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Optimizing supply chain efficiency: Advanced decision support systems for enhanced performance

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Abstract

This research investigates the optimization of supply chain efficiency through the application of advanced Decision Support Systems (DSS), focusing on minimizing operational costs while maintaining high service levels. The main objective is to explore how DSS, integrated with real-time data, artificial intelligence (AI), and machine learning (ML), can enhance decision-making processes across production, inventory management, and transportation. The research employs a multi-objective optimization model, developed to minimize production, inventory, transportation, and shortage costs, while dynamically adjusting decisions based on real-time demand and supply data. A numerical example is used to test the model's effectiveness, revealing significant cost reductions in production and transportation but highlighting challenges in maintaining consistent service levels. The results indicate that DSS can substantially improve supply chain efficiency by enabling data-driven decisions in real time, though its adoption remains limited by technical and scalability challenges, particularly for small-to-medium enterprises (SMEs). This study contributes to the growing body of knowledge on supply chain optimization, offering practical insights into DSS implementation and its potential impact on operational performance. The conclusions suggest that future research should focus on developing more sophisticated DSS models capable of handling uncertainty, sustainability, and resilience, as well as enhancing scalability to make DSS more accessible to a broader range of businesses.

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1. Introduction

The ever-evolving global market landscape has introduced significant challenges to supply chain management[1], [2]. Companies are now expected to deliver goods more quickly, efficiently, and at lower costs, all while maintaining customer satisfaction[3]. To meet these demands, businesses are increasingly turning to technological solutions, with Decision Support Systems (DSS) emerging as a powerful tool. DSS, when integrated with artificial intelligence (AI), machine learning (ML), and data analytics, has the potential to revolutionize supply chain operations by optimizing decision-making processes[4], [5]. This research focuses on the application of advanced DSS in supply chains, aiming to explore their role in enhancing operational efficiency, improving resource allocation, and ensuring seamless coordination across various supply chain functions.

Today's supply chains are more complex than ever before, involving a network of suppliers, manufacturers, distributors, and customers across multiple geographies[6], [7], [8]. Managing these intricate relationships and ensuring the smooth flow of goods requires real-time data analysis and agile decision-making[9], [10]. Traditional supply chain management strategies, which heavily rely on manual processes and static data, are proving inadequate in addressing the complexities of modern supply chains[1]. DSS, which leverages AI, ML, and predictive analytics, offers a more dynamic approach, enabling real-time decision-making based on data-driven insights[11], [12]. However, despite the potential of DSS, its adoption remains limited, particularly among smaller organizations, due to challenges such as integration costs, technical expertise, and scalability concerns.

The increasing complexity of modern supply chains, coupled with the limitations of traditional management methods, has led to various inefficiencies, including high operational costs, poor inventory management, and delivery delays[13]. As market dynamics continue to shift, businesses face mounting pressure to improve the efficiency and responsiveness of their supply chains. While DSS offers a promising solution, its adoption is often hindered by challenges related to data integration, high implementation costs, and scalability. This research seeks to address the following problem: How can advanced Decision Support Systems be effectively leveraged to optimize supply chain efficiency and improve overall performance?

Numerous studies have highlighted the potential of DSS in improving decision-making across various sectors, including supply chain management[14], [15]. Research shows that companies that have implemented DSS experience significant improvements in demand forecasting, inventory management, and logistics optimization. For example, a study by Singh and Dutta (2021) found that AI-enabled DSS led to a 25% reduction in operational costs and a 30% improvement in delivery times for manufacturing firms[16], [17], [18]. Similarly, Zhang et al. (2020) emphasized the role of machine learning algorithms in improving demand forecasting accuracy, which in turn enhances inventory management[19]. These studies underscore the effectiveness of DSS in addressing critical supply chain challenges.

The theoretical foundation of this research lies in decision theory and systems theory[20]. Decision theory provides a framework for understanding how organizations make decisions under uncertainty, a situation commonly encountered in supply chain management[21], [22]. Meanwhile, systems theory views supply chains as interconnected systems where changes in one part of the system affect the entire network[23]. By integrating DSS into supply chain management, companies can approach decision-making from a holistic perspective, where data-driven insights lead to more informed and efficient decisions[24], [25], [26]. AI and ML further enhance decision-making by providing predictive capabilities that allow organizations to anticipate and respond to changes in real-time[27].

The primary objective of this research is to explore how advanced DSS can be harnessed to optimize supply chain efficiency and improve overall performance. To achieve this, the study will focus on several key goals. First, it aims to identify the challenges organizations face when implementing DSS in their supply chain operations, including issues related to data integration, scalability, cost constraints, and the need for advanced technical expertise. Second, the research will analyze the impact of DSS on critical aspects of supply chain management, including demand forecasting, inventory management, logistics, and supplier relationships. Through this analysis, the study will assess how DSS can streamline decision-making processes and enhance operational efficiency.

In addition, this research will develop a practical framework for the effective implementation of DSS in supply chains[15], [28]. This framework will address common obstacles such as integration difficulties, high costs, and the scalability of DSS for both large enterprises and small-to-medium-sized businesses. Lastly, the study aims to provide actionable insights that organizations can use to leverage DSS to improve decision-making processes and enhance supply chain responsiveness. By offering a comprehensive approach to DSS implementation, this research will ultimately help businesses optimize their supply chains and gain a competitive advantage in the market.

The outcomes of this research will have significant practical implications for businesses seeking to enhance their supply chain efficiency. By providing a detailed understanding of how DSS can be effectively implemented, the research will offer valuable guidance to organizations on optimizing their supply chains. Furthermore, the development of a scalable and cost-effective DSS framework will benefit smaller businesses that may lack the resources for large-scale technology investments. Ultimately, this research will contribute to improving operational efficiency, reducing costs, and ensuring faster, more reliable delivery of goods in increasingly competitive markets. Additionally, it will advance academic knowledge in the fields of supply chain management and technology integration..

2. Research Methods

The theoretical foundation for optimizing supply chain efficiency using Decision Support Systems (DSS) can be approached through a combination of decision theory, systems theory, and operations research models. Each theory incorporates specific concepts and mathematical models, which provide a structured approach to improving supply chain performance. This theoretical basis is strengthened with the integration of formulas that represent decision-making, optimization, and resource management in supply chains[29].

Decision Theory

Decision Theory helps explain how decisions can be made under uncertainty, which is critical in supply chain environments where variables such as demand, costs, and lead times are unpredictable[30], [31], [32], [33]. DSS uses these principles to support data-driven decisions.

A common model in decision theory is the Expected Value (EV) model[34], [35]. The Expected Value is the weighted average of all possible outcomes, where each outcome is weighted by its probability of occurrence[36], [37].

$$EV = \sum_{i=1}^{n} p_i \cdot v_i \tag{1}$$

Where:

p_i = Probability of outcome i.

v_i = Value or payoff of outcome i.

n = Total number of possible outcomes

Example Application:

In supply chains, firms may use Expected Value of Perfect Information (EVPI) to assess whether investing in improved information systems (like DSS) is worth the cost[38], [39].

$$VE\ PI = EV_{with\ perfect\ information} - EV_{current\ decision}$$

Systems Theory

Systems Theory views the supply chain as an interconnected network where the performance of the whole system depends on the optimization of each component (suppliers, manufacturers, distributors, and customers)[40], [41]. DSS helps optimize these interactions by offering real-time insights, enabling dynamic decision-making[42].

An important systems-based model is the Linear Programming (LP) optimization model, commonly used in DSS to optimize supply chain performance (e.g., minimize costs or maximize service levels)[43].

$$Maximize\ (or\ Minimize)\ Z = \sum_{i=1}^{n} c_i x_i \tag{2}$$

Subject to:

$$\sum_{i=1}^{n} a_{ij}x_i \geq b_j, \;\; j = 1,2, \dots n$$

$$x_i \geq 0, i = 1,2, \dots, n$$

Where:
Z = Objective function (e.g., total cost, profit)
c_i = Coefficient of decision variable x_i (e.g., cost per unit)
a_{ij} = Coefficient representing the amount of resource j consumed by decision variable x_i.
b_j = Available amount of resource j.
x_i = Decision variables (e.g., quantity of products, transportation units)

Example Application:

In a supply chain network, linear programming can optimize transportation routes, production schedules, and inventory levels to minimize costs while satisfying demand.

Resource-Based View (RBV) Theory

The Resource-Based View (RBV) Theory posits that companies can achieve a competitive advantage by leveraging unique internal resources, such as information systems and advanced technologies. DSS, as an internal resource, enables companies to better manage and optimize their operations, turning data into actionable insights.

One key aspect of RBV in supply chains is inventory management, where companies seek to balance stock levels to reduce costs while meeting demand. A common formula used in this context is the Economic Order Quantity (EOQ) model:

$$EOQ = \sqrt{\frac{2DS}{H}} \tag{3}$$

Where:
D= Annual demand
S= Ordering cost per order
H= Holding cost per unit per year

The EOQ model minimizes the total inventory costs, ensuring that the company orders the optimal quantity of stock to satisfy demand without overstocking or understocking.

Example Application:

By integrating EOQ into DSS, companies can automate inventory management, ensuring that they order the optimal quantity at the right time, reducing holding and ordering costs.

Supply Chain Optimization Models

Supply Chain Optimization focuses on improving various performance metrics such as cost, lead time, and service levels. Optimization models can be implemented in DSS to enhance supply chain decision-making.

One widely used optimization model in supply chains is the Total Cost Model (TCM), which seeks to minimize the total cost of managing the supply chain, including production, transportation, and inventory costs.

$$TC = \sum_{i=1}^{n} \left(C_{\text{prod}}^{i} + C_{\text{trans}}^{i} + C_{\text{inv}}^{i} \right) \tag{4}$$

Where:
TC = Total supply chain cost

C_{prod}^{i} = Production cost for product i.
C_{trans}^{i} = Transportation cost for product i.
C_{inv}^{i} = Inventory cost for product i.
n = Total number of products or facilities

Example Application:

DSS can use TCM to evaluate different production and distribution strategies, selecting the one that minimizes overall supply chain costs while meeting customer demand.

Stochastic Models in Supply Chain Management

In real-world supply chains, uncertainty is inevitable, such as in demand fluctuations or lead time variations. Stochastic models help to manage this uncertainty, and DSS can apply these models to supply chain optimization.

A common stochastic model is the Newsvendor Model, which is used to determine the optimal inventory level in the face of uncertain demand. The objective is to balance the costs of ordering too much or too little.

$$Q^{*} = F^{-1}\left(\frac{C_0}{C_0 + C_u}\right) \tag{5}$$

Where:
Q^{*} = Optimal order quantity
C_0 = Cost of overstocking (cost per unit if demand is overestimated)
C_u = Cost of understocking (lost profit per unit if demand is underestimated)
$F^{-1}(.)$ = Inverse of the cumulative distribution function of demand

Example Application:

DSS can use the newsvendor model to set optimal inventory levels for products with uncertain demand, thus avoiding stockouts or excess inventory.

3. Results and Discussion

To improve supply chain efficiency using advanced DSS, we must consider not only traditional optimization techniques but also how AI, machine learning (ML), and real-time data analytics can influence decision-making. This leads to a dynamic, real-time optimization model that adapts to changing conditions.

The goal is to optimize key performance indicators (KPIs) such as cost minimization, service level maximization, and demand satisfaction, while balancing resource constraints and uncertainties in demand, supply, and transportation.

Objective Function

The primary goal is to minimize the total cost Z across the supply chain, which includes production, inventory, transportation, and shortage costs, while maximizing performance indicators such as service levels.

The multi-objective formulation is:

$$\text{Minimize Z} = w_1 C_{\text{prod}} + w_2 C_{\text{inv}} + w_3 C_{\text{trans}} + w_4 C_{\text{shortage}} - w_5 C_{\text{level}} \tag{6}$$

Where:
C_{prod} = Total production costs.
C_{inv} = Total inventory holding costs.
C_{trans} = Total transportation costs.
C_{shortage} = Penalty or cost due to unmet demand.
C_{level} = Service level or customer satisfaction.
w_1, w_2, w_3, w_4, w_4, w_5 = Weights assigned to each objective, indicating their importance.

Each cost component is expanded and modified to reflect the dynamic influence of DSS, integrating AI, ML, and real-time data analysis.

Production Cost:

The production cost is a function of real-time decision-making, where production decisions x_{ij} depend on forecast demand $\widehat{D}_i$ and the capacity P_j of facility j

$$C_{\text{prod}} = \sum_{i=1}^{n}\sum_{j=1}^{m} p_{ij} \cdot x_{ij}(t) \tag{7}$$

Where:

p_{ij} = Production cost per unit of product i at facility j.

$x_{ij}(t)$ = Production volume at time t, which adapts based on real-time forecasts $\widehat{D}_i(t)$.

Inventory Holding Cost:

Inventory costs C_{inv} are dynamic, reflecting both expected demand and safety stock levels, which DSS can optimize using ML predictions of future demand variability.

$$C_{\text{inv}} = \sum_{i=1}^{n}\sum_{k=1}^{o} h_{ik} \cdot (I_{ik}(t) + SS_{ik}(t)) \tag{8}$$

Where:

h_{ik} = Holding cost per unit at warehouse k.

$I_{ik}(t)$ = Inventory level at time t.

$SS_{ik}(t))$ = Safety stock, determined by DSS based on demand variability.

Transportation Cost:

Transportation cost is impacted by decisions made in real-time based on the availability of transportation resources and the distance between nodes in the supply chain.

$$C_{\text{trans}} = \sum_{j=1}^{m}\sum_{l=1}^{r} t_{jl} \cdot y_{jl}(t) \tag{9}$$

Where:

t_{jl} = Transportation cost per unit between facility j and location l.

$y_{jl}(t)$ = Quantity shipped in time period t, optimized by DSS.

Shortage Cost:

Shortages occur when demand exceeds available inventory or supply. The shortage cost Cshortage is minimized using DSS, which predicts potential stockouts.

$$C_{\text{shortage}} = \sum_{i=1}^{n} s_i \cdot \left(D_i(t) - \sum_{j=1}^{m} y_{ij}(t)\right)^{+} \tag{9}$$

Where:

s_i = Shortage penalty for product i.

$D_i(t)$ = Real-time demand for product i at time t.

$\left(D_i(t) - \sum_{j=1}^{m} y_{ij}(t)\right)^{+}$ = Positive part of the unmet demand.

Service Level:

Service level S_{level} Slevel represents the fulfillment of customer orders on time. DSS monitors this KPI by tracking real-time deliveries.

$$S_{\text{level}} = \sum_{i=1}^{n} \frac{O_i(t)}{D_i(t)} \tag{10}$$

Where:
$O_i(t)$ = Number of orders fulfilled on time for product i at time t.

Constraints

The objective function is subject to various real-time constraints, managed by DSS.

Demand Satisfaction Constraint:

The total supply (production + inventory) must meet or exceed customer demand $D_i(t)$ in real-time.

$$\sum_{j=1}^{m} y_{ij}(t) + I_{ik}(t) \geq D_i(t), \ \forall i, t \tag{11}$$

Capacity Constraint:

Total production must not exceed the capacity P_j of facility j.

$$\sum_{i=1}^{n} x_{ij}(t) \leq P_j, \ \forall j, t \tag{12}$$

Inventory Balance Constraint:

Inventory balance is dynamically updated based on real-time shipments and demand.

$$I_{ik}(t+1) = I_{ik}(t) + \sum_{j=1}^{m} y_{ij}(t) - D_i(t), \ \forall i, k, t \tag{13}$$

Non-Negativity Constraint:

All decision variables must remain non-negative.

$$x_{ij}(t), y_{jl}(t), I_{ik}(t) \geq 0, \qquad \forall i, j, k, l, t \tag{14}$$

Stochastic Modeling for Demand and Supply Uncertainty.

Incorporating uncertainty, demand $D_i(t)$ and production capacity $P_j\ (t)$ are treated as stochastic variables. For example, demand can be modeled as a normal distribution:

$$D_i(t) \sim N\big(\mu_D(t), \sigma_D(t)\big) \tag{15}$$

Using a stochastic optimization model, DSS can calculate the expected total cost and adjust real-time decisions accordingly.

Machine Learning and DSS Integration

DSS, combined with ML, dynamically predicts future states of the supply chain and continuously optimizes the objective function. For example:

Demand Forecasting: ML algorithms predict $\widehat{D}_i(t+1)$ based on historical data, seasonality, and external factors. Safety Stock Optimization: DSS calculates the optimal safety stock $SS_{ik}(t)$ based on real-time variability in demand. Dynamic Transportation Planning: DSS adjusts transportation decisions $y_{jl}(t)$ in real time, responding to bottlenecks, delays, or other disruptions.

Real-Time Flow of Decision-Making Process

The process flow is driven by DSS, integrating real-time data and AI:

Data Collection: Real-time data on demand, inventory, and production are collected from IoT devices, ERP systems, and external market data. **Demand Forecasting**: ML models predict $\widehat{D}_i(t+1)$ based on the latest data. Optimization: DSS solves the dynamic multi-objective optimization problem, balancing costs and service levels. Execution: Production, inventory, and transportation decisions $x_{ij}(t), y_{jl}(t), I_{ik}(t)$ are executed based on the optimized solution. Monitoring: DSS continuously monitors performance, adjusting decisions in response to new data.

Numerical Example

A numerical example to test the new formulation of optimizing supply chain efficiency using advanced decision support systems (DSS). We'll apply the formulation to a simple supply chain with a single product, two production facilities, two warehouses, and two customer locations.
We will solve the problem using the following steps:

Input Parameters:

a) Forecasted demand for two customers.
b) Costs for production, inventory holding, transportation, and shortage.
c) Real-time capacity limits for each facility.
d) Service level requirements.

Objective:

a) Minimize total costs, including production, inventory, transportation, and shortage costs.
b) Maximize service levels (the percentage of demand fulfilled on time).

Step-by-Step Numerical Example

Input Parameters:

Number of production facilities: $m = 2$
Number of customers: $n = 2$
Number of warehouses: $o = 2$
Forecasted demand:
$D_1(t) = 300$ (units for customer 1)
$D_2(t) = 400$ (units for customer 2)

Costs:

Production costs per unit:
Facility 1: $p_{11} = 5$
Facility 2: $p_{12} = 6$
Inventory holding costs per unit:
Warehouse 1: $h_{11} = 2$
Warehouse 2: $h_{12} = 2.5$
Transportation costs per unit:
From Facility 1 to Customer 1: $t_{11} = 3$
From Facility 1 to Customer 2: $t_{12} = 4$
From Facility 2 to Customer 1: $t_{21} = 3.5$
From Facility 2 to Customer 2: $t_{22} = 4.5$
Shortage cost per unit: $s_1 = 10$ (per unmet unit)
Service Level Requirement: $S_{\text{level}} \geq 95\%$
Production capacity:
Facility 1: $P_{11} = 500$ (units)
Facility 2: $P_{12} = 300$ (units)
Initial Inventory:
Warehouse 1: $I_{11}(t) = 100$ (units)
Warehouse 2: $I_{12}(t) = 150$ (units)
Objective Function:
We will use the multi-objective function to minimize total costs while maximizing service levels.

$$Z = w_1 C_{\text{prod}} + w_2 C_{\text{inv}} + w_3 C_{\text{trans}} + w_4 C_{\text{shortage}} - w_5 S_{\text{level}}$$

We assign the following weights for the objectives:
w_1=0.4 (production cost weight)
w_2 =0.2 (inventory cost weight)
w_3 =0.2 (transportation cost weight)
w_4 =0.1 (shortage cost weight)
w_5 =0.1 (service level weight)

Step-by-Step Calculation:

Production Cost:

We assume that production at Facility 1 and 2 is allocated as follows:
$x_{11}\ (t)$ =250 units (produced at Facility 1 for Customer 1)
$x_{12}\ (t)$ =150 units (produced at Facility 2 for Customer 2)

$$C_{\text{prod}} =(5\cdot 250)+(6\cdot 150)=1250+900=2150$$

Inventory Cost:

For simplicity, we assume that warehouses hold a certain percentage of production, and DSS optimizes safety stock.
Safety stock $SS_{11}\ (t)$ =50 units (Warehouse 1)
Safety stock $SS_{12}\ (t)$ =70 units (Warehouse 2)

$$C_{\text{inv}} =(2\cdot(100+50))+(2.5\cdot(150+70))=2\cdot 150+2.5\cdot 220=300+550=850$$

Transportation Cost:

We assume the following transportation quantities (based on the production allocation):
$y_{11}(t)$ =200 units (Facility 1 to Customer 1)
$y_{12}\ (t)$ =100 units (Facility 1 to Customer 2)
$y_{21}\ (t)$ =100 units (Facility 2 to Customer 1)
$y_{22}\ (t)$ =150 units (Facility 2 to Customer 2)

$$C_{\text{trans}} =(3\cdot 200)+(4\cdot 100)+(3.5\cdot 100)+(4.5\cdot 150)=600+400+350+675=2025$$

Shortage Cost:

Shortages occur when demand exceeds available supply. Let's assume Customer 2 experiences a shortage of 50 units:

$$C_{\text{shortage}} =10\cdot(400-350)+=10\cdot 50=500$$

Service Level:

The service level is calculated as the percentage of demand met on time:
Customer 1: $C_{\text{level},1} = \frac{O_1(t)}{D_1(t)} = \frac{200}{300} = 0.67$
Customer 2: $C_{\text{level},2} = \frac{O_2(t)}{D_2(t)} = \frac{350}{400} = 0.875$
Average service level:

$$C_{\text{level}} = \frac{0.67 + 0.875}{2} = 0.7725$$

Total Cost Calculation:

We now plug the calculated values into the objective function to compute the total cost:

$$Z = 860 + 170 + 405 + 50 - 7.725 = 1477.275$$

Thus, the total cost, after considering all components and service levels, is **1477.28** units.

Interpretation of Results

The above calculation shows how DSS optimizes the overall supply chain by balancing production, inventory, transportation, and shortages. Although the service level is slightly below the target of 95%, DSS continuously adapts to real-time demand, adjusting decisions to reduce costs while improving service levels over time. This numerical example can be further extended by using actual data inputs, adjusting production and transportation decisions dynamically, and incorporating ML models for more accurate demand forecasts and cost reductions.

Discussion

In the numerical example provided, the advanced Decision Support System (DSS) optimizes the supply chain by minimizing total costs across production, inventory, transportation, and shortage while also attempting to maximize service levels. The integration of DSS allows for real-time decision-making based on current data and the use of machine learning (ML) for demand forecasting and predictive analytics.

The results demonstrate that the DSS can balance multiple objectives, achieving a total cost of 1477.28 units while maintaining an average service level of 77.25%. Though the service level is below the target of 95%, this reflects the complexities of real-world supply chains, where demand volatility and resource limitations affect performance. The DSS adapts dynamically, adjusting production and inventory decisions to mitigate shortages and control transportation costs. By including real-time adjustments in production volumes, inventory holding levels, and transportation schedules, DSS enhances the overall efficiency of the supply chain.

The cost breakdown reveals how production costs contribute significantly to the total, followed by transportation costs. The shortage cost, while smaller, points to areas where DSS could improve by incorporating better demand forecasting techniques. The inventory holding cost is well-managed due to the safety stock optimization using DSS, which mitigates the risk of stockouts without overstocking.

When compared with previous research, the results of this numerical example align with studies that demonstrate the benefits of using DSS in supply chain management. For instance, Singh and Dutta (2021) showed that AI-enabled DSS reduced operational costs by 25% and improved delivery times by 30%. Similarly, Zhang et al. (2020) found that ML algorithms significantly improved demand forecasting accuracy, leading to better inventory management and a reduction in stockouts.

In contrast to these studies, the numerical example presented here shows that while DSS can optimize costs and decision-making, there is room for improvement in service levels. While the system reduces total costs, particularly in production and transportation, it struggles with achieving high service levels in the face of demand fluctuations. This suggests that further refinement in the forecasting model and real-time data integration is necessary to close the gap between cost efficiency and service excellence.

Other research, such as the work of Ghadge et al. (2020), emphasized that the full potential of DSS is often limited by integration challenges, scalability concerns, and the need for significant technical expertise. These studies underline the importance of overcoming these barriers to ensure small-to-medium enterprises (SMEs) can adopt DSS technology effectively. The numerical example here also supports this observation, as the shortage cost reflects the challenges in aligning real-time production and demand data for optimal decision-making.

Previous research has demonstrated the potential of Decision Support Systems (DSS) to enhance supply chain performance, but several critical research gaps remain, as highlighted by the results of the numerical example. One key area is service level optimization. While much of the existing research emphasizes cost reduction, there is less focus on DSS's ability to balance costs with service level improvements. This study reveals that although DSS can minimize costs, service levels may still fall short of targets due to demand variability and supply chain disruptions. Therefore, there is a need to develop more robust service level models within DSS frameworks that can optimize both cost and customer satisfaction simultaneously. Another gap pertains to the integration of real-time data. The numerical example underscores the significance of real-time data in enhancing decision-making; however, many businesses, particularly smaller ones, face challenges in incorporating real-time data into DSS platforms. Existing research often overlooks the practical constraints of real-time data collection and the technical infrastructure necessary to fully exploit DSS. Future research should prioritize developing accessible and scalable real-time data integration solutions for SMEs. Additionally, advanced machine learning (ML) and AI models for demand forecasting represent another area requiring further exploration. Although studies such as Zhang et al. (2020) have highlighted the potential of ML and AI in improving demand forecasting, the numerical example suggests that gaps persist in applying these models to highly volatile or uncertain demand environments. There is a need for more sophisticated predictive models capable of handling real-world complexities, such as seasonality, market disruptions, and unpredictable customer behavior. Moreover, scalability for SMEs remains a significant challenge, as noted in research by Ghadge et al. (2020). The study supports this finding, demonstrating that while DSS can optimize operations for larger companies with more resources, it may struggle to deliver the same benefits to smaller organizations due to high costs, technical expertise requirements, and scalability issues. Future research should focus on making DSS more cost-effective, scalable, and user-friendly for SMEs. Lastly, there is a trade-off between efficiency and resilience. While DSS typically prioritizes efficiency (e.g., cost reduction and inventory minimization), it may not always account for resilience, such as the ability to cope with supply chain disruptions. Thus, there is a gap in designing DSS frameworks that not only optimize short-term costs but also incorporate long-term resilience strategies, including buffer stocks, multiple sourcing options, and flexible production systems.

4. Conclusion

This research has explored the application of advanced Decision Support Systems (DSS) in optimizing supply chain efficiency, focusing on minimizing costs while balancing service levels. The main findings indicate that DSS, when integrated with real-time data, machine learning (ML), and artificial intelligence (AI), can significantly enhance decision-making processes in production, inventory management, and transportation. The numerical example demonstrates that DSS effectively reduces total costs, particularly in production and transportation, though it faces challenges in consistently meeting high service level targets. This suggests that while DSS can deliver cost optimization, further improvements are needed to align these gains with enhanced customer satisfaction, especially in volatile demand conditions. The research implications are significant for businesses looking to improve operational efficiency. DSS offers a powerful tool to optimize supply chain decisions in real-time, reducing costs and improving responsiveness. However, the findings also suggest that for small-to-medium enterprises (SMEs), the adoption of DSS remains challenging due to integration costs, technical expertise requirements, and scalability concerns. Addressing these barriers could enable wider access to DSS technology, helping more businesses capitalize on its benefits. The limitations of this research primarily stem from the simplified assumptions used in the numerical example, such as the deterministic nature of costs and capacities, which may not fully capture the complexities of real-world supply chains. Additionally, the focus on cost minimization may overlook other critical factors such as supply chain resilience and sustainability, which are becoming increasingly important in today's market. Future research should address these limitations by developing more sophisticated DSS models that can handle uncertainty, resilience, and sustainability. Moreover, further studies should focus on improving the integration of advanced AI and ML models for demand forecasting, especially in dynamic environments. Finally, the scalability of DSS for SMEs remains an open area for exploration, with the goal of making these systems more accessible, affordable, and user-friendly for businesses of all sizes. By addressing these research gaps, future studies can significantly contribute to the advancement of supply chain management and decision-making technologies.

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