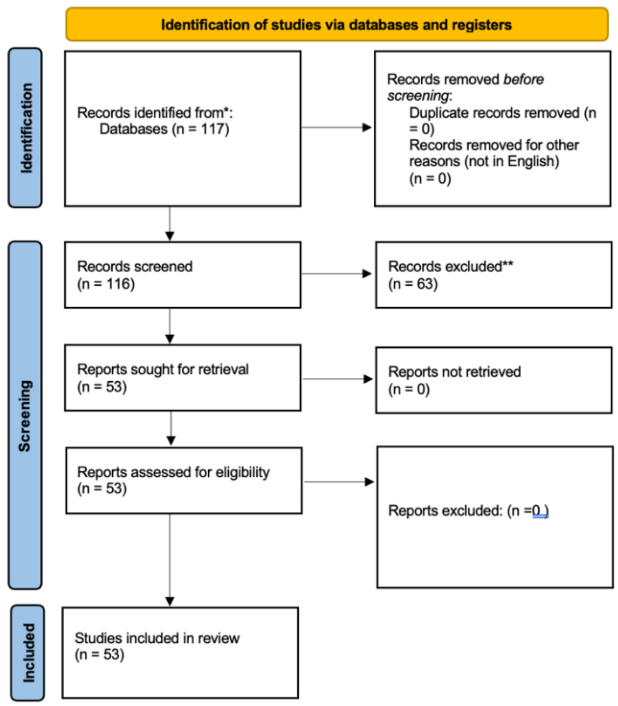

Figure 1. PRISMA Flow Diagram

4.2 Numerical Results by Dimensions

The 53 retrieved articles were classified into three main dimensions: data type, method, and supply chain (SC) function (Table 3).

Table 3. Summary of Included Studies by Key Dimensions

Dimension	Category	Count
Type of Data	Real	53
Method	ML/AI	16
	Traditional	7
	Hybrid	30
SC Function	Procurement/Planning or Forecasting	28
	Delivery & Logistics	19
	Inventory Management	6

The majority of the studies focused on procurement and planning (28 articles), followed by delivery and logistics (19 articles). Inventory management was the least represented area, with only six studies, showing that it remains a significantly underexplored area in hospital supply chain research. Given its main contribution in minimizing shortages and waste, future research should prioritize this function to strengthen operational efficiency and resilience.

Methodologically, hybrid approaches dominated, appearing in over half of the studies (30 articles), while pure ML/AI methods were applied in 16 studies, and traditional methods accounted for only 7. This trend indicates growing acceptance of hybrid models yet also reveals that pure ML/AI and traditional approaches remain underutilized. Expanding the application of AI-driven methods, particularly in underrepresented areas such as inventory management, could support more adaptive and data-driven decision-making in healthcare supply chains.

Overall, the results underscore two key research gaps: the limited focus on inventory management and the underutilization of both pure ML/AI and traditional methodologies. Addressing these gaps aligns with the objective of this review to identify areas requiring deeper investigation and to inform the development of DSSs for more effective and resilient HSCM solutions.

5. Discussion

The reviewed studies collectively reveal that hospital supply chain research is shifting from traditional statistical models toward ML and AI methods. These data-driven approaches have enhanced forecasting precision, improved delivery coordination, and enabled more responsive control of medical inventories. Yet, despite these advances, most studies remain focused on individual functions rather than fully connected systems, and few have been validated under real hospital conditions. This demonstrates that while technical capabilities have advanced, practical implementation and integration across procurement, logistics, and inventory functions are still limited.

5.1 Procurement and Planning

In procurement and planning, recent studies show a clear transition from traditional statistical models toward machine ML and DL methods that can better handle demand fluctuations and uncertainty. These models have improved forecasting accuracy and responsiveness by capturing complex, non-linear relationships between variables such as patient admissions and supplier lead times. However, most studies still focus on developing or comparing algorithms rather than testing them under real operational conditions. Validation often takes place within a single hospital, restricting generalizability across healthcare systems. These limitations often result from institutional and data related barriers, procurement records, supplier data, and clinical demand indicators, are usually stored in separate systems, making integration and large scale validation difficult. Moreover, procurement decisions are tied to administrative approvals and budgeting cycles, which restrict experimentation and model testing in real hospital settings.Although ML and DL frameworks such as LSTM, RF, and hybrid approaches are widely applied and show strong predictive performance even with small or inconsistent data histories, their effectiveness in practice still depends on the availability of integrated hospital data systems and clear performance validation standards.

5.2 Delivery and Logistics

Delivery and logistics research demonstrate a clear move toward intelligent, data-driven systems that enhance hospital supply efficiency and resilience. ML, AI, and hybrid optimization models have improved delivery scheduling, route planning, and responsiveness, especially during crises where conventional approaches often fail. Yet, evidence consistently demonstrates that forecasting alone is insufficient, as the greater results arise when forecasting models are integrated with optimized delivery planning and restocking procedures. Despite these advancements, many studies remain confined to controlled or single region contexts, which limits their scalability and generalization. The continued reliance on disconnected hospital systems also restricts real-time coordination and data exchange, hindering the adoption of technologies such as blockchain and live tracking. Overall, progress toward adaptive logistics is evident, but stronger collaboration between hospitals and suppliers, shared data standards, and integrated digital systems are still needed to support the practical and reliable application of these models in real hospital environments.

5.3 Inventory Management

Inventory management research shows clear progress toward smarter, data-driven control of hospital stocks, yet its practical use is still limited. Most studies illustrate that hybrid models combining ML and optimization can better balance supply and cost, reducing both shortages and waste. These methods work well for short-term demand fluctuations, but they are mostly tested in small scale or single hospital settings, which makes it difficult to compare results or develop shared standards. One reason for this slow uptake is that inventory decisions often happen inside hospital departments rather than at a network level, making them harder to monitor and study. Hospital databases for inventory, pharmacy, and patient care also operate separately, creating internal barriers to data sharing. Many existing tools also lack transparency, which makes their results harder for clinicians to review or validate. Collectively, inventory management is evolving toward data-driven control, but further progress requires connected hospital systems, clearer decision tools, and closer coordination between developers and healthcare staff.

Altogether, fragmented data systems, confidentiality restrictions, and the complexity of real-world hospital operations continue to limit large-scale validation and system integration across healthcare research. Consequently, inventory management remains one of the least explored areas of hospital supply chain optimization, facing both limited research attention and significant operational challenges. Advancing this field will require research that prioritizes cross-functional integration, real-time data connectivity, and robust validation frameworks to ensure scalable and practical implementation within healthcare environments.

6. Conclusion & Future Considerations

This study conducted a SLR on HSCM, following the PRISMA 2020 guidelines to ensure rigor and transparency. A structured Boolean search in the Web of Science initially retrieved 119 articles, of which 56 studies met the inclusion criteria after excluding non-English studies and those without real data.

This review analyzed the identified studies across three dimensions: data type, method, and supply chain function. The findings revealed two major gaps. First, inventory management was represented in only 11% of the studies, making it the least explored function despite its critical role in reducing waste and ensuring availability of medical supplies. Second, only 32% of the studies relied exclusively on AI/ML methods, showing that the full potential of advanced data-driven approaches remains underutilized. Both gaps are significant, as inventory management and AI/ML applications are essential for building responsive and resilient HSCM.

Future research should address why inventory management remains underexplored in hospital supply chain studies. Is it due to limited data availability, confidentiality barriers, or the complexity of modeling hospital systems? Future research should focus on these unexplored areas by developing scalable, data-driven solutions that integrate inventory management with AI/ML methodologies. Addressing these gaps will provide a robust foundation for designing decision-support systems capable of enhancing operational resilience, optimizing resource allocation, and strengthening overall healthcare supply chain performance.

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Biographies

Sarah Al Zaied is a final-year Industrial Engineering student at the Rochester Institute of Technology, Dubai Campus. She is completing her cooperative placement in Procurement, Gas Services with Siemens Energy, supporting supplier evaluation, sourcing, and alignment with procurement processes. She previously participated in a mentorship program at Schneider Electric focused on supply chain management, enhancing her expertise in supplier performance and strategic procurement. Her experiences provide practical insights into procurement operations, supplier evaluation, and efficiency improvements. Academically, she has co-authored a paper on supplier evaluation and performance assessment, bridging practical experience with research. With a strong focus on procurement and supply chain management, Sarah is committed to driving innovation, sustainability, and value in global supply chains.

Tala Hassouna is a senior Industrial Engineering student at the Rochester Institute of Technology. She is currently a Supply and Quality Intern at Hilti, where she contributes to supplier evaluation, quality monitoring, and logistics improvement initiatives. Her professional background also includes roles at General Motors, DAR Middle East, Honda Motors, and Nestlé, giving her practical exposure to business analysis, business development, client engagement, and operations management across multiple sectors. In addition to her industry experience, Tala has published an article on supplier evaluation and selection with her colleagues, bridging her applied research interests with real-world practice. She is particularly interested in supply chain efficiency, sustainable operations, and decision-support systems, with the goal of advancing more adaptive and resilient industrial supply networks. Tala has also been active in academic and extracurricular initiatives, and continues to seek opportunities to drive innovation across engineering and management practices through collaborative projects and leadership roles.

Rokia Elshahhat is a senior Industrial Engineering student at Rochester Institute of Technology, Dubai. She recently completed her internship in Global Sourcing, where she co-managed multi-figure projects, evaluated suppliers, and developed automated solutions to streamline sourcing workflows. In this role, she designed advanced Power BI dashboards using DAX, Power Query, and data modeling to transform complex datasets into clear insights that guided strategic sourcing decisions. She also applied Lean Six Sigma principles and optimization tools to improve efficiency across sourcing processes. Her earlier internship in project management at Emerson allowed her to lead cross-functional initiatives focused on operational improvement and sustainability. Her drive for efficiency and innovation has also extended into research, where her work on supplier evaluation and process automation earned second place in the Lean Six Sigma Competition at the 8th European International Conference on Industrial Engineering and

Operations Management. Building on these experiences, she is now focused on optimization and data analytics, using Python and Power BI for analysis, visualization, and decision-support.Through these tools, she aims to create smarter, automated systems that enhance efficiency and provide actionable insights for complex, real-world challenges.

Mohamad Chaaban is currently a senior student in Computing and Information Technologies at the Rochester Institute of Technology, Dubai Campus. He brings a strong academic and professional background in data analysis, networking, and information systems, with expertise in SQL, Python, project management, and big data handling. Mohamad completed two co-op placements at the Sharjah Finance Department: first as a Data Analyst Intern, where he developed data cleaning and forecasting models, and later as a Networking Intern, focusing on IT infrastructure and operations. With additional experience as the owner of Al Sendian Arabian Horse Stud, Mohamad integrates data-driven strategies into pedigree evaluation, breeding management, and customer engagement, enhancing business effectiveness and profitability. His leadership and technical skills reflect a passion for applying AI and data analysis to real-world problems. Fluent in English and Arabic, he is dedicated to leveraging innovative technologies to optimize business performance, mentor peers, and foster collaboration across academic and industrial platforms

Seifeldin Faidallah is a senior student in Computing and Information Technologies at the Rochester Institute of Technology, Dubai Campus, which he joined in 2022. He has strong skills in networking, computer clouding, and data handling, with additional experience in UI/UX design, HTML, CSS, and Java programming. He completed an internship at a hospital, where he applied his technical knowledge to healthcare IT operations and gained valuable insight into how technology supports patient care. His academic work also reflects interests in cloud computing, digital forensics, and healthcare technologies. Fluent in both Arabic and English, Seifeldin is passionate about leveraging cloud solutions, user-centered design, and data-driven approaches to enhance efficiency, resilience, and innovation in the medical field.

Omar Abdelmoaty is a senior Electrical Engineering student at the Rochester Institute of Technology, Dubai Campus. He has a strong background in electrical devices testing, product conformity assessment, and safety compliance, with expertise in MATLAB, PSpice, C/C++, and engineering instrumentation. Omar completed multiple internships, including at Dubai Central Laboratory – Dubai Municipality as an Electrical Devices Testing Intern, where he trained on IEC safety standards, conducted risk assessments, and developed safe practices, and at El Ghonemy Green Tech, contributing to product conformity assessments, troubleshooting, and R&D for product safety. He also worked at CERTIS Occupational Safety Consultancy, focusing on inspection, compliance, and certification management, and at W Motors Group Holding Limited – Dubai Branch as an Electrical Engineering Intern, supporting technical teams in designing and testing solutions for product safety and regulatory compliance. Omar's technical skills span circuit analysis, embedded systems, product safety, and regulatory affairs, with proficiency in tools such as oscilloscopes, logic analyzers, and automation systems.

Dr. Dua Weraikat, Ph.D., Eng., is currently an Assistant Professor and MEIE Program Coordinator at the Rochester Institute of Technology, Dubai Campus. She brings a strong academic and research background in industrial engineering, with expertise in operations research, supply chain management, and sustainable reverse logistics. Prior to joining RIT Dubai in 2017, she held research and teaching positions at Concordia University, Canada, where she completed her Ph.D., and later served as a postdoctoral researcher at Université Laval, focusing on value chain coordination in the forest industry. With over 15 years of experience across academia and industry, Dr. Weraikat has contributed to several impactful publications, including journal articles and book chapters, in areas such as green supply chains and pharmaceutical logistics. She has also taught various courses including production planning, operations research, and project management. Her leadership is reflected in her current role on the Operations Research Division Board of the Institute of Industrial and Systems Engineers (IISE) for the 2025–2027 term. Fluent in English, Arabic, and French, Dr. Weraikat is passionate about integrating smart and sustainable solutions into engineering education and research, mentoring students, and fostering collaboration across academic and industrial platforms.