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# Optimisation Model of SPD Supply Chain for Medical Consumables under DRG Background Based on Mixed Integer Programming

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**ABSTRACT**
In the context of diagnosis related groups (DRG) payment systems, hospitals are facing dual pressures of controlling medical costs and improving service quality. The supply, processing and distribution (SPD) process of medical consumables is an important component of hospital operations, and optimising this supply chain can help achieve cost savings and efficiency improvements. This article proposed a medical consumables SPD supply chain optimisation model based on mixed integer programming (MIP), aiming to optimise the procurement, inventory and transportation strategies of medical consumables through scientific decision-making methods. The model construction comprehensively considered the cost control requirements and various constraints under the DRG system, including demand fulfilment, inventory capacity, supplier supply capacity and logistics transportation capacity. By using the solver CPLEX to solve the model, the results showed that the optimised supply chain strategy could significantly reduce total costs while improving supply chain service levels, with a demand fulfilment rate of up to 97%. The research in this article provides an effective optimisation tool for hospitals' medical consumables supply chain management under the DRG payment system, with significant theoretical significance and practical application value.

**KEYWORDS**
healthcare supply chain optimisation; mixed integer programming; DRG payment system; supply, processing and distribution (SPD); cost control.

## 1. INTRODUCTION

As the healthcare industry focuses on cost control and quality of service, hospitals are facing increasing challenges in their operations, especially in the supply, processing and distribution (SPD) of medical consumables [1, 2]. Conventional SPD supply chain management for medical consumables [3, 4] relies on empirical and intuitive decision-making methods, and suffers from insufficient and inaccurate data as well as modelling complexity, which not only affects supply chain efficiency and cost control but also makes it difficult for hospitals to formulate scientific and effective strategies to cope with changing demands and cost pressures. Supply chain management in hospitals is facing new challenges due to the application of diagnosis-related group (DRG) payment systems [5, 6]. These systems provide fixed reimbursement for each patient in a hospital on a case-by-case basis, requiring hospitals to control healthcare costs and provide high-quality services. Conventional optimisation methods cannot cope with these complex problems because of the demand for medical consumables and the higher requirements of supply chain management.

To address the aforementioned issues, a medical consumables SPD supply chain optimisation model based on mixed integer programming (MIP) [7, 8] is proposed. Specifically, this article incorporates considerations of reimbursement policies and performance indicators in the model construction to ensure compliance with the DRG system's cost control and expense reimbursement requirements while optimising the supply chain strategy. The model not only considers the cost control demand under the DRG payment system but also considers various constraints in the supply chain [9, 10], such as demand fulfilment, inventory capacity, supplier's supply capacity and logistics and transportation capacity. By solving the model, this article aims to achieve the optimal strategy for medical consumables procurement, inventory and transportation, reduce total costs, improve supply chain efficiency, and ensure maximum service level and resource utilisation of hospitals under the DRG system. The construction of the model is detailed, involving decision variables, objective functions and constraints. Additionally, the methods for solving the model and the experimental results are discussed, along with an analysis of the model's effectiveness and practical significance in reducing costs and improving service levels. Finally, the research findings are summarised, and prospects for future research directions are proposed.

## 2. RELATED WORK

In the field of medical consumables supply chain management, research mainly focuses on optimising inventory management [11, 12], procurement strategies [13, 14] and logistics distribution [15, 16]. Traditional methods such as linear programming [17, 18], dynamic programming [19, 20] and heuristic algorithms [21, 22] have been widely applied and achieved results. However, with the increasing complexity of the medical environment, such as the application of DRG payment systems, hospitals are facing new challenges in controlling costs and improving service quality. The DRG system controls medical expenses through unified payment standards, improving resource utilisation efficiency, but at the same time, it also increases the difficulty of supply chain optimisation. To address these challenges, researchers have begun exploring more advanced optimisation methods. Liu Wei et al. [23] evaluated the effectiveness of SPD-based medical consumables management methods in reducing management costs, solving management problems and improving consumables information traceability capabilities through literature review and questionnaire surveys. The results showed that it was superior to traditional models. Chen Jingtao et al. [24] developed a medical device information management system based on C# and SQL Server databases, which improved management efficiency and reduced loss and return rates. Zhang Lei et al. [25] further constructed a full process supervision system for medical consumables by integrating advanced technologies such as QR (quick response) codes, barcodes and chip scanning, achieving intelligent management and cost monitoring, and ensuring the safe, reliable and low-cost use of medical consumables.

In recent years, significant progress has been made in inventory management, procurement strategies and logistics distribution in the supply chain management of medical consumables. In addition to traditional linear programming and dynamic programming methods, inventory management has begun to incorporate more advanced optimisation techniques [26, 27] and data-driven strategies, such as inventory prediction models based on machine learning algorithms, which can accurately predict demand fluctuations and reduce inventory backlog and shortage risks. At the same time, the secondary warehouse management system for medical low-value consumables in SPD mode optimises inventory distribution through intelligent allocation, improving turnover and response speed [28, 29]. The procurement strategy is transitioning towards multi-objective optimisation [30, 31] and supply chain collaboration. The multi-objective decision support system comprehensively considers cost, quality and supplier reliability to ensure the scientific and comprehensive nature of procurement decisions [32, 33]. In addition, the SPD-based full process precise management mode enhances the transparency and traceability of the procurement process, improves efficiency and reduces management costs. As a key link, logistics distribution is also highly valued for optimisation. Researchers have conducted in-depth optimisation of the joint distribution path of medical consumables under SPD mode [34, 35] and achieved more efficient logistics distribution strategies by constructing a multi-vehicle multi-objective model.

With the development of technology, MIP has gradually become an important tool for supply chain optimisation. Maimaiti Hailili [36] and Yu Guoqing et al. [37] respectively used Gurobi software and the MIP model for supply chain optimisation, verifying their effectiveness and feasibility. Particularly, the study of Yu Guoqing et al. maximised the overall benefit by constructing a multi-link supply chain optimisation model, showing the potential of MIP in the overall optimisation of the supply chain. Although some studies have introduced machine learning algorithms to predict demand fluctuations or transform procurement strategies to multi-objective optimisation, they have not effectively combined the characteristics of the DRG system, resulting in limited applicability of existing models in practice. To address this gap, the current study proposed a medical consumables supply chain optimisation model based on mixed integer programming, aiming to scientifically solve problems such as insufficient data, high model complexity and insufficient consideration of the impact of the DRG system.

## 3. MODEL CONSTRUCTION

The construction of the MIP model is an important component of optimising the supply chain for medical consumables SPD. The MIP model is employed to optimise the procurement, inventory management and distribution strategies of medical consumables, aiming to achieve cost control and service level optimisation within the DRG payment system. In the SPD supply chain management of medical consumables, the challenges and complexities are constantly increasing, especially in the context of DRG payment systems. The DRG payment system forces hospitals to operate efficiently within strict budget constraints by providing fixed payments for different diseases and treatment processes. Therefore, the optimisation of the SPD supply chain for medical consumables is particularly important.

### 3.1 Problem definition

*Supply chain structure and process*

The supply chain structure of medical consumables is complex, covering the entire process from supplier raw material procurement to final distribution in various departments of the hospital, including the three core links of SPD, as shown in *Figure 1*. Suppliers are responsible for producing, inspecting and initially distributing consumables to the hospital's warehouse or distribution centre. The selection and procurement decisions at this stage directly affect subsequent management. The warehouse receives, inspects, classifies and stores consumables and conducts quality inspections, label processing and special storage according to demand while implementing systematic inventory management to balance supply and demand. Subsequently, consumables are delivered to various departments of the hospital through an efficient and accurate delivery process, ensuring the quality and efficiency of medical services. The entire supply chain needs to coordinate various links, use information technology to improve management efficiency and respond to changes in demand, especially under the DRG payment system. Optimising management is particularly crucial for hospital cost control and service quality assurance.

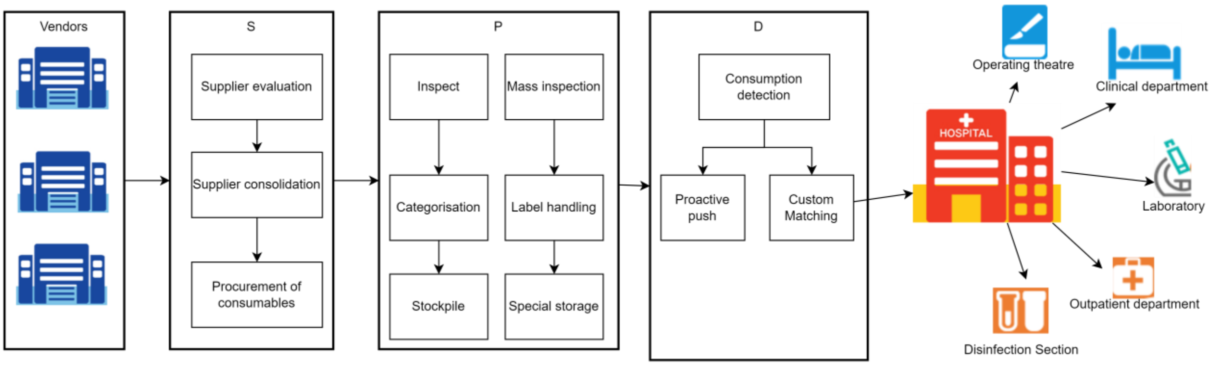


*Figure 1 – Supply chain structure*

*Optimisation objectives*

The optimisation objectives mainly include minimising the total cost and improving the service level, as shown in *Table 1*. The minimisation of total cost is the main optimisation objective, covering all relevant cost components in the supply chain. The total cost usually includes procurement costs, inventory holding costs and transportation costs. The procurement cost includes purchasing medical consumables from suppliers, which is influenced by the procurement volume, supplier pricing strategy and negotiation ability. The inventory holding cost includes storing medical consumables in the warehouse, which includes storage costs, insurance costs and the cost of expired or damaged inventory. By reducing these costs, the entire supply chain can be more economical.

In addition to minimising the total cost, one of the optimisation goals is to maximise the service level. The maximisation of service level involves multiple aspects, among which the most important are inventory availability and order fulfilment rate. The order fulfilment rate is the proportion of hospital orders completed within a specified time frame, which reflects the response speed and efficiency of the supply chain. Inventory availability refers to the quantity of medical consumables available in the warehouse to ensure the timely fulfilment of the hospital's needs. Optimising service levels not only helps improve hospital satisfaction but also reduces operational risks caused by stockouts or delayed deliveries. By improving service levels, hospitals can ensure timely access to necessary medical consumables, thereby improving the quality and efficiency of medical services.

*Table 1 – Optimisation objectives table*

| Optimisation objective | Key element | Specifics | Strategies |
|---|---|---|---|
| Total cost min. | Procurement cost | Cost of supplies from supp | Centralised purchasing, negotiation, long-term partnerships |
| | Inventory cost | Storage, insurance, wastage | Lean management, inventory systems |
| | Transportation cost | Delivery costs | Optimise routes, mode selection, sharing |
| Service level enhancement | Order fulfilment | Timely order completion | Automate processing, rapid response |
| | Inventory avail. | Stock levels for demand | Real-time monitoring, safety stock, multi-source suppliers |

*Constraints*

The setting of constraints involves ensuring that the medical consumables supply chain is feasible in practical operations and meets various business needs and limitations. The main constraints include demand fulfilment, inventory capacity, supplier supply capability and logistics transportation capability. These conditions not only ensure the normal operation of various links in the supply chain but also ensure the feasibility of the model in reality. The specific expressions and symbolic representations of each constraint condition are shown in *Table 2*.

*Table 2 – Constraints*

| Constraint | Definition | Mathematical expression | Symbol definition |
|---|---|---|---|
| Demand fulfilment constraint | Satisfy hospital demand | $x_{jk} - D_k \geq 0$ | $x_{jk}$: Shipment quantity from warehouse $j$ to hospital $k$ |
| | | | $D_k$: Demand of hospital $k$ |
| Inventory capacity constraint | Inventory does not exceed warehouse capacity | $I_j - C_j \leq 0$ | $I_j$: Inventory level in warehouse $j$ |
| | | | $C_j$: Maximum storage capacity of warehouse $j$ |
| Supplier capacity constraint | Supply does not exceed supplier capacity | $y_{\text{ij}} - S_i \leq 0$ | $y_{\text{ij}}$: Procurement quantity from supplier $i$ to warehouse j |
| | | | $S_i$: Maximum capacity of supplier $i$ |
| Transportation capacity constraint | Transportation does not exceed warehouse capacity | $x_{jk} - T_j \leq 0$ | $T_j$: Maximum transportation capacity of warehouse $j$ |

*Table 2* shows the mathematical expressions and definitions of related symbols for each constraint condition. Requirement satisfaction constraints ensure that the needs of each hospital are met, thereby avoiding situations of insufficient supply; inventory capacity constraints prevent warehouse inventory from exceeding its storage capacity; supplier supply capacity constraints ensure that suppliers do not exceed their supply capacity; the logistics transportation capacity constraint ensures that the transportation volume is within the warehouse's capacity range. Non-negative constraints ensure that all decision variables are non-negative values to maintain the logical consistency and operability of the model.

### 3.2 Decision variables

In the optimisation model of the medical consumables supply chain, the setting of decision variables is crucial to ensure the feasibility and effectiveness of the model. These decision variables include purchase quantity, inventory quantity, transportation quantity, temporary demand quantity and emergency purchase quantity. *Table 3* summarises these decision variables and their related constraints.

*Table 3 – Decision variables*

| Decision variable | Definition | Symbol | Constraint |
|---|---|---|---|
| Purchase quantity | Quantity purchased from supplier $i$ to warehouse $j$ | $x_{ij}$ | $\sum_j x_{ij} \le S_i$ |
| Inventory level | Quantity of medical supplies stored in warehouse $j$ | $I_j$ | $I_j \le C_j$ |
| | | | $I_j = \sum_i x_{ij} - \sum_k y_{jk}$ |
| Transportation volume | Quantity transported from warehouse $j$ to hospital $k$ | $y_{jk}$ | $\sum_j y_{jk} \ge D_k + z_k$ |
| Temporary demand | Unexpected demand from hospital $k$ | $z_k$ | - |
| Emergency purchase | Additional purchase from supplier $i$ to warehouse $j$ in emergencies | $x'_{ij}{}'$ | - |

The purchase quantity represents the purchase quantity from the supplier to the warehouse. Its optimisation not only affects inventory levels and distribution plans but also reduces total costs and ensures the timely satisfaction of hospital needs while also meeting the maximum supply capacity limit of suppliers. The inventory level represents the medical consumables inventory in the warehouse, which directly affects the inventory holding cost and supply chain service level. The inventory level must be within the capacity of the warehouse and balance the demand for consumables purchased from suppliers and transportation to hospitals. The transportation volume variable determines the total weight of goods from the warehouse to the hospital. Optimising transportation volume can reduce delivery costs and ensure that hospital needs, including sudden demands, are met. Temporary demand is used to describe the hospital's sudden demand to respond to emergency situations and ensure supply chain flexibility. Emergency purchase quantity refers to the quantity of additional goods purchased from suppliers to warehouses in emergency situations, which is used to respond to unexpected situations in the supply chain in order to quickly meet demand in emergency situations. The emergency purchase quantity cannot exceed the remaining supply capacity of the supplier.

### 3.3 Objective function

In the optimisation model of the medical consumables supply chain, the core task of the objective function is to minimise the total cost. The objective function integrates procurement costs, inventory holding costs and transportation costs to achieve cost control and benefit optimisation. Its basic form can be expressed as:

$$Minimise\ Z = \sum_i\sum_j c_{ij}x_{ij} + \sum_j h_j I_j + \sum_j\sum_k t_{jk}y_{jk} \quad (1)$$

Among them, Z represents the total cost. The procurement cost $c_{ij}$ is the unit procurement cost; the inventory holding cost $h_j$ is the unit inventory cost; the transportation cost $t_{jk}$ is the unit transportation cost.

The calculation formula for the procurement cost:

$$Procurement\ cost = \sum_i\sum_j c_{ij}x_{ij} \quad (2)$$

Among them, $c_{ij}$ is the unit procurement cost, and $x_{ij}$ is the procurement quantity.

The calculation formula for the inventory holding cost:

$$Stockholding\ cost = \sum_j h_j I_j \quad (3)$$

Among them, $h_j$ is the unit inventory holding cost, and $I_j$ is the inventory quantity.

The formula for calculating transportation costs:

$$Transportation\ cost = \sum_j \sum_k t_{jk}\, y_{jk} \tag{4}$$

Among them, $t_{jk}$ is the unit transportation cost, and $y_{jk}$ is the transportation volume.

In considering the impact of the DRG system, the objective function needs to take into account both cost control and expense reimbursement requirements. Since the DRG system has strict standards for controlling healthcare costs, the model must not only reduce procurement, inventory and transportation costs but must also ensure compliance with cost control requirements under the DRG system, including cost control, expense reimbursement policies and performance metrics. These combined considerations can help improve the overall performance of the supply chain.

# 4. MODEL SOLVING

## 4.1 Data collection and processing

*Data source*

The data sources for the SPD supply chain optimisation model of medical consumables are extensive. These data come from hospital information systems, supplier cooperation data, market analysis reports and medical insurance systems, covering the period from January 2022 to December 2023, ensuring the timeliness and coverage of the data. *Table 4* provides a detailed list of the composition, sources and main uses of the dataset, providing a solid foundation for model construction and optimisation.

*Table 4 – Dataset composition*

| Data type | Description | Source | Time frame |
|---|---|---|---|
| **Hospital data** | | | |
| Demand history | Usage records of medical supplies | Hospital system | Jan 2022 – Dec 2023 |
| Procurement data | Purchase quantities and costs | Procurement dept. | |
| Inventory data | Stock levels and holding costs | Warehouse system | |
| Transportation data | Supply transport records and costs | Logistics system | |
| **Market data** | | | |
| Supplier capacity | Supplier capabilities and historical supply data | Supplier partnerships | Jan 2022 – Dec 2023 |
| Market prices | Medical supplies market prices | Market reports | |
| Logistics capacity | Transport capacity and costs | Logistics providers | |
| **DRG data** | | | |
| Cost standards | DRG-related cost standards | Healthcare system | Jan 2022 – Dec 2023 |
| Reimbursement policies | DRG reimbursement rates and conditions | Healthcare system | |
| DRG group data | Disease classifications and DRG groups | Hospital system | |

*Data processing*

In data processing, statistical methods (box plots) and data analysis tools are employed for data cleaning, removing outliers, duplicate values and erroneous records to ensure data quality. Subsequently, multiple sources of data are merged into a unified format and logically consistent dataset using data integration techniques, with a focus on temporal consistency to avoid computational errors. Finally, the programming language Python is used for data format conversion to meet the requirements of the solver, and the conversion process strictly ensures the integrity and accuracy of the data.

To visually demonstrate the impact of outlier handling on data quality, box plots before and after outlier handling are presented, as shown in *Figure 2*. The left box plot shows the data distribution before outlier processing, with some data points deviating from the box range, indicating the presence of outliers. These outliers may mislead subsequent analyses and affect the accuracy of the model. The box plot on the right shows the distribution of processed data, with outliers removed and data points concentrated within the box. This indicates that data cleaning effectively improves the quality and consistency of the data, providing a reliable foundation for model construction.

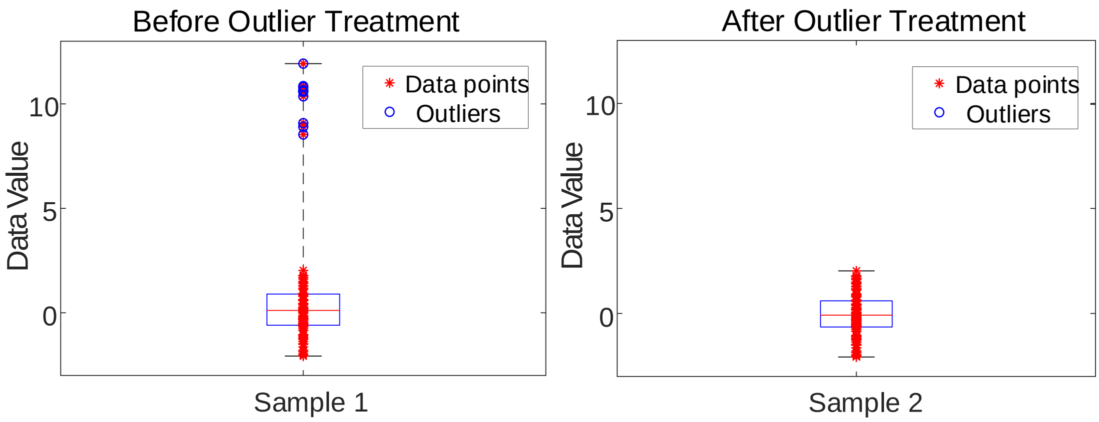


*Figure 2 – Display of outlier handling*

*The impact of assumptions in data collection and processing*

When constructing a medical consumables SPD supply chain optimisation model based on mixed integer programming (MIP), assumptions made during data collection and processing become key factors that have a potential impact on the accuracy of the model results. Assuming data integrity means that all data from hospital information systems, supplier cooperation, market analysis and medical insurance systems are complete and not missing. However, in practice, incomplete data may occur due to system failures, losses or recording errors, which can affect the completeness of model inputs and the accuracy of final results. At the same time, data accuracy is also an important assumption. Although it is assumed that the collected data truly reflect the demand, procurement, inventory and transportation of consumables, the presence of errors or outliers may mislead the model analysis and reduce optimisation efficiency. In addition, the assumption of data timeliness cannot be ignored. We analysed the data from January 2022 to December 2023 and believe that it can represent future trends. However, the dynamic changes in the market environment may prevent historical data from fully reflecting the true situation in the future, thereby affecting the predictive ability of the model.

## 4.2 Solution methods

*Selection of solver*

The research utilises IBM ILOG CPLEX Optimisation Studio as the solver. CPLEX is a widely used optimisation tool in the industry, specifically designed to address large-scale linear programming, integer programming and mixed integer programming problems [38-39]. Its main advantages include powerful solving ability, high efficiency and stability in handling large-scale problems. In addition, CPLEX has flexible interfaces that support multiple programming languages and integrated development environments, making it easy to integrate with practical application systems.

*Solution process*

In the process of using CPLEX to solve the optimisation model of the medical consumables supply chain, the entire solving process is shown in *Figure* 3. When using CPLEX for solving, the study accurately inputs the decision variables, objective function and constraints of the model into CPLEX through the Python API (application programming interface). The decision variables are set to non-negative integers to ensure practical significance, and the objective function is defined as minimising the total cost, covering procurement, inventory and transportation costs. The constraints include demand fulfilment, inventory capacity and transportation capacity limitations. Afterwards, the solver parameters are optimised to improve the solution efficiency and accuracy. A solution time limit of 3,600 seconds is also set, and the RINS (relaxation induced neighbourhood search) heuristic algorithm [40] is enabled to speed up the initial solution. A relative error limit of 0.01 and an absolute error limit of 0.001 are also set to ensure the accuracy of the results. During the solution process, CPLEX uses advanced algorithms such as branch-and-bound and interior-point methods for iterative optimisation to monitor the changes of objective function values and constraints in real time. At the same time, the solution parameters are adjusted as necessary to avoid falling into local optimal solutions. Finally, after multiple iterations and parameter tuning, CPLEX returns the optimal solution and verifies the results to ensure that it meets the actual requirements. By further verifying the robustness of the solution through sensitivity analysis, the optimised results provide scientific support for the hospital's medical consumables procurement, inventory management and logistics arrangements, meeting the requirements of the DRG system.

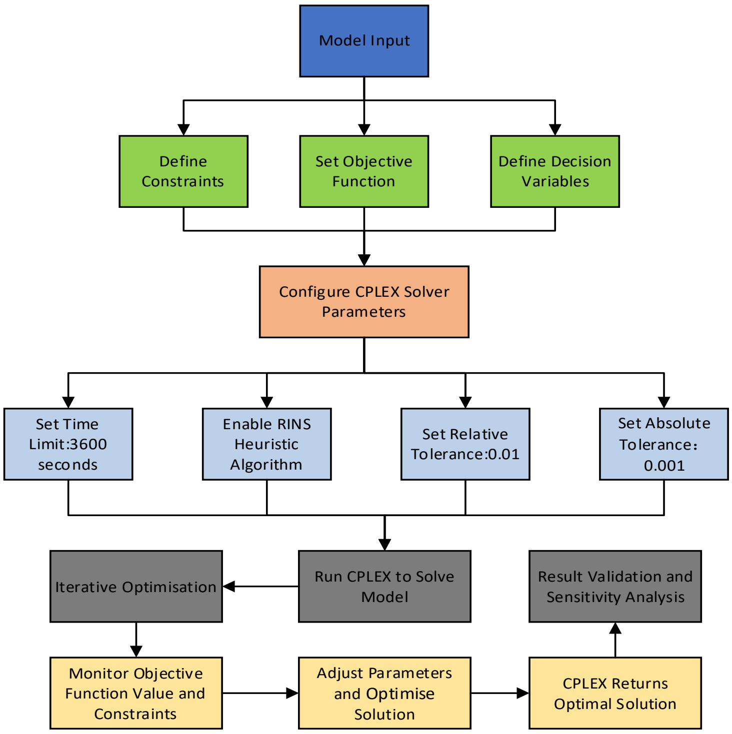


*Figure 3 – CPLEX solving process*

Based on the model solution results, formulate procurement, inventory and transportation strategies, and adjust the strategies according to actual operational conditions. This includes determining monthly purchase quantities, inventory levels and transportation routes.

## 4.3 Experimental design and methods

*Experimental design*

The performance of the medical consumables SPD supply chain optimisation model based on mixed integer programming under DRG background is tested by accurately setting conditions. The core of the experiment is to build an environment that reflects the actual medical consumables supply chain and improve the overall efficiency of the supply chain through optimising the model. The experimental objective is to evaluate the model's ability to control total costs, optimise inventory management and improve service levels. To this end, multiple experimental scenarios are set up and simulated using real data, and the optimisation effects of the models are compared.

*Table 5 – Demand quantity*

| Medical supply | Average demand (per day) | Demand fluctuation range | Procurement cycle (days) |
|---|---|---|---|
| Medical dressings | 487 dressings/day | 437-537 dressings/day | 3 days |
| Syringes | 311 syringes/day | 281-341 syringes/day | 2 days |
| Medicines | 204 doses/day | 184-224 doses/day | 5 days |
| Gloves | 394 pairs/day | 354-434 pairs/day | 4 days |

*Table 5* shows the daily average demand, demand fluctuation range, safety stock level and procurement cycle of medical consumables involved in the experiment. By selecting commonly used consumables such as medical dressings, syringes, medicines and gloves, data can comprehensively reflect the demand situation in actual medical operations. These four items were chosen due to their high usage frequency and critical role in patient care, ensuring that the demand data provide a practical basis for optimising the model to accurately reflect the hospital's actual needs.

*Table 6 – Suppliers*

| Supplier | A | B | C |
|---|---|---|---|
| Medical dressings price (yuan/dressing) | 1.20 | 1.15 | 1.35 |
| Syringes price (yuan/syringe) | 0.80 | 0.78 | 0.87 |
| Medicines price (yuan/dose) | 2.50 | 2.45 | 2.65 |
| Medical dressings supply capacity (dressings/month) | 10,000 | 12,200 | 8,500 |
| Syringes supply capacity (syringes/month) | 6,000 | 7,200 | 5,200 |
| Medicines supply capacity (doses/month) | 4,000 | 4,600 | 3,200 |

*Table 6* lists the quoted prices of the three main suppliers and their supply capacity. Supplier price and availability data are critical to the optimisation model because these factors directly affect purchasing decisions and supply chain costs. By comparing supplier quotes and delivery capabilities, sourcing strategies can be optimised to reduce overall costs and ensure supply chain stability.

*Table 7 – Transport vehicles*

| Vehicle | Maximum load (tons) | Daily transportation capacity (km) | Transportation cost (yuan/km/ton) |
|---|---|---|---|
| A | 12 | 520 | 105 |
| B | 16 | 610 | 100 |
| C | 18 | 470 | 125 |
| D | 22 | 540 | 115 |

*Table 7* presents information on the maximum capacity of the trucks, the daily transportation capacity and the transportation costs. Transportation costs are a key factor affecting the total cost of the supply chain, and data on the capacity of the trucks are useful for assessing the cost and efficiency of different transportation conditions. Therefore, these data are essential for optimising transportation scheduling and cost control.

*Table 8 – Inventory of medical consumables*

| Medical supply | Maximum inventory (units) | Minimum inventory (units) | Holding cost (yuan/unit/month) |
|---|---|---|---|
| Medical dressings | 1,050 dressings | 220 dressings | 0.55 yuan/dressing/month |
| Syringes | 1,050 syringes | 210 syringes | 0.52 yuan/syringe/month |
| Medicines | 1,020 doses | 220 doses | 0.48 yuan/dose/month |
| Surgical masks | 520 masks | 110 masks | 0.32 yuan/mask/month |

*Table 8* shows the maximum and minimum inventory levels for each medical consumable, as well as the holding cost per unit of inventory. These data are used to evaluate the effectiveness of inventory management and optimise the practical application of strategies. By setting inventory limits and holding costs, inventory levels can be optimised to balance holding costs and supply risks.

To comprehensively evaluate the performance and adaptability of the optimised model, the experimental scenarios established for this study include baseline scenarios and multiple changing scenarios. The baseline scenario represents the supply chain situation under standard operating conditions. In this scenario, the demand, supplier quotes and transportation costs remain unchanged, providing a baseline reference point for evaluating the performance of the optimisation model under normal conditions. The demand fluctuation scenario simulates the demand changes in the actual environment. The experimental scenario data for demand quantity are shown in *Figure 4*. During peak demand periods, the demand for medical dressings increases by 20% to 585 units per day; the demand for syringes increases by 15% to 358 units per day; the demand for medicines increases by 10% to 225 units per day. During the low demand period, the demand decreases by 15%, 10% and 5%, respectively. This scenario is used to test the adaptability and robustness of the model in the face of demand fluctuations.

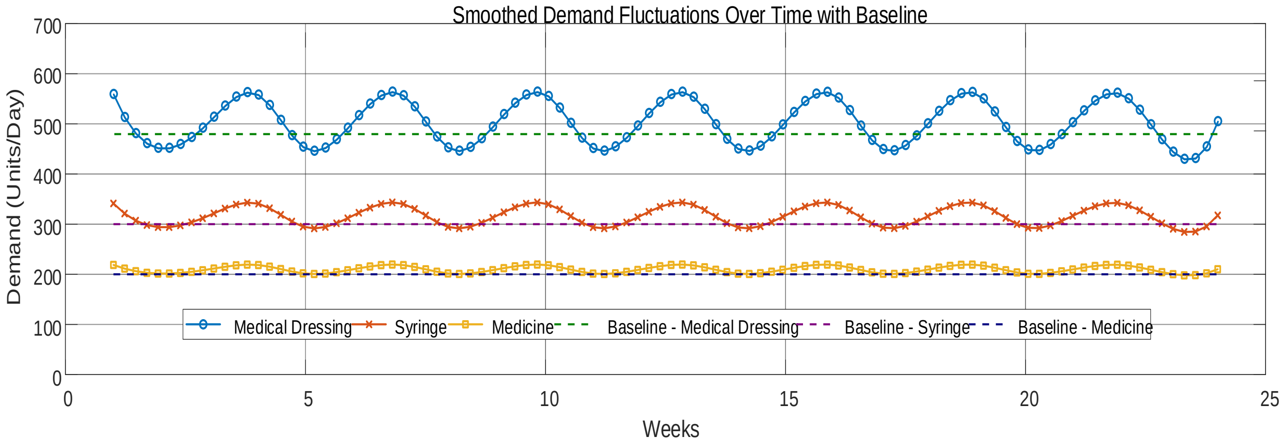


*Figure 4 – Experimental scenario of demand quantity*

The impact of changes in supplier quotes and supply capabilities on optimisation results is tested in the scenario of supplier changes, as shown in *Figure 5*. In the baseline scenario, Supplier A quotes 1.20 yuan/unit for medical dressings, 0.80 yuan/unit for syringes and 2.50 yuan/unit for medicines, with corresponding supply capacities of 10,000 units/month, 6,000 units/month and 4,000 units/month, respectively. In this scenario, Supplier A's quotation is adjusted to 1.21 yuan/unit for medical dressings, 0.88 yuan/unit for syringes and 2.75 yuan/unit for medicines. At the same time, the supply capacity is also adjusted. The supply capacity of medical dressings is adjusted to 8,330 units/month, syringes to 4,930 units/month and medicines to 3,230 units/month.

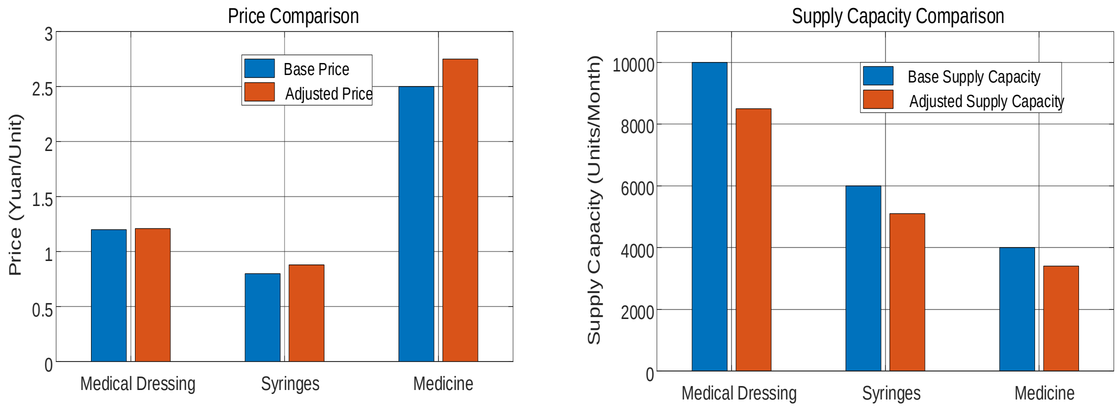


*Figure 5 – Supplier experimental scenario*

The scenario of inventory capacity adjustment leads to changes in inventory capacity. The maximum inventory level has increased from 1050 to 1100 units, while the minimum inventory level has decreased to 190 from 195 units. The purpose of this adjustment is to evaluate the performance of the model when inventory capacity changes to ensure that the model remains effective under various inventory constraints. The scenario of transportation cost changes simulates the increase in transportation costs, raising them from 105 to 110 yuan/kilometre/ton. This scenario is used to evaluate the impact of changes in transportation costs on logistics strategies and total costs. How the model adjusts during fluctuations in transportation costs is also tested.

During the experiment, the MIP solver CPLEX is used to input the model and data, perform the optimisation process and record the results of each experimental scenario, including indicators such as total cost, inventory level and service level. The variables in the procurement cost formula include purchase unit price, purchase quantity and possible discounts or preferential conditions. These variables collectively determine the hospital's procurement cost. In practice, the procurement unit price is usually determined through market inquiry or bidding methods. The procurement quantity is adjusted according to the actual needs and inventory strategy of the hospital. Discounts or preferential conditions may be provided by suppliers or linked to the purchase quantity. By using models, the optimisation effects in different scenarios are evaluated, and the advantages and disadvantages of the optimisation scheme are compared with traditional methods.

*Experimental methods*

Experiments are conducted to run optimisation algorithms using an MIP solver to determine the optimal policy for various scenarios. First, six months' worth of procurement data are collected and organised, including transportation costs, inventory levels, purchase quantities and procurement quantities of each material. Based on these data, the input parameters of the optimisation model are constructed, which aim to reduce the total cost and maintain a reasonable inventory level. The study takes into account multiple factors, such as supplier reputation, product quality, on-time delivery, price competitiveness and after-sales service. By comprehensively evaluating these factors, we selected representative suppliers that meet the hospital's needs as model inputs. Based on these inputs, the optimisation algorithm then calculates the types and quantities of materials that should be purchased each month. The optimisation algorithm also takes into account transportation costs and inventory holding costs to ensure that demand is met while minimising costs. During the optimisation process, the algorithm also takes into account changes in circumstances, such as changes in supplier quotations, fluctuations in demand and adjustments in inventory capacity. After running the model, the algorithm outputs specific procurement plans, inventory levels and transportation arrangements.

The study takes into account multiple performance indicators, such as total cost, demand fulfilment rate, maximum inventory and minimum inventory, to ensure that the optimised supply chain strategy can enhance economic efficiency while meeting the hospital's service quality requirements. The total cost includes procurement, inventory holding and transportation expenses. These data are summarised through optimisation models, and their effectiveness in reducing costs is evaluated; a lower total cost indicates good resource allocation and cost control; a high satisfaction rate indicates that the model can effectively meet demand, while a low satisfaction rate indicates insufficient supply. The inventory shortage rate displays the frequency of unmet demand due to insufficient inventory. A low shortage rate indicates good inventory management, while a high shortage rate indicates management issues. Inventory management analysis uses average, maximum and minimum inventory levels to evaluate the performance of the model in controlling inventory backlog and maintaining reasonable inventory levels. Reasonable inventory levels and low inventory backlog indicate the effectiveness of the model; excessive or insufficient inventory may lead to low management efficiency or a decline in service level.

To verify the stability of the model, a sensitivity analysis is conducted by adjusting key parameters such as demand fluctuations, transportation costs and inventory capacity. Changes in the results are observed, and their sensitivity and robustness to parameter changes are evaluated. If the performance remains good under different conditions, it indicates that the model has robustness, and a significant decrease indicates high sensitivity.

## 5. RESULTS

### 5.1 Optimisation effect evaluation

*Cost*

The experimental results are shown in *Figure 6*, and the optimised model significantly reduces the total cost. Before the optimisation implementation, the total cost was relatively high, mainly due to higher procurement and inventory holding costs. After optimisation, these costs are significantly reduced, especially the significant decrease in procurement costs, demonstrating the effectiveness of the model in resource utilisation and cost control. The transportation cost remains unchanged, indicating that optimisation is mainly focused on procurement and inventory management. The line graph of the total cost clearly shows a significant decrease after optimisation, further verifying the optimisation effect of the model.

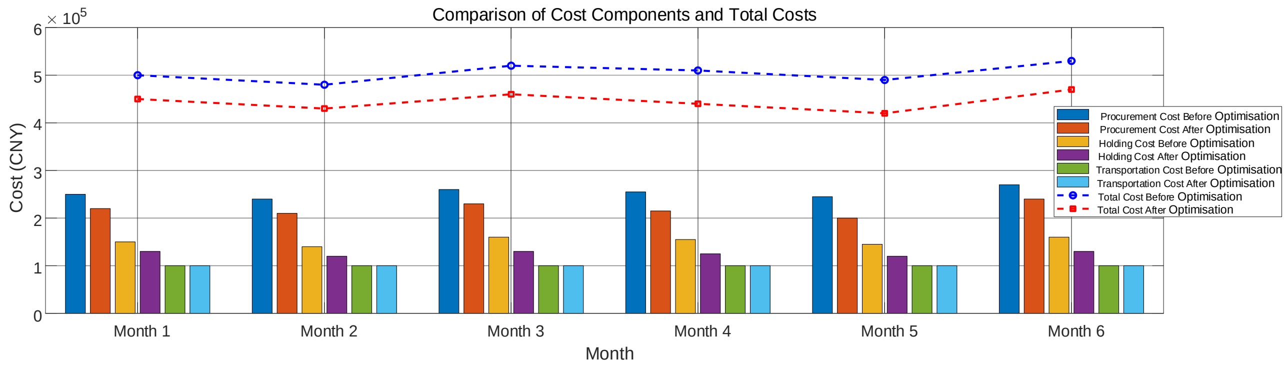


*Figure 6 – Cost analysis*

*Service level improvement*

The improvement of service level is measured by two indicators: demand fulfilment rate and inventory shortage rate. From *Figure 7*, it can be seen that the demand fulfilment rate has generally improved after optimisation, especially reaching 96%, 96% and 97% in the second, fourth and fifth months, respectively, while the lowest value before optimisation was 84%. The inventory shortage rate significantly decreased after optimisation, especially dropping to 3% in the fifth month. A lower inventory shortage rate and a higher demand fulfilment rate are of great significance in the medical supply chain. A low inventory shortage rate indicates that medical supplies can be supplied in a timely manner, reducing treatment delays or interruptions caused by shortages and ensuring timely treatment and care for patients. A higher demand fulfilment rate indicates that supply chain management can effectively predict and meet actual demand, reducing the waste of medical resources caused by insufficient supply.

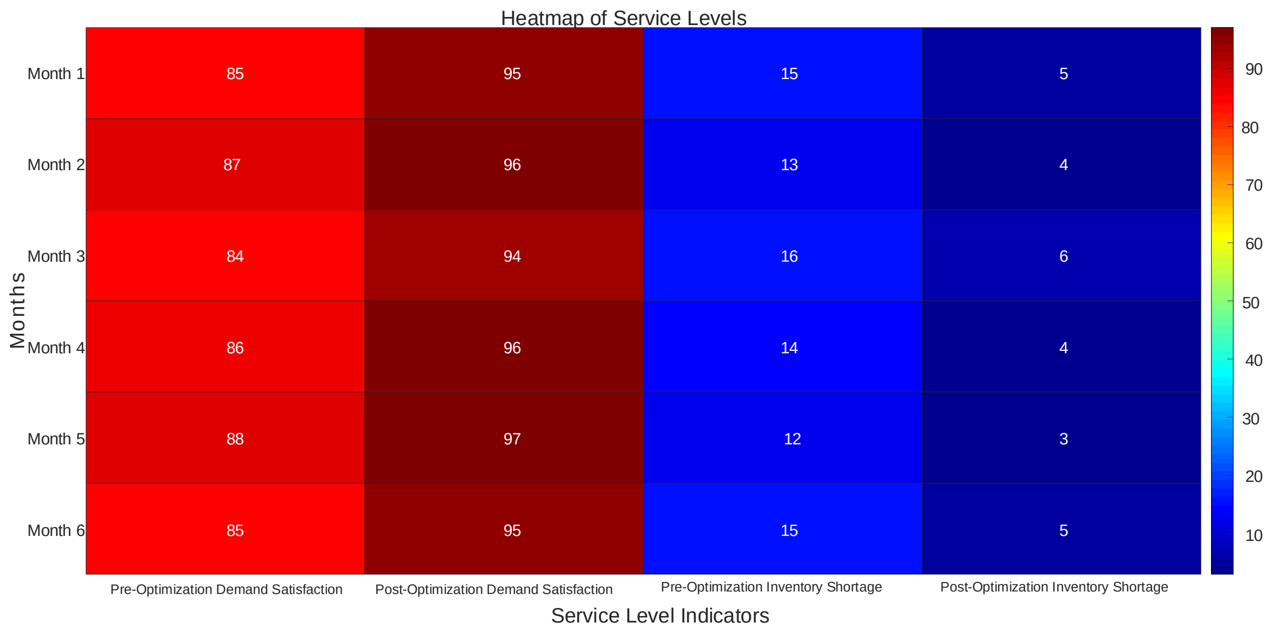


*Figure 7 – Service level*

*Improvement of inventory level*

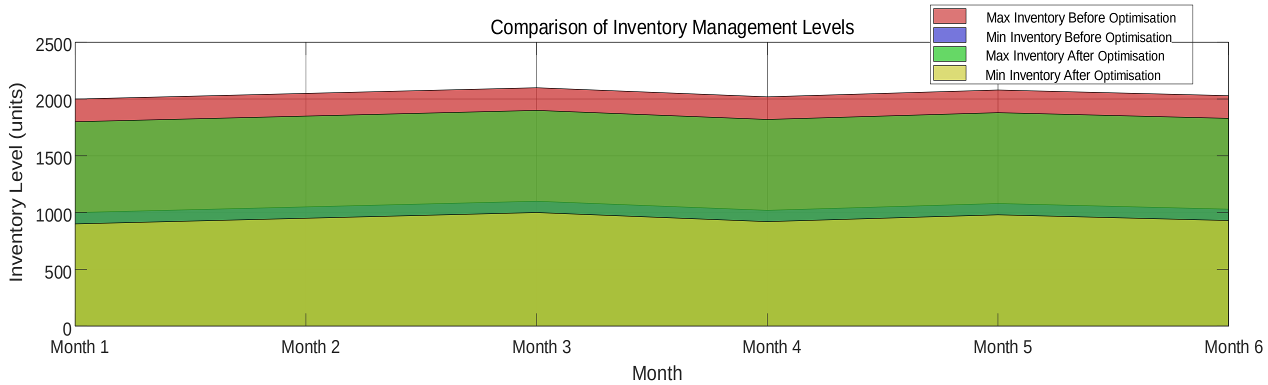


*Figure 8 – Inventory management level*

A regional chart is utilised to compare and analyse the maximum and minimum inventory of the hospital's stock warehouse over a six-month period, as illustrated in *Figure 8*. Within the six months after optimisation, the overall inventory level shows a downward trend, especially with a significant decrease in the maximum inventory level, indicating that the implementation of optimisation algorithms effectively reduces inventory holdings and inventory costs. In addition, the optimised minimum inventory level also slightly decreases, indicating that while reducing inventory backlog, the accuracy of inventory management has been improved. Overall, the optimisation strategy has successfully reduced the total cost while ensuring the efficiency of inventory management and the stability of the supply chain.

## 5.2 Model sensitivity

In order to verify the stability and adaptability of the model, this paper conducted a detailed sensitivity analysis, particularly considering the dynamics of the healthcare market and supply chain. By adjusting key parameters such as demand fluctuations, transportation costs and inventory capacity, this article observed the changes in model results and evaluated their sensitivity and robustness to parameter changes. In *Figure 9*, under standard operating conditions, the total cost of the baseline scenario is 5 million. The total cost of demand fluctuation scenarios increases to 5.2 million. The total cost of the supplier change scenario is the highest, reaching 5.4 million, mainly due to the increase in supplier quotations and the decrease in supply capacity, resulting in an overall increase in procurement and transportation costs. The total cost of the inventory capacity adjustment scenario is 5.1 million, indicating that the model can effectively adjust when inventory capacity changes. The total cost of the transportation cost change scenario is 5.3 million, indicating the impact of increased transportation costs on overall logistics costs. The demand satisfaction rate of the supplier change scenario is the highest, reaching 96%, indicating that the model can better meet the demand when dealing with changes in supplier conditions. The demand fulfilment rates for both the baseline scenario and the demand fluctuation scenario are 95%, indicating the stability of the model under both normal and demand fluctuation conditions. The demand fulfilment rate of inventory capacity adjustment and transportation cost change scenarios is 94%, slightly lower than other scenarios, which may be due to the impact of inventory adjustment and transportation cost increase on demand fulfilment rate. When demand fluctuates, the model maintains a high demand satisfaction rate by adjusting procurement quantities and inventory levels, thereby ensuring the stable operation of the supply chain. In the scenario of supplier change, the model can quickly identify and optimise new supplier combinations to reduce costs and improve service levels. Inventory capacity adjustment demonstrates the flexibility of the model in responding to changes in inventory constraints by adjusting inventory strategies to balance costs and service levels. Changes in transportation costs directly affect logistics strategies, and the model reduces transportation costs by optimising transportation routes and batches. Hospitals should establish a diversified supplier system, reduce reliance on a single supplier, and strengthen supplier evaluation and negotiation to strive for more favourable procurement prices and supply conditions. Hospitals should scientifically set inventory upper and lower limits based on actual demand and market forecasts to avoid inventory backlog and stockouts. Meanwhile, adopting advanced inventory management systems and lean management strategies can further improve inventory turnover and reduce inventory costs. As transportation costs increase, the total cost also increases accordingly. Therefore, hospitals should optimise their logistics transportation network, choose more cost-effective transportation methods and partners to reduce transportation costs. In summary, the sensitivity analysis results show the changes in total costs under different scenarios and the management implications behind them. Hospital managers should closely monitor changes in key factors such as market demand, supplier dynamics, inventory capacity and transportation costs, and develop flexible operational decisions and management strategies accordingly.

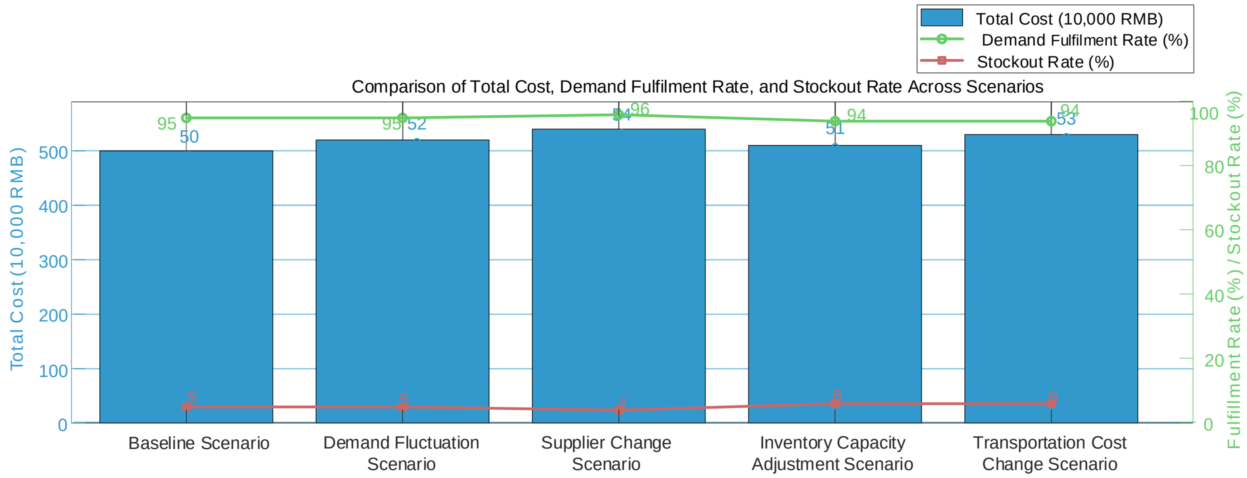


*Figure 9 – Sensitivity analysis of the model*

The time and memory consumption required for model solving in different experimental scenarios were recorded using IBM ILOG CPLEX Optimisation Studio as the solver. Specifically, under standard operating conditions (i.e. baseline scenario), the model solution time is approximately 5 minutes, and the memory usage is 133 MB. In complex scenarios such as demand fluctuations, supplier changes, inventory capacity adjustments and transportation cost changes, the solution time has increased, but it is within an acceptable range, and the memory usage remains stable. These analyses indicate that despite the high complexity of MIP models, they can still be effectively solved and applied to the optimisation of actual medical consumables SPD supply chains with reasonable computing resources.

The medical consumables SPD supply chain optimisation model based on mixed integer programming (MIP) significantly reduces total costs and improves service levels in the context of DRG payment systems. To comprehensively evaluate its advantages, comparisons with other optimisation methods are explored. The genetic algorithm (GA), a heuristic search algorithm, is well-suited for addressing complex, large-scale and nonlinear problems. It has high flexibility and does not require precise mathematical models but may face premature convergence and speed issues, and the quality of results is affected by the initial population and genetic operations. On the other hand, machine learning methods, especially deep learning, utilise big data to predict demand and optimise strategies in supply chain management but rely on large amounts of historical data and lack explicit mathematical models in the decision-making process, which affects precise control and transparency. In contrast, the mixed integer programming method employed here combines the accuracy of linear programming with the discreteness of integer programming, effectively handling complex constraints while ensuring scientific and accurate decision-making. This approach offers a valuable tool for optimising the supply chain of medical consumables in the SPD process.

## 6. CONCLUSIONS

The research has established an optimised medical consumables supply chain model using MIP, leading to cost savings and service improvements. To further refine the model's scalability and efficiency, we plan to incorporate advanced MIP techniques and metaheuristic methods. Decomposition algorithms and multi-objective optimisation are considered, with the former simplifying complex problems into smaller, more manageable sub-problems and the latter balancing multiple objectives to achieve comprehensive optimisation. In the context of the medical SPD supply chain, MIP can integrate with decomposition algorithms to address procurement, inventory and transportation sub-problems individually, then synthesise solutions through coordination mechanisms. Additionally, multi-objective optimisation could consider factors like cost, service levels, inventory levels and supply chain agility to meet hospital needs.

This MIP-based model addresses cost control and service levels by considering various factors, yet it faces limitations in demand and supplier capacity forecasting. To enhance prediction accuracy, we propose integrating machine learning techniques like SVM, random forests or deep learning models. These algorithms can process large datasets, identify complex patterns and adjust predictions in real time, improving demand forecasting and aiding in the development of procurement and inventory plans. Supplier capabilities significantly impact supply chain stability. Traditional models struggle with the uncertainties and complexities of supplier reliability. Machine learning can construct a prediction model to analyse real-time production data and historical records, dynamically assessing supplier capabilities and risks, thus ensuring supply chain continuity and stability.

A medical consumables SPD supply chain optimisation model based on mixed integer programming (MIP) has been successfully developed in the context of DRG. This model significantly reduced the total cost of the medical consumables supply chain and effectively improved service levels by deeply considering cost control requirements and various constraints. The model achieved the optimisation of various links in the supply chain by finely managing key decision variables such as procurement volume, inventory level and transportation volume. The experimental results showed that the model performed well in dealing with complex scenarios such as demand fluctuations, supplier changes and transportation cost changes, ensuring the stability and efficient operation of the supply chain. Although the mixed integer programming model proposed in this study has achieved significant results in optimising the supply chain of medical consumables SPD, there are still data limitations and room for further research. The current model mainly relies on internal hospital system data, which limits its data volume and quality to a certain extent. To overcome this limitation, future research can explore the integration of more external data sources, such as market dynamics, policy changes, etc., to enhance the universality and accuracy of the model. In addition, models that can adaptively adjust to the complex and ever-changing medical environment should be developed. In addition, with the continuous development of technology, it is also possible to consider integrating emerging technologies such as artificial intelligence and big data into models to further enhance the intelligence level and decision support capabilities of supply chain management.

## DATA AVAILABILITY STATEMENT

The data used to support the findings of this study are available from the corresponding author upon request.

## CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## ETHICAL STATEMENT

This study did not involve any human or animal experimentation.

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DRG 背景下基于混合整数规划的医疗耗材 SPD 供应链优化模型

摘要
在诊断相关组（DRG）支付体系的背景下，医院正面临控制医疗成本与提升服务质量的双重压力。医疗耗材的供应、处理与分发（SPD）流程是医院运营的重要组成部分，优化这一供应链可帮助实现成本节约与效率提升。本文基于混合整数规划（□IP）提出了一种医疗耗材 SPD 供应链优化模型，旨在通过科学方法优化医疗耗材的采购、库存及运输策略，从而提升供应链整体效率。本文提出了一种基于混合整数规划（□IP）的医疗耗材 SPD 供应链优化模型，旨在通过科学决策方法优化医疗耗材的采购、库存和运输策略。该模型构建综合考虑了 DRG 系统下的成本控制要求及各类约束条件，包括需求满足、库存容量、供应商供货能力及物流运输能力。模型构建全面考虑了 DRG 系统下的成本控制要求及各类约束条件，包括需求满足率、库存容量、供应商供货能力及物流运输能力。通过 CPLEX 求解器对模型进行求解，结果显示优化后的供应链策略可显著降低总成本并提升供应链服务水平，需求满足率最高可达 97%。本文研究为 DRG 支付体系下医院医疗耗材供应链管理提供了有效的优化工具，具有重要的理论意义和实践应用价值。本文研究为医院在 DRG 支付系统下医疗耗材供应链管理提供了有效的优化工具，具有重要的理论意义和实践应用价值。

关键词
医疗保健供应链优化、混合整数规划；DRG 支付系统；“供应、处理和分配”（SPD）；成本控制