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Article

Selecting Hospital Blood Inventory Policies under Seasonal Shortage Using Agent-Based Simulation and Multi-Criteria Decision Analysis

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Abstract

Ensuring the availability of blood products during seasonal shortage conditions is challenging due to uncertain supply and demand and the perishable nature of blood products. Hospitals must balance shortages and outdating when selecting inventory strategies. This study develops an agent-based simulation model of a regional blood supply chain that captures interactions among donors, bloodmobiles, blood centers, and hospitals, incorporating stochastic supply and demand, blood age dynamics, cross-matching, and transshipment. Simulation outputs are evaluated using a multi-criteria decision-support framework to compare alternative strategies. Results show that no single policy is universally optimal. The (T, S) policy performs best for platelets, while the EWA-based strategy is more suitable for red blood cells. Sensitivity analysis indicates that key parameters, including reorder levels and shelf life, significantly affect performance. These findings highlight the importance of adopting differentiated inventory strategies and demonstrate the value of integrating simulation with multi-criteria evaluation in healthcare supply chains.

Keywords: Blood inventory; Perishable supply chains; Inventory policy selection; TOPSIS; Grey relational analysis; Sensitivity analysis

1. Introduction

Ensuring a reliable supply of blood products is critical to healthcare systems, as shortages can directly compromise patient outcomes. However, blood supply chains (BSCs) are inherently vulnerable due to their dependence on voluntary donations, stochastic demand, and the perishable nature of blood products. Over the past decade, demand for blood products has outpaced supply growth, increasing pressure on healthcare systems (Wang and Wang, 2022). This imbalance was further exacerbated during the COVID-19 pandemic, when blood collection declined significantly due to restrictions and resource limitations (Wang et al., 2020; Franchini et al., 2020). In addition, seasonal fluctuations in donor availability further intensify supply–demand mismatches (Zhou et al., 2021).

Hospitals, as the final nodes of the BSC, must manage blood inventories under multiple sources of uncertainty. Blood products have limited shelf lives, requiring hospitals to balance shortages and outdating (World Health Organization, 2017). Meanwhile, both supply and demand are highly variable due to unpredictable donor behavior and fluctuating clinical needs (Zhu et al., 2017; Govender and Ezugwu, 2018). Operational complexities—including heterogeneous blood components, patient-specific requirements, and cross-matching processes—further complicate decision-making (Kenan and Diabat, 2022; Moslemi and Pasandideh, 2021). These challenges make inventory strategy selection a critical yet difficult problem.

Existing studies have applied optimization and simulation approaches to address blood inventory management. Mathematical programming models provide structured decision support (Gunpinar and Centeno, 2015), but they often rely on simplifying assumptions and struggle to capture the nonlinear and dynamic nature of BSCs. Simulation-based approaches offer greater flexibility but typically fail to represent decentralized interactions and adaptive behaviors among system participants (Pirabán et al., 2019). Recent reviews further highlight the need for more comprehensive modeling approaches that can capture uncertainty, perishability, and system complexity in blood supply chains (Asadpour et al., 2022). Given that BSCs operate as complex adaptive systems, these limitations underscore the need for more integrated modeling frameworks.

To address this gap, this study investigates hospital blood inventory strategy selection under seasonal shortage conditions using an agent-based modeling (ABM) framework. The model represents donors, bloodmobiles, blood centers, and hospitals as interacting agents and incorporates key operational features, including stochastic supply and demand, blood age dynamics, transshipment, and cross-matching. Within this framework, multiple inventory strategies are evaluated using blood shortage and outdating as primary performance metrics.

This study contributes to the literature in both theoretical and managerial dimensions.

Theoretical contributions. First, this study extends the literature on perishable inventory systems by developing a multi-agent modeling framework that explicitly incorporates blood age dynamics, cross-matching, and transshipment within a unified setting. Second, it advances methodological approaches in healthcare operations by combining agent-based simulation with multi-criteria decision-support methods (TOPSIS and grey relational analysis) to evaluate inventory strategies under uncertainty. Third, it contributes to the understanding of complex adaptive supply chains by capturing decentralized interactions among multiple stakeholders and their impact on system-level performance.

Managerial contributions. From a practical perspective, this study provides decision support for hospitals and blood supply systems by identifying inventory strategies that are better suited to different blood components. In particular, the results highlight the importance of tailoring policies to product characteristics such as shelf life. In addition, the sensitivity analysis quantifies how key operational parameters—such as reorder points, order-up-to levels, and transshipment—affect the tradeoff between shortage and outdating. These insights offer actionable guidance for improving inventory control and enhancing the resilience of blood supply chains during periods of shortage.

Overall, this study provides a comprehensive framework for inventory strategy selection in complex, uncertain, and perishable supply chains, contributing both to theory and to practice in healthcare operations management.

The remainder of this paper is organized as follows: Section 2 provides a literature review; Section 3 introduces the multi-agent-based BSC model; Section 4 presents simulation experiments and analysis of inventory control parameters under different blood product scenarios; and Section 5 offers concluding remarks and directions for future work.

2. Literature Review

Research on blood supply chain (BSC) management has evolved from analytical inventory models to simulation-based and data-driven approaches. Due to the perishable nature of blood products, uncertainty in supply and demand, and the critical consequences of shortages, managing blood inventories remains a challenging problem. Existing studies can be broadly categorized into three streams: (1) blood inventory control models, (2) simulation and advanced modeling approaches, and (3) multi-criteria decision-making methods for strategy evaluation.

2.1. Blood Inventory Control in Blood Supply Chains

Early research on blood inventory management adapted classical inventory models to perishable products, beginning with Millard (1965). Subsequent studies extended these approaches to incorporate uncertainty and operational constraints. For example, stochastic and mixed-integer programming models have been widely used to determine optimal ordering and allocation policies (Gunpinar and Centeno, 2015; Meneses et al., 2023). In addition, age-based inventory policies have been shown to improve system performance by accounting for the remaining shelf life of blood products (Duan and Liao, 2014; Kenan and Diabat, 2022).

More recent studies emphasize the importance of incorporating additional operational features, such as transshipment and system-wide coordination, to improve flexibility under uncertainty (Jafarkhan et al., 2018; Abbasi et al., 2020). Furthermore, recent reviews highlight the increasing complexity of BSC management and the need for integrated approaches that jointly consider perishability, uncertainty, and system interactions (Asadpour et al., 2022).

Recent contributions have also explored forecasting and multi-echelon optimization methods to improve supply–demand matching. Imamoglu et al. (2023) provide a comprehensive review of BSC research and identify key gaps in modeling approaches. Thakur et al. (2024) demonstrate how demand forecasting can improve inventory planning for perishable blood products. Similarly, Khiabani et al. (2025) develop a multi-echelon model for blood distribution under crisis conditions, highlighting the importance of coordination across supply chain levels. Alhadad et al. (2025) further propose an intelligent decision framework incorporating multi-criteria analysis to reduce shortages and wastage.

Table 1. Summary of Recent Studies on Blood Supply Chain and Inventory Management

Study	Method	Application	Insight
Imamoglu et al. (2023)	Systematic review	Identifies research trends and gaps in BSC	Limited operational modeling
Thakur et al. (2024)	Forecasting	Improves demand prediction and inventory planning	Ignores system interactions
Khiabani et al. (2025)	Optimization	Multi-echelon blood distribution under crisis	Focused on disruption scenarios
Alhadad et al. (2025)	AI + MCDM	Reduces shortage and wastage	Limited dynamic modeling

In summary, most existing models rely on either analytical formulations or simplified assumptions, limiting their ability to capture the dynamic and interactive nature of real-world BSC operations.

2.2. *Simulation and Advanced Modeling Approaches*

To address the limitations of analytical models, simulation-based approaches have been widely adopted in BSC research. Discrete event simulation (DESS) and system dynamics (SD) models have been used to analyze inventory policies under uncertainty and evaluate system performance (Katsaliaki et al., 2007; Lowalekar and Ravichandran, 2017; Zahraee et al., 2015). These approaches improve the representation of stochastic processes but often rely on aggregated assumptions and fail to capture decentralized decision-making.

Agent-based modeling (ABM) provides a more flexible framework for modeling complex systems with interacting agents. By explicitly representing heterogeneous entities and their interactions, ABM is particularly suitable for BSCs, which involve donors, blood centers, and hospitals operating in a decentralized environment (Singh et al., 2016). However, relatively few studies have applied ABM to blood inventory strategy selection while simultaneously incorporating key operational features such as blood age, cross-matching, and transshipment.

Table 2. Simulation and Advanced Modeling in Blood Supply Chains

Study	Method	Application	Insight
Pirabán et al. (2019)	Survey	Compares optimization and simulation approaches	Limited focus on ABM
Zahraee et al. (2015)	System dynamics	Captures system-level interactions	Aggregated modeling
Lowalekar and Ravichandran (2017)	DESS	Models stochastic inventory processes	Limited interaction modeling
Singh et al. (2016)	ABM framework	Enables modeling of interacting agents	Not BSC-specific

Overall, while simulation methods improve realism, there remains a need for integrated approaches that capture both operational complexity and decentralized decision-making in BSCs.

2.3. Multi-Criteria Decision-Making Methods (TOPSIS and GRA)

Selecting an appropriate inventory strategy in BSCs requires balancing multiple conflicting objectives, such as minimizing shortages while reducing outdating. Multi-criteria decision-making (MCDM) methods provide a structured framework for evaluating such trade-offs.

Table 3. Applications of Multi-Criteria Decision-Making Methods in Healthcare Supply Chains

Study	Method	Application	Insight
Alhadad et al. (2025)	GRA + MCDM	Blood supply chain strategy evaluation	Captures shortage–waste trade-off
Sibevei and Roozkhosh (2024)	MCDM	BSC resilience prioritization	Supports structured decision-making
Hwang and Yoon (1981)	TOPSIS	General ranking method	Widely applicable
Deng (1989)	GRA	Evaluation under uncertainty	Handles incomplete information

Among these methods, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Grey Relational Analysis (GRA) are widely used due to their ability to handle multiple criteria and uncertain information. TOPSIS ranks alternatives based on their relative distance to ideal and anti-ideal solutions (Hwang and Yoon, 1981), while GRA evaluates the similarity between alternatives and a reference sequence under incomplete information (Deng, 1989).

Recent studies demonstrate the growing application of MCDM methods in healthcare supply chains. Alhadad et al. (2025) apply grey relational analysis to evaluate blood supply chain strategies and balance shortages and wastage. Similarly, Sibevei and Roozkhosh (2024) use multi-criteria decision-making methods to prioritize resilience factors in blood supply chains. Despite these advances, the integration of MCDM methods with simulation-based models for blood inventory strategy selection remains limited. In particular, their integration with agent-based simulation for hospital inventory strategy selection under seasonal shortage conditions remains largely unexplored.

In general, we notice several important limitations in the existing studies. First, key operational features—such as blood age, cross-matching, and transshipment— are rarely incorporated within a unified modeling framework. Second, simulation-based approaches often lack systematic methods for comparing alternative inventory strategies. Third, although multi-criteria decision-making methods such as TOPSIS and grey relational analysis are widely used, their integration with simulation models for blood inventory strategy selection remains limited. In addition, relatively limited attention has been given to inventory strategy selection under seasonal shortage conditions.

To address these gaps, this study develops a multi-agent simulation framework that integrates detailed operational characteristics of the blood supply chain with multi-criteria decision-making methods. This approach enables a comprehensive evaluation of inventory strategies under realistic and uncertain conditions.

3. Multi-agent-based modeling of BSC inventory

3.1. Methodology of developing the ABM method

We first present the structure of a Blood Supply Chain (BSC) involving blood donors, bloodmobiles, blood centers, and hospitals, as depicted in Figure 1. In this configuration, there is only one local blood center per region. However, in periods of seasonal blood shortage, non-local blood centers might transship blood products to the local blood center. Based on this proposed structure, we have designed a multi-agent system framework for the BSC, which is illustrated in Figure 2.

The donor agents are the driving force of the BSC system, independently choosing between bloodmobiles or blood donation stations for their blood donation. The bloodmobile agent, in turn, assesses the health status of blood donors, collects, and transports the blood products. The blood center agent distributes these products based on its current inventory level and the replenishment orders from each hospital agent. If a significant shortage of blood products arises, the blood center agent decides on transshipment to satisfy the demand for blood products as much as possible.

The hospital agent utilizes its inventory to meet the clinical demand for blood products. Outdated blood products are removed by the hospital agent, who also updates the inventory. Blood inventory replenishment decisions are then made, and orders are sent to the blood center agent.

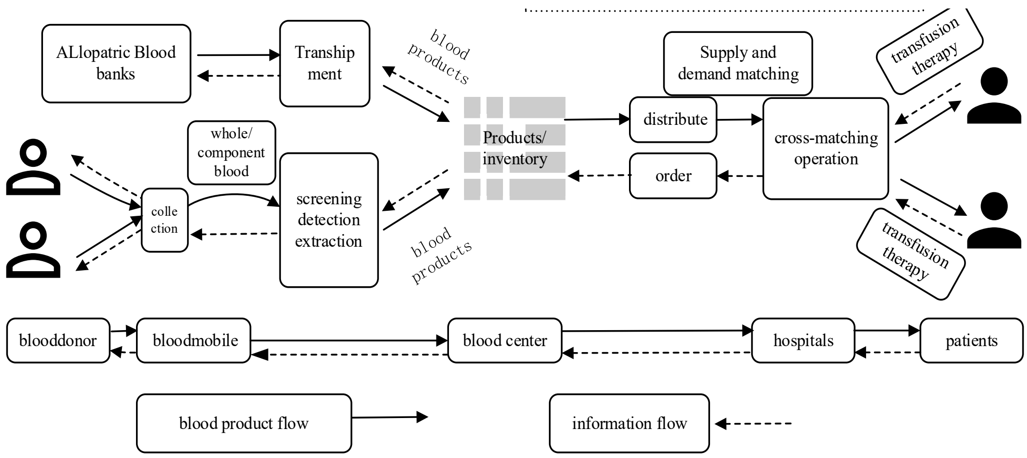

Figure 1. The Overall Conceptual Model of the BSC System.

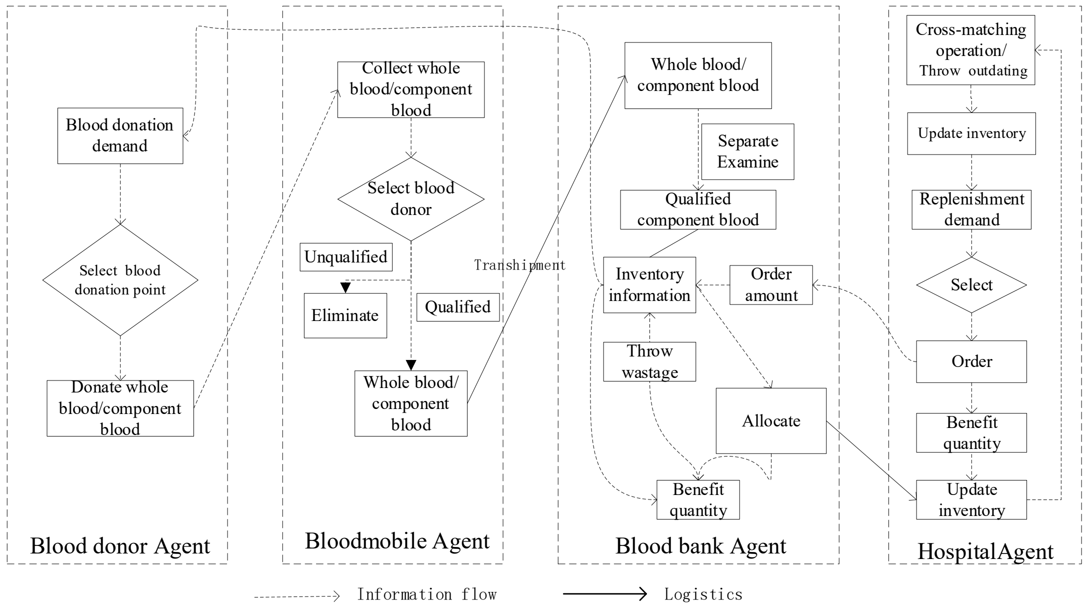

Figure 2. The Framework of the Multi-agent System for BSC Based on CAS

As a Complex Adaptive System (CAS), principal agents within the BSC interact, centering around the blood center agent, thus streamlining information, logistics, and benefits flow.

Our research method for the multi-agent BSC inventory strategy, grounded in CAS theory, comprises 14 steps:

1) Analyze supply and demand information in the BSC system, including data on blood collection, blood issues by the blood center, and hospitals' blood demand information characteristics.
2) Assess the critical behaviors of each agent within the BSC system.
3) Construct a multi-agent simulation model based on CAS. Key data from Step 1 is input, and the model is debugged to ensure the BSC system's accuracy and stability. A reality testing experiment is conducted using historical data on blood donors and hospitals' blood product demand, verifying the model's effectiveness.
4) Execute simulation experiments once the model has passed checks.
5) The blood center processes orders from all hospitals.
6) The blood center determines whether transshipment conditions are met.
7) The blood center distributes blood products to hospitals following blood allocation decisions and issue policies.
8) The blood center updates its blood inventory level using inventory updating rules, removes outdated blood products, and adds fresh ones to the inventory.
9) At the beginning of each period, hospitals receive blood products delivered by the blood center and document the initial inventory level.
10) Hospitals predict the day's blood product demand.
11) Hospitals use blood products according to the blood cross-matching strategy and calculate any blood shortages.
12) At the end of each period, hospitals update the inventory level using the inventory updating rules and calculate the blood outdating.
13) Control parameters in the multi-agent model are applied to adopt a blood inventory strategy. Hospitals generate blood demand orders following the inventory strategy and send these orders to the blood center.
14) Proceed to the next cycle.
15) Specific behavior rules for each agent within this method will be discussed in the following section.

3.2. Designing the Behavior of the Multi-Agent BSC System

3.2.1. Blood Donors and Bloodmobile Agent

Human beings remain the sole source of blood; hence, donors voluntarily make their contributions. Bloodmobiles, on the other hand, carry out the initial eligibility screening of blood donors and proceed to collect and transport whole blood and blood components. The blood gathered is then transported to the blood center on the same day. We set up the following assumptions to guide their behaviors:

1) The count of blood donors is established through probability statistics.
2) Blood donors select the bloodmobile closest to them for blood donation.
3) Blood donors have the option of donating whole blood or undergoing apheresis, with the selection probability based on actual average data.
4) Each blood donation falls into one of three categories, determined according to the actual average data.
5) Bloodmobiles have no capacity constraints.

3.2.2. Blood Center Agent

The blood center receives daily restocking orders from hospitals. It first decides, based on the current inventory level, if transshipment orders will be sent to other blood centers outside the region. Then, it employs the appropriate allocation decision and issuance policy to fulfill hospitals' demand at the post-reallocation inventory level. Afterward, the blood center welcomes the daily collected blood and replenishes its blood product stock after inspection and processing. Ultimately, the blood center updates the blood product age distribution every day and removes any expired blood products from inventory.

The inventory level of blood products can be illustrated using an age-based strategy and recursive equations. Here is the mathematical depiction of the blood center agent's behavior:

1) Inventory levels are recorded in t[th] matrix $x_{0,k}^{t} = \{x_{0,1}^{t}, x_{0,2}^{t}, \cdots x_{0,r}^{t}, \cdots, x_{0,M}^{t}\}$, which represents the inventory level of *k*-type blood product at *t*-period in the blood center. $x_{i,r}^{t}$ means represents the inventory quantity of *k*-type blood product with a remaining blood age of *r* at station *i* (*i*=0 is the local blood center, *i*=1,2,3, ... are the hospitals).

2) The blood center's determination of transshipment necessity is a critical process. Each period's demand for blood products at the blood center equates to the cumulative orders placed by all hospitals in the preceding period. However, in instances of seasonal blood shortages, the blood center must evaluate whether its current inventory level can adequately fulfill the combined demand from all hospitals. If the inventory quantity of the blood center, denoted as I_{O}^{t} , is equal to or greater than the total demand D_{O}^{t}, (i.e., $I_{O}^{t} \geq D_{O}^{t}$), then the blood center doesn't require to transship blood from external blood centers beyond the local region. Conversely, if the inventory quantity at the blood center I_{O}^{t} falls below the total demand $D\ _{O}^{t}$, (i.e., $I_{O}^{t} < D_{O}^{t}$), the blood center needs to initiate a transship blood from other blood centers. During this process, it's important to consider the available inventory $n_{b,r}$ eligible for transshipment at these external blood centers. Only when the available inventory from external blood centers $n_{b,r} > 0$ can be effectively transshipped, $I_{O}^{t} < D_{O}^{t},\ 0 < \sum_{r=1}^{M} n_{b,r} \leq I_{O}^{t} - D_{O}^{t}, \forall b$. The blood center holds the capability to dispatch effective transshipment directives to other blood centers when needed.

3) Blood Product Dissemination. The need for k-type blood products in any given period at the blood center corresponds to the total orders placed by all hospitals in the prior period. Given the perishable, scarce, and irreplaceable nature of blood, it becomes imperative to minimize the wastage due to expiration, all while meeting the blood demand and maintaining its freshness. Therefore, to address this demand, the blood center employs the FIFO (First In, First Out) policy. The mathematical representation of this policy can be described as follows:

$$q_{i,k}^{t} = \{q_{i,k,1}^{t}, q_{i,k,2}^{t}, \cdots, q_{i,k,r}^{t}, \cdots, q_{i,k,M}^{t}\} \tag{4}$$

where

$$q_{i,k,r}^{t} = q_{1+2+\cdots+i,k,r}^{t} \times \frac{Q_{i,k}^{t-1}}{Q_{1,k}^{t-1} + Q_{2,k}^{t-1} + \cdots + Q_{i,k}^{t-1}} \tag{5}$$

$$q_{i,k,r}^{t} = q_{ie,k,r}^{t} + q_{is,k,r}^{t} + q_{ig,k,r}^{t} \tag{6}$$

$$q_{ie,k,r}^{t} = q_{1+2+\cdots+ie,k,r}^{t} \times \frac{Q_{is,k}^{t-1}}{Q_{1e,k}^{t-1} + Q_{2e,k}^{t-1} + \cdots + Q_{ie,k}^{t-1}} \tag{7}$$

$$q_{is,k,r}^{t} = q_{1+2+\cdots+is,k,r}^{t} \times \frac{Q_{ie,k}^{t-1}}{Q_{1s,k}^{t-1} + Q_{2s,k}^{t-1} + \cdots + Q_{is,k}^{t-1}} \tag{8}$$

$$q_{ig,k,r}^{t} = q_{1+2+\cdots+ig,k,r}^{t} \times \frac{Q_{ig,k}^{t-1}}{Q_{1g,k}^{t-1} + Q_{2g,k}^{t-1} + \cdots + Q_{ig,k}^{t-1}} \tag{9}$$

At the same time, these expressions satisfy the constraints,

$$q_{ie,k,r}^{t} = Q_{ie,k}^{t-1}, \sum_{i} Q_{ie,k}^{t-1} \le IP_{o}^{t} \le \sum_{i} Q_{ie,k}^{t-1} + \sum_{i} Q_{is,k}^{t-1} \tag{10}$$

$$q_{ie,k,r}^{t} + q_{is,k,r}^{t} = Q_{ie,k}^{t-1} + Q_{is,k}^{t-1}, IP_{o}^{t} \ge \sum_{i} Q_{ie,k}^{t-1} + \sum_{i} Q_{is,k}^{t-1} \tag{11}$$

$$\frac{q_{ie,k,r}^{t}}{Q_{ie,k}^{t-1}} \ge \frac{q_{is,k,r}^{t}}{Q_{is,k}^{t-1}} \ge \frac{q_{ig,k,r}^{t}}{Q_{ig,k}^{t-1}} \tag{12}$$

4) Following the fulfillment of the day's replenishment requests from hospitals and the addition of fresh blood products to the inventory, the blood center simultaneously discards any outdated blood products. The inventory level is then updated to reflect these changes. The formulation of this updated inventory $x_{0,k}^{t'}$ level is as follows:

$$x_{0,k}^{t'} = x_{0,k,1}^{t'}, \cdots, x_{0,k,r}^{t'}, \cdots, x_{0,k,M-1,}^{t'}\, x_{0,k,M}^{t'} = \{x_{0,k,2}^{t^{+}}, \cdots, x_{0,k,r+1}^{t^{+}}, \cdots, x_{0,k,M}^{t^{+}}, 0\} \tag{13}$$

5) The blood center restocks blood products. The center incorporates the fresh blood products collected during the day into its inventory. Consequently, the inventory level at the close of period t, which simultaneously marks the beginning of period t+1, can be articulated as follows:

$$x_{0,k}^{t+1} = \{x_{0,k,1}^{t+1}, x_{0,k,2}^{t+1}, \cdots, x_{0,k,r}^{t+1}, \cdots, x_{0,k,M}^{t+1}\} = \{x_{0,k,1}^{t'}, x_{0,k,2}^{t'} \cdots, x_{0,k,r}^{t'}, \cdots, x_{0,k,M}^{t'} + N_{k}^{t}\} \tag{14}$$

The term N_k^t signifies the replenishment of k-type blood products at the blood center during period t.

In instances of seasonal blood shortages, the availability of blood products commonly fails to meet demand. To address this, the blood center implements a (T, S) inventory strategy to regulate the collection and production of blood products. However, due to the restricted quantities of blood products that can be gathered, achieving the maximum inventory level can be difficult.

3.2.3. The Hospital Agent

Hospitals fulfill patients' blood needs from their daily inventory. In this study, we posit that the blood demand for each hospital adheres to a weekly normal distribution. However, the daily average value of this distribution varies. After satisfying daily demands, hospitals update the blood age distribution. Furthermore, with an assigned replenishment strategy, hospitals submit replenishment orders to the blood center. The current period's order quantity will be processed in the subsequent period. Occasionally, a hospital's blood inventory may not suffice to cater to its blood needs, leading to shortages.

The hospital agents' inventory level and behaviors are mathematically depicted based on the blood age strategy. The specifics are as follows:

1) Formulate the blood inventory level matrix of hospitals: At the onset of period t for the hospitals, the inventory level of type-k blood products can be articulated as follows:

$$x_{k}^{t} = \{x_{1}^{t}, x_{2}^{t}, \cdots x_{r}^{t}, \cdots, x_{M}^{t}\}, \qquad i = 1,2,3\cdots \tag{13}$$

2) Receive blood product allocation from the blood center: At the beginning of period t, hospitals receive their allocated blood products. By combining the remaining inventory amount at period t-1 with the allocated amount of blood, the updated inventory level at the start of period t can be computed. This matrix can be presented as follows:

$$x_{i,k}^t = \{x_1^t, x_2^t, \cdots x_r^t, \cdots, x_M^t\} = \{x_1^{t-1} + q_{i,1}^t, x_2^{t-1} + q_{i,2}^t, \cdots x_{i,k,r}^{t-1} + q_{i,k,r}^t, \cdots, x_{i,k,M}^{t-1} + q_{i,k,M}^t\} \quad (14)$$

3) Design blood usage behaviors and implement cross-matching in hospitals: Hospitals employ a cross-matching strategy to satisfy clinical blood requirements. When the unallocated inventory level exceeds the demand for blood cross-matching — that is, when $x_i^t > \gamma_i^t$ — cross-matching takes place, as illustrated in Figure 3.

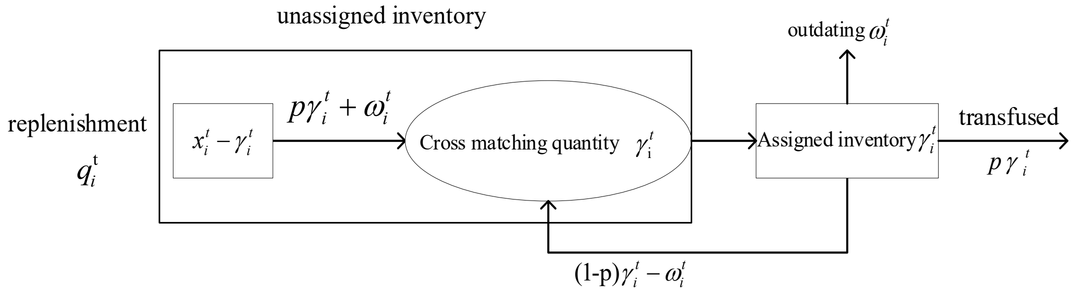

Figure 3. Cross-matching Process Diagram

Here, γ_i^t represents the requirement for blood cross-matching at hospital i during period t, and this follows a normal distribution (μ_γ,σ_γ^2). The term ω_i^t denotes the outdated blood products at hospital i during period t. Additionally, p represents the cross-matching to transfusion ratio, which is the proportion of transfused units relative to cross-matched units. At the same time, we define $q_i^t = p\gamma_i^t + \omega_i^t$.

Freshly ordered blood products will only be cross-matched after completing the cross-matching of existing inventory. The cross-matching process adheres to the FIFO (First In, First Out) policy. In this context, the age of the freshly ordered blood products is L_0. This age refers to the time fresh blood products spend in unassigned inventory before their turn for cross-matching. When first entering the unassigned inventory, the blood products without cross-matching amount to $a = x_i^t - \gamma_i^t$, which equals $x_i^t - u_\gamma$. Therefore, the age of the freshly ordered blood products is:

$$L_0 = \frac{x_i^t - \gamma_i^t}{p\gamma_i^t + \omega_i^t} \quad (15)$$

At this point, the time the fresh blood products spend in unassigned inventory before they are first cross-matched is represented by a random variable Λ. Since cross-matching requirements approximately conform to a normal distribution, they are subjected to an inverse Gaussian distribution. Consequently, Λ also adheres to a normal distribution. This allows us to determine $E(\Lambda) = \frac{a}{v}$,$D(\Lambda) = \frac{a\sigma^2}{v^3}$,$a = S_0 - \mu_\gamma$.

$R_i^t = \left(\gamma_i^t - \left(\gamma_i^{t-d}\right) - p\gamma_i^{t-d} - \varphi_i^{t-d}\right)$ defines the cross-matching quantity of blood products from the unassigned inventory during this period. This quantity must consider the release of the cross-matched blood products from the inventory of the previous period. Here, d denotes the Cross-Matching Release Period, which is a cycle from cross-matching to release.

Owing to the unpredictable demand for blood products, the daily level of unassigned inventory undergoes dynamic changes. We posit that the unassigned inventory level x_i^t cannot fall below the optimal inventory level S_0. Hence, the probability distribution of x_i^t can be expressed as follows:

$$p' = P, x_i^t > S_0 \quad (16)$$

$$1 - p' = P, x_i^t = S_0 \quad (17)$$

The average blood products usage is:

$$v = E(R_i^t) = pu_\gamma + \varphi_i^t \tag{18}$$

The variance of blood products usage is:

$$\sigma^2 = D(R_i^t) = \sigma_\gamma^2(2 + p^2 - 2p) \tag{18}$$

The average inventory days of blood products are:

$$E(\wedge) = \frac{a}{E(R_i^t)} = \frac{S_0 - u_\gamma}{pu_\gamma + \varphi_i^t} \tag{19}$$

The variance of fresh inventory days in blood products are:

$$D(\wedge) = \frac{a\sigma^2}{E(R_i^t)^3} \tag{20}$$

The outdating amount of blood products are:

$$\omega_i^t = p\mu_\gamma + p\mu_\gamma E\left(\frac{1}{1 - (1-p)^{\frac{(L-\Lambda)}{d}}}\right) \tag{21}$$

When the demand for cross-matched blood exceeds the unassigned inventory level, the average blood shortage can be represented as follows:

$$E(x_i^t - \gamma_i^t)^- = (u_x - u_\gamma)P\left(Z \le -\frac{u_x - u_\gamma}{\sqrt{D(x_i^t - \gamma_i^t)}}\right) - \frac{\sqrt{D(x_i^t - \gamma_i^t)}}{\sqrt{2\pi}} e^{-\frac{(u_x - u_\gamma)^2}{D(x_i^t - \gamma_i^t)^2}} \tag{22}$$

4) Implement the distribution policy of the hospital agent: the hospital adopts a FIFO policy to fulfill their daily blood demand. The distribution policy, which is based on blood age and adheres to FIFO principles, is outlined as follows:

$$x_{i,r}^{t^+} = \left(x_{i,r}^{t^+} - \gamma_i^t\right)^+, \qquad r = 1 \tag{23}$$

$$x_{i,r}^{t^+} = \left(x_{i,r}^{t^+} - \left(\gamma_i^t - \sum_{j=1}^{r-1} x_{i,j}^t\right)^+\right)^+, \qquad r > 1 \tag{24}$$

Where $x^+ = max\{x, 0\}$. $x_{i,r}^{t^+}$ means the blood inventory level after the hospitals meet the cross-matching demand. γ_i^t indicates the demand for cross-matching blood products of hospitals i at period t. After the hospitals have decided to meet the blood demand for cross-matching, the blood demand for cross-matching may not be fully satisfied because of the inadequate blood inventory level of the hospital. Currently, the unfulfilled demand is regarded as the blood shortage in the hospital at the current period. The blood shortage in hospitals is calculated as follows:

$$S_i^t(x_i^t) = \left(\gamma_i^t - \sum_r x_{i,r}^t\right)^+ \tag{25}$$

5) Update inventory level: Following the fulfillment of the current day's demands and the distribution of blood products, it becomes essential to tally both the inventory amount and the amount of outdated blood in preparation for making replenishment decisions. The amount of outdated blood refers to the blood products with a blood age of one, represented as $O_i^t(x_i^t) = (x_{i,1}^{t^+}, 0)$. Subsequently, hospitals decrease the blood age of those blood products with an age greater than one to update the inventory status. To update the inventory level, the blood age of blood products with an age greater than one is reduced by one. Presently, the distribution of the updated blood age in hospitals is as follows:

$$x_i^{t'} = \left\{x_{i,1}^{t'}, \dots, x_{i,r}^{t'}, \dots, x_{i,M-1}^{t'}, x_{i,M}^{t'}\right\} = \left\{x_{i,2}^{t^+}, \dots, x_{i,r}^{t^+}, \dots, x_{i,M}^{t^+}, 0\right\} \tag{25}$$

6) Generate replenishment orders: After hospitals have met their clinical blood demands and updated their inventory levels, they proceed to the decision-making phase for replenishment orders for that day. Utilizing an inventory strategy controlled by specific parameters, hospitals generate their replenishment orders in line with this strategy. To ensure consistency with the overall policy of minimizing blood outdating and shortages, it is assumed that all hospitals adopt a centralized inventory strategy while making decentralized decisions based on their unique inventory situations.

4. Simulation analysis

4.1. Scenario description

The data in this section is derived from actual data from a blood center in western China. Four types of inventory strategies are employed to simulate the Blood Supply Chain (BSC). We examine the impact of these inventory strategies on blood shortage and outdating to determine the optimal strategy for hospitals. Additionally, based on the chosen strategy, we conduct sensitivity analysis experiments on key parameters. Accordingly, four simulation scenarios are designed to study the effect of blood product characteristics, inventory strategies, and control parameters on BSC operations.

1) Reality Testing: We validate the simulation model using historical data on blood donors and hospitals' blood demand information.

2) Inventory Strategy Analysis: We conduct sensitivity analyses on factors such as safety inventory level, order-point inventory level, order-up-to-level, economic order quantity, order cycle, and threshold value to pinpoint the optimal parameter combination for each inventory strategy.

3) Performance Analysis: We compare key performance indicators like shortage and outdating under various inventory strategies to select the best one.

4) Sensitivity Analysis of Key Parameters under the Optimal Strategy: We investigate the impact of key parameters within the context of the chosen strategy.

5) To evaluate the impact of each scheme, we conducted 20 stochastic experiments for each simulation scenario. Key indicators were then averaged across all simulation runs.

4.2. Parameter Settings

The simulation model comprises a local blood center and 20 hospitals within the region. Additionally, four blood centers surrounding the local one can transfer blood products to it. Each blood center’s daily unassigned blood inventory level is communicated to the blood center via an information system daily. Prior to this study, we analyzed the lifespan, supply, and demand characteristics of different types of blood products. Consequently, we chose platelets and Red Blood Cells (RBCs) as the primary focus for studying hospital blood inventory strategies. Platelets have a maximum shelf life of 5 days, with a remaining shelf-life threshold of 2 days, whereas RBCs have a maximum shelf life of 35 days, with a remaining shelf-life threshold set at 15 days. The lead time in hospitals is 1 day.

In China, college students comprise a significant portion of blood donors. Since universities are usually located in central cities, the return of students during summer vacation often leads to a seasonal blood shortage. Thus, we chose summer vacation as our research period, simulating the BSC under conditions of seasonal blood shortage. Considering that Chinese colleges and universities have about 8 weeks of summer vacation and that vacation times differ across institutions, we selected actual data from the middle period of the summer vacation as the simulation model's test standard. Furthermore, to accurately encompass the seasonal blood shortage cycle and facilitate data observation, we set the simulation operation cycle to 52 weeks. We obtained the actual data by partnering with a blood center (see Appendix A for details). The average crossmatch-to-transfusion ratio among used clinical blood in each hospital is 0.4. The daily demand for blood products in each hospital follows an independent normal distribution. Donation amounts are fitted according to the blood center's collection data. The BSC's service level is 95%. Specifics on hospital demands in simulation experiments and parameter settings for blood donors can also be found in Appendix A.

4.3. Simulation Model Results and Analysis

4.3.1. Simulation Model Validity Testing

Once the parameters are established, all simulation experiments are performed using ANYLOGIC 8.7.0. The suite of experiments includes validity tests, controlled parameter analyses, performance analyses, and sensitivity analyses of key parameters based on the optimal inventory strategy. The validity tests are employed to ensure that the key supply and demand elements of the simulated BSC model align with reality. Fundamental factors such as the number of blood donors and the demand situation, which are not affected by the input of the inventory strategy, don't impact the core supply and demand data of the simulation model. For instance, the (s, Q) strategy is utilized in this paper to run the simulation model. Through observation of the degree of coincidence of absolute data and analysis of statistical data, we determined that the cumulative number of blood donors reached approximately 13,000 on the 31st day. As displayed in Figure 6, this aligns with the actual scenario. These tests indicate that the BSC simulation model can effectively mimic the operation of the BSC during periods of blood shortage. The model's analysis results are presented in Figure 6. The blood product supply to hospitals follows a normal distribution, which accurately reflects the operation of the BSC.

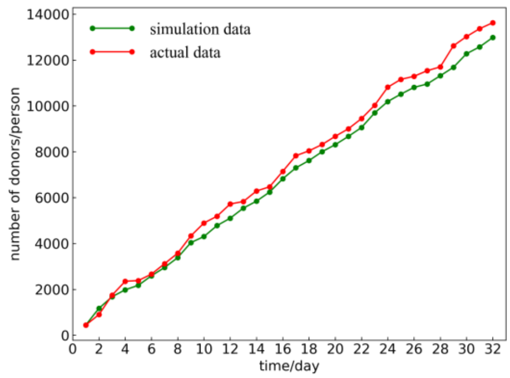

Figure 5. Cumulative Blood Donors

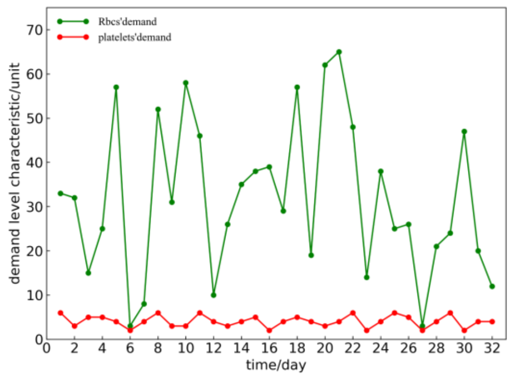

Figure 6. Characteristics of Blood Demand for Hospital

4.3.2. Analysis of inventory strategy

The simulation experiments can be run after the model checking is passed. Firstly, we simulated the demand events 20 times. Because BSC management is complex under shortage, it is impossible to directly obtain the best inventory control parameters through optimal modeling and calculation. The hospitals' historical demand information is used to calculate the value range of inventory control parameters to obtain a better inventory control parameter. Different combinations of inventory parameters are input into the multi-agent simulation model. Then, the performance of blood outdating and shortage under different combinations of inventory parameters can be used to compare and obtain a better inventory control parameter. The process of analysis is shown in Figure 7.

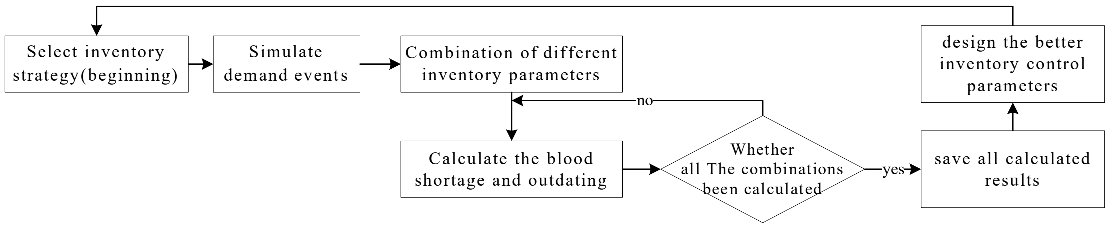

Figure 7. The Process of Analyzing Control Parameters of Inventory Strategies

(1) Analysis of (s, Q) Strategy

The (s, Q) strategy, also known as the quantitative order control strategy, involves setting a reorder point s in advance and continuously monitoring the inventory level. When a hospital places an order, it needs to verify the inventory level each time to see whether the inventory has fallen below the preset s. If the inventory level drops to s, a new order is triggered with the purchasing quantity set at Q, which is the economical batch quantity. The order quantity is Z_i^t, and the decision is expressed as follows:

$$Z_i^t = Q, I_i^t < s \tag{26}$$

$$Z_i^t = 0, I_i^t \geq s \tag{27}$$

Firstly, the s is determined as s= $SS + D^L$, $SS = Z\sigma_L$. where SS is the safety stock level, and D^L is the maximum possible demand for blood products during the lead time. Z signifies the number of standard deviations under the given service level of blood products, while $\sigma_L$represents the standard deviation of blood product demand during the lead time.

Having calculated s for each day of a week, we can analyze the effect of different parameter combinations on key indicators, such as blood shortage and outdating, through parameter comparison operation experiments. This analysis allows us to determine the optimal inventory control parameters, a suitable (s, Q) combination.

Simulations enable us to arrive at an appropriate parameter combination (s, Q). The settings for s and the economical batch quantity Q are detailed in Appendix B.

(2) Analysis of (s, S) Strategy

The (s, S) strategy involves establishing minimum and maximum inventory control levels in advance. The minimum inventory level (reorder point) is denoted s, and the maximum inventory level (order-up-to-level) is denoted s. After the hospital satisfies the blood demand, the inventory level is checked at the end of the period. If the inventory level $I_i^t$is less than the reorder point s, replenishment orders are dispatched to the blood center. Otherwise, no orders are placed. The decision-making expression is:

$$Z_i^t = S - I_i^t, \qquad I_i^t < s \tag{28}$$

$$Z_i^t = 0, \qquad I_i^t \geq s \tag{29}$$

The reorder point s is determined as in section (1). The order-up-to-level s is examined through parameter comparison experiments to identify the optimal parameter combination. Results are presented in Appendix B. When the reorder point s and the order-up-to-level s are set to the current level, blood shortage and outdating are relatively balanced, with a better performance observed in terms of blood shortage.

(3) Analysis of (T, S) Strategy

The (T, S) strategy involves periodical inventory control, where replenishment occurs at regular intervals T to the order-up-to-level s. The purchasing quantity is:

$$Z_i^t = S - I_i^t, t = nT \tag{30}$$

$$Z_i^t = 0, \qquad t \neq nT \tag{31}$$

Initially, the order-up-to-level s is set as in Section (2). Simulations are run with periods T=1, T=2, and T=3, and s is adjusted bidirectionally to find the optimal parameter combination. When the ordering cycle T and the target inventory s are set at the current level, blood shortage is relatively balanced, and the shortage level is relatively low.

(4) Analysis of EWA-based Strategy

This paper presents an inventory strategy based on the traditional EWA strategy. This strategy accounts for potential outdated amounts in replenishment decision-making, catering to the dynamic process of blood product replenishment while aiming to minimize blood shortages. It also considers the inventory of older blood products when deciding whether to increase replenishment quantities.

The decision-making process involves two steps. First, the hospital decides on the production quantity based on the current inventory level and the order-up-to-level, in line with the traditional order point replenishment strategy. Second, the hospital calculates the ratio of older blood inventory (remaining validity threshold j) to total inventory. If this ratio surpasses the predetermined threshold δ, this portion of older blood is added to the production plan. The decision is as expressed as follows.

First, $Z_i^t = S - I_i^t,\ I_i^t < s$

Second, $Z_i^t = S - I_i^t + \sum_{r=1}^{j} x_{i,r}^{t'}\ ,\ \frac{\sum_{r=1}^{j} x_{i,r}^{t'}}{\sum_{r=1}^{M} x_{i,r}^{t'}} \geq \delta$

We find the optimal inventory control parameters for this strategy as follows: the reorder point s is set as in Section 4.3.2.1, and the optimal order-up-to-level s is as in Section 4.3.2.2. We then adjust s in combination with different thresholds to find the optimal inventory control parameters. Simulations suggest that setting the EWA-based strategy control parameters as per Appendix B results in less hospital blood shortage and improved performance in terms of blood outdating.

In conclusion, by considering the relative balance of blood shortage and outdating, this paper optimally sets the above parameters. It compares the simulation results of the BSC under different inventory strategies, selecting the optimal inventory strategy according to key performance indicators and evaluation methods. Furthermore, the paper analyzes the sensitivity of relevant parameters based on the optimal inventory strategy.

4.4. Comparison of Main Inventory Strategies

Key indicators used to measure the performance of inventory strategies include the amounts of blood shortage and outdating. This section delves into an analysis of the performance of different inventory strategies. Moreover, all performance indicator analyses are predicated on the sensitivity analysis and optimization parameters of inventory conducted above.

4.4.1. The analysis of blood shortage

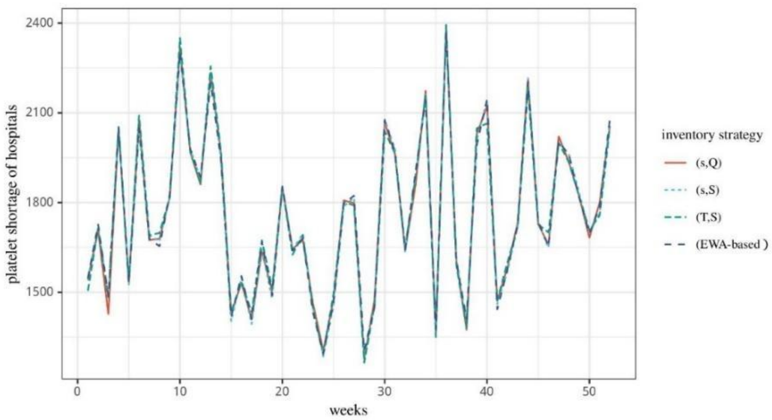

Figure 8. Time Series of Platelets Shortage under Different Inventory Strategies

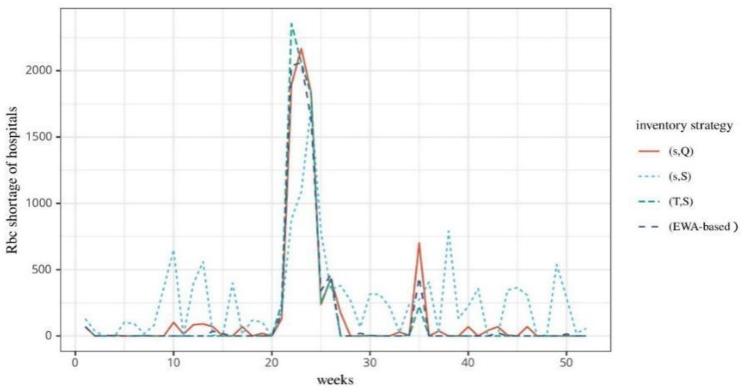

Figure 9. Time Series of RBCs Shortage under Different Inventory Strategies

Figures 8 and 9 exhibit the simulation results corresponding to different blood product shortage time series under varying strategies, while Table 4 displays the results of the weighted average of total shortages for different blood components under these strategies. Figure 8 demonstrates that for platelets, the shortage time series of hospital agents exhibit a cyclical rise-and-fall pattern irrespective of the inventory strategy employed. After an increase, a downward trend ensues, and after a period of decline, shortages ascend once more. This occurrence is primarily due to hospitals' need for redistribution from blood centers, which themselves have insufficient inventory. The proportional distribution of blood products from the blood center sometimes fails to fully satisfy hospital demand. Furthermore, hospital blood demand is unpredictable, leading to varying levels of shortages. Finally, hospitals make replenishment decisions based on their inventory level; in cases of severe shortages, they will place orders for higher replenishment levels, whereas after shortages have been mitigated, orders will reflect lower replenishment volumes, causing the time series of hospital shortages to show an oscillating pattern.

As illustrated in Figure 9, the shortage differences of red cells in hospital agents under different inventory controls are more conspicuous. Sharp increases and decreases occur under all four inventory strategies due to severe blood supply shortages. However, after such shortages, the number of blood donors may rise due to transshipments, increased media coverage, organized blood donations, and other proactive operations of BSCs. Consequently, the downward trend post severe shortage is often accelerated.

4.4.2. The analysis of blood outdating

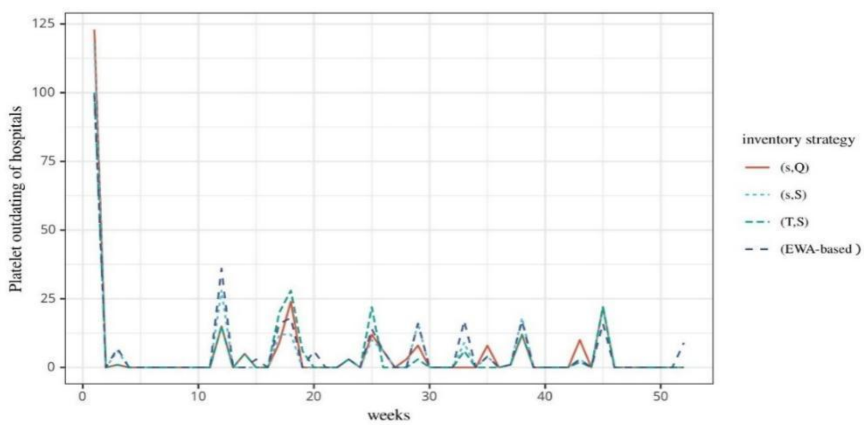

Figure 10. Time Series of Platelets Outdating under Different Inventory Strategies

Given that Red Blood Cells (RBCs) have a longer shelf life than platelets, their outdating volume is relatively minimal. Consequently, we'll focus solely on the outdating number of platelets for strategy comparison. Figure 10 showcases the simulation results associated with the outdating quantity of platelets under different strategies, while Table 4 presents the averaged total outdated volume of platelets in hospitals under these varying strategies. Post model stabilization, the volume of outdated platelets in hospitals inevitably fluctuates, showcasing a cyclical trend of initial decrease, subsequent stabilization, and eventual increase. This trend aligns with the cause of the platelet shortage phenomenon.

4.4.3. Results under reasonable inventory strategy parameter

Owing to the differing characteristics, supply levels, and demand levels of various blood product types, different blood products may be more suitable for specific inventory strategies. As demonstrated in Table 4, the (T, S) strategy emerges as a relatively optimal inventory strategy for platelets, considering the volume of blood outdating. However, from a blood shortage perspective, the EWA-based strategy appears to be the most reasonable choice. Given that the performance of the four inventory strategies is identical with regards to blood shortage, for RBCs, the EWA-based inventory strategy is the most rational choice when blood shortage is the critical consideration.

Table 4. Normalized Data of Each Index by Different Strategies

Strategies	Platelets' Shortage	RBCs' Shortage	Platelets' Outdating	RBCs' Outdating
(s， Q)	0.25002	0.22619	0.31310	0.2500
(s， S)	0.24989	0.37676	0.23243	0.2500
(T， S)	0.25025	0.20003	0.18821	0.2500
EWA-based	0.24984	0.19702	0.26626	0.2500

To determine the most suitable inventory strategy for platelets, we employ two classic multi-attribute decision-making methods for a comprehensive evaluation: the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Grey Relational Analysis. Table 5 displays the complete evaluation results based on the TOPSIS method, with the decision indicators of different inventory strategies during the blood shortage represented in the following tables. The evaluation results via the TOPSIS method suggest that the (T, S) inventory strategy is the most suitable, while the (s, Q) strategy is the least feasible.

The comprehensive evaluation results, based on the Grey Correlation Analysis method, are illustrated in Table 6. The results drawn from this analysis concur with the TOPSIS method, indicating that the (T, S) strategy is the most suitable while the (s, Q) strategy is the least effective. Hence, it can be inferred that the (T, S) inventory strategy is indeed effective for managing platelets.

Table 5. The Relative Proximity Ranking of TOPSIS Method

Strategies	(s，Q)	(s，S)	(T，S)	EWA-based
D_i^+	0.0005	0.1587	0.2457	0.0921
D_i^-	0.2457	0.0870	0.0008	0.1536
C_i	0.9981	0.3541	0.0033	0.6249
ranking	4	2	1	3

Note: The length of the maximum distance is D_i^+. The length of the minimum distance is D_i^-. The relative closeness is C_i

Table 6. Correlation Coefficient of Grey Correlation Method

Performance indicators	(s，S)	(s，Q)	(T，S)	EWA-based
outdating	0.2081	0.2081	0.2079	0.2082
shortage	0.1663	0.2118	0.2491	0.1900
grey correlation degree	0.1872	0.20995	0.2285	0.1991
ranking	4	2	1	3

The conclusion drawn from the TOPSIS method aligns closely with the Grey Correlation method, solidifying the inference that the (T, S) inventory strategy is effective for platelets.

4.5. Sensitivity Analysis of Key Parameters

After selecting the optimal inventory strategies for different blood products, we employ blood shortage and outdating as the core performance indicators for the blood supply chain system. We then conduct a sensitivity analysis of the key parameters under these selected inventory strategies.

4.5.1. Sensitivity Analysis of Transshipment Strategy

Operating on the foundation of the previously determined optimal inventory strategies, we perform a sensitivity analysis of the transshipment strategy. Our research, presented in Table 7, reveals that an effective transshipment strategy profoundly impacts the performance of the Blood Supply Chain (BSC). While successful transshipment can mitigate blood shortage, it may concurrently lead to an increase in the volume of outdated blood. Given the relatively short shelf life of platelets, the influence of transshipment on platelet shortage is more substantial.

Table 7. Sensitivity Analysis of Transshipment Strategy

Strategies	Platelets Shortage	Platelets' Outdating	RBCs' Shortage	RBCs' Outdating
EWA-based	0.539	0.378	0.523	0.50
(Ewa-based, Transshipment)	0.461	0.622	0.477	0.50

4.5.2. Sensitivity Analysis of Reorder Point

In the context of the EWA-based inventory strategy, we hold the order-up-to-level S and the threshold constant and analyze the sensitivity of the reorder point's inventory level, s. To streamline the parameter changes, we uniformly increase or decrease the reorder point s for all hospitals, maintaining the same step size based on the settings discussed in Section 4.4. As presented in Table 8, s1, s2, and s3 represent three incremental inventory levels for the reorder points, each with an increase of 5 units. When the reorder point's inventory level is set relatively high, the efficacy of this inventory decision-making process is enhanced, and the blood shortage noticeably diminishes. However, this approach also results in a corresponding rise in the volume of outdated blood.

Table 8. Sensitivity Analysis of Reorder Point

Order-up-to-level	Order Level	Shortage	Outdating
	s1	17557	0
S	s2	15098	0
	s3	7349	0

4.5.3. Sensitivity Analysis of Order-Up-To-Level

In this analysis, we maintain the ordering cycle T for platelets and both the reorder point s and threshold for RBCs. We conduct a sensitivity analysis on the order-up-to-level S. To streamline parameter changes, we uniformly increase or decrease the order-up-to-level for all hospitals. As illustrated in Table 9, within the platelets inventory simulation system, TSL1, TSL2, and TSL3 represent three incremental increases in the order-up-to-level, each with a step size of 2. In the RBCs inventory simulation system, TSL1, TSL2, and TSL3 correspond to three progressive increases in the order-up-to-level, each with an increment of 5 units. The settings for the order-up-to-level significantly influence the efficacy of inventory decision-making. Appropriately elevating the order-up-to-level can decrease the blood shortage. However, for blood products with relatively short shelf life, this may also lead to an increase in the volume of outdated blood.

Table 9. Sensitivity Analysis of Order-up-to-level

TSL	Platelets Shortage	Platelets' Outdating	Shortage	RBCs' Outdating	Total Outdating
TSL1	91610	206	15161	0	206
TSL2	91514	217	14752	0	217
TSL3	91463	230	7349	0	230

4.5.4. Sensitivity Analysis of Shelf Life

The preceding analysis underscores that the shelf life and supply-demand characteristics of different types of blood products significantly influence the settings of the order-up-to-level and their resultant impacts. Given that there's a wide variety of blood products in reality, each with a distinct shelf life, we investigate how varying the order-up-to-level impacts blood shortage and outdating for hospitals handling blood with different shelf lives. We use the blood simulation scenario of platelets as an example, given their shelf life of approximately 3-5 days. This study sets 3 different shelf life levels and 6 incremental increases in the order-up-to-level, each with an increment of 2. The simulation results for platelets are illustrated in Figure 11.

With a constant shelf life, hospital blood shortage decreases with the escalation of the order-up-to-level, while blood outdating increases correspondingly. The rate of decrease in shortage slows down, while the rate of increase in blood outdating is initially stable and then accelerates. This pattern arises because increasing the order-up-to-level in hospitals progressively diminishes blood shortage. Once the platelet inventory in the hospital is sufficient to meet clinical demand and even surplus, the clinical blood requirement does not correspondingly escalate. Therefore, continually increasing the order-up-to-level does not consistently decrease the level of shortage or even exacerbates it, resulting in outdated platelets.

When a hospital's order-up-to-level is fixed, a longer shelf life results in lower blood shortage and outdating ratios. This trend is due to the extended shelf life reducing platelet outdating to a certain degree, thereby increasing platelet utilization efficiency in hospitals and lowering blood shortage. However, against the backdrop of blood shortage, blood centers often lack sufficient platelets to meet demands. Therefore, throughout the entire simulation cycle, an increase in shelf life gradually reduces both blood shortage and outdating in hospitals.

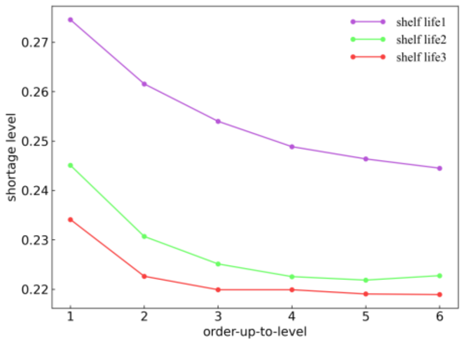

Figure 11. Sensitivity Analysis of Order-up-to-Level and Platelet Shelf Life: Impact on Hospital Shortage

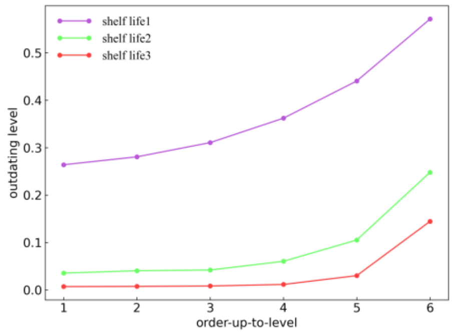

Figure 12. Sensitivity Analysis of Order-up-to-Level and Platelet Shelf Life: Impact on Hospital Platelet Outdating

5. Conclusion

This study investigates hospital blood inventory strategy selection under seasonal shortage conditions, where uncertainty in supply and demand, combined with the perishable nature of blood products, creates a critical tradeoff between shortages and outdating. To address this problem, we develop an agent-based simulation model of a regional blood supply chain that captures interactions among donors, bloodmobiles, blood centers, and hospitals. The model incorporates key operational features, including stochastic supply and demand, blood age dynamics, cross-matching, and transshipment. Simulation outputs are further evaluated using a multi-criteria decision-support framework to systematically compare alternative inventory strategies.

The results indicate that no single inventory policy is universally optimal. Instead, strategy performance depends on product characteristics. In particular, the (T, S) policy performs best for platelets by effectively balancing shortages and outdating, while the EWA-based strategy is more suitable for red blood cells due to its ability to account for age-related dynamics. Sensitivity analysis further shows that key parameters—such as reorder levels, order-up-to levels, shelf life, and transshipment—significantly influence system performance and the shortage–outdating tradeoff.

These findings have important managerial implications. Hospitals and blood supply systems should adopt differentiated inventory strategies for different blood components rather than relying on a single policy. In addition, careful calibration of inventory parameters and the use of transshipment can enhance system resilience, particularly during seasonal shortages. More broadly, this study demonstrates the value of combining simulation with multi-criteria evaluation to support decision-making in complex and uncertain healthcare supply chains.

From a theoretical perspective, this study contributes to the literature on perishable inventory management and healthcare operations by developing an integrated simulation-based decision-support framework. This study directly addresses the gaps identified in prior literature by integrating operational realism, decentralized interactions, and systematic multi-criteria evaluation within a unified framework. By capturing decentralized interactions and operational complexity within a unified model, the study provides a more comprehensive approach to analyzing inventory strategy selection in blood supply chains.

Despite these contributions, several limitations should be noted. The model is calibrated using data from a specific regional setting, which may limit generalizability. In addition, certain real-world factors—such as donor behavioral responses, emergency disruptions, and policy constraints—are not explicitly modeled. The analysis also focuses on a selected set of inventory strategies and performance metrics.

Future research can extend this work by incorporating real-time and multi-regional data to improve generalizability, exploring adaptive or data-driven decision methods, and modeling broader system interactions such as inter-regional coordination and emergency response mechanisms. These extensions would further enhance the applicability of the proposed framework and deepen understanding of resilience in blood supply chains.

Author Contribution

The research with four authors, and their contribution are **Conceptualization** (Z. Li & G. Mao), **Formal analysis** (Z. Li), **Finding acquisition** (Z. Li), **Investigation** (Z. Li, G. Mao, X. Hu, & X. Hu), **Methodology** (Z. Li & G. Mao), **Project administration** (X. Hu), **Software** (Z. Li), **Supervision** (X. Hu), **Validation** (X. Hu & X. Hu), **Visualization** (X. Hu & X. Hu), **Writing – original draft** (Z. Li & G. Mao), **Writing – review & editing** (X. Hu & X. Hu).

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Appendix A. Demand Information of blood supply chain

Table A1. The Demand Information for Platelets in Hospitals under the Seasonal Blood Shortage

hospital	MON		TUE		WED		THU		FRI		SAT		SUN	
	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD
1	7.03	3.63	6.56	1.93	6.36	3.44	4.01	6.79	6.6	1.30	6.13	2.19	6.83	3.98
2	7.69	3.81	5.61	1.99	7.02	4.62	6.88	8.32	7.26	1.16	5.67	2.95	6.37	4.50
3	13.48	4.25	9.14	1.78	9.81	4.93	8.27	7.40	11.05	1.28	10.78	2.90	12.48	3.28
4	7.37	2.83	6.32	2.58	6.7	3.41	4.98	9.49	6.94	0.99	6.58	2.54	7.28	4.46
5	6.89	2.26	5.37	2.35	6.22	4.84	5.11	8.12	6.46	1.42	6.19	2.96	6.89	3.27
6	7.06	2.2	5.49	2.59	6.39	3.33	6.29	9.93	6.63	1.37	6.36	2.66	7.06	4.30
7	6.66	1.56	5.62	1.91	5.62	4.42	5.08	9.29	6.23	1.34	5.55	2.09	7.25	3.47
8	7.57	3.09	5.14	2.58	6.9	4.59	4.77	8.68	7.14	1.37	6.38	2.52	6.08	3.40
9	13.61	5.92	12.2	2.47	10.94	4.18	9.99	7.19	11.18	1.16	9.66	2.17	13.36	3.14
10	6.91	2.93	5.88	2.28	6.24	4.76	7.25	10.13	6.48	1.28	6.17	2.24	6.87	2.96
11	6.93	2.32	5.24	2.16	6.26	4.78	5.19	7.53	6.5	1.26	6.62	2.78	8.32	3.32
12	3.39	1.94	2.73	2.00	2.33	4.33	1.66	10.01	2.96	1.23	2.98	2.57	2.68	4.13
13	7.55	3.91	5.69	2.43	6.88	3.52	4.76	7.37	7.12	1.11	4.48	2.41	5.18	4.24
14	2.97	0.97	1.9	1.97	1.31	3.65	0.27	7.93	2.54	1.10	2.16	2.67	4.86	4.07
15	7.67	3.6	5.87	1.82	7	3.60	5.18	6.86	7.24	1.20	6.22	2.88	6.92	2.73
16	6.92	2.28	5.92	2.45	6.25	3.36	5.09	8.94	5.49	1.09	5.54	2.65	6.24	4.36
17	8.07	3.84	6.31	2.36	7.4	3.47	4.84	7.21	7.64	1.37	5.86	2.60	6.56	4.52
18	3.95	0.83	2.21	2.40	0.68	4.31	0.97	6.70	2.56	1.46	2.73	2.65	5.43	4.22
19	7.34	3.58	6.41	2.34	5.67	4.84	2.26	9.25	6.91	0.99	6.51	2.55	3.21	2.80
20	7.47	3.92	5.78	2.14	4.87	3.88	3.08	7.84	5.04	1.24	6.17	1.94	6.87	3.45

Table A2. The Demand Information for RBCs in Hospitals under The Seasonal Blood Shortage

hospital	MON		TUE		WED		THU		FRI		SAT		SUN	
	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD	ED	SD
1	86.91	20.34	73.42	11.26	71.86	12.04	68.64	10.28	82.74	11.16	37.19	2.752	43.36	86.91
2	56.58	16.94	49.34	10.58	47.8	11.26	45.6	9.952	57.04	10.14	23.75	2.662	29.81	56.58
3	94.07	22.17	75.32	15.54	73.72	16.39	69.62	12.29	85.98	18.72	30.09	3.522	36.35	94.07
4	46.48	14.62	42.34	11.05	40.82	10.29	39.14	9.222	49.26	10.02	22.03	2.392	28.05	46.48
5	69.62	19.52	58.37	13.68	56.81	14.43	53.96	10.82	67.1	13.46	25.95	2.982	32.09	69.62
6	16.06	6.772	21.26	4.252	19.8	4.72	19.64	4.532	25.76	4.932	16.89	1.12	22.75	16.06
7	4.56	4.312	13.27	2.522	11.84	2.182	12.27	2.162	16.88	3.852	14.93	0.662	20.73	4.56
8	29.51	10.12	30.57	6.902	29.1	7.442	28.26	6.832	36.14	6.912	19.16	1.282	25.09	29.51
9	37.4	12.34	36.04	8.052	34.54	7.342	33.31	7.52	42.24	9.942	20.49	1.732	26.46	37.4
10	38.04	5.432	36.5	8.092	35	7.412	33.74	7.562	42.74	9.022	20.6	1.752	26.59	38.04
11	17.31	7.012	22.12	4.422	20.66	4.882	20.46	4.662	26.74	5.132	17.09	1.252	22.96	17.31
12	3.8	0.462	2.635	0.62	1.22	0.612	2.44	0.582	5.04	0.392	12.33	0.142	18.05	3.8
13	44.42	11.34	40.9	10.45	39.4	9.082	37.81	7.062	47.66	8.782	21.68	1.332	27.69	44.42
14	16	5.772	21.20	5.252	19.76	4.72	19.60	4.522	25.72	4.922	16.87	1.22	22.73	16
15	54.06	13.62	47.58	11.35	46.06	10.03	43.98	9.772	55.1	12.86	23.31	2.592	29.37	54.06
16	17.96	6.132	22.56	5.52	21.1	4.972	20.86	4.732	27.24	5.242	17.2	1.272	23.07	17.96
17	11.86	5.942	18.33	4.672	16.88	4.092	16.96	3.072	22.52	4.232	16.17	1.132	22.01	11.86
18	1.74	3.092	11.32	2.022	9.9	2.352	10.46	2.072	14.7	2.252	14.45	0.452	20.25	1.74
19	14.98	4.572	20.5	4.112	19.06	5.052	18.96	3.412	24.94	5.062	16.7	1.062	22.55	14.98
20	9.76	1.082	3.355	0.682	1.96	0.662	3.1	0.692	5.84	0.752	12.51	0.152	18.23	9.76

Table A3. Collectable Volume Information of Blood Products under The Seasonal Blood Shortage

Time	Statistical distribution	Characteristic parameter
Monday	Normal	$N \sim N(410,33^2)$
Tuesday	Normal	$N \sim N(560，134^2)$
Wednesday	Normal	$N \sim N(575,143^2)$
Thursday	Normal	$N \sim N(480,141^2)$
Friday	Normal	$N \sim N(410,168^2)$
Saturday	Normal	$N \sim N(350,89^2)$
Sunday	Normal	$N \sim N(370,88^2)$

Appendix B. Control parameters of blood inventory in each hospital

Table B1. Reorder Points for Platelets under The Seasonal Blood Shortage

Hospital	MON	TUE	WED	THU	FRI	SAT	SUN
1	10.2065	13.158	19.883	8.613	11.5915	14.684	12.6565
2	9.2565	13.818	22.753	9.273	11.1315	14.224	13.3165
3	12.7865	16.608	24.143	13.063	16.2415	20.334	19.1065
4	9.9665	13.498	20.853	8.953	12.0415	15.134	12.9965
5	9.0165	13.018	20.983	8.473	11.6515	14.744	12.5165
6	9.1365	13.188	22.163	8.643	11.8215	14.914	12.6865
7	9.2665	12.418	20.6065	8.243	11.0115	15.104	12.2865
8	8.7865	13.698	20.2965	9.153	11.8415	13.934	13.1965
9	15.8465	17.738	25.5165	13.193	15.4845	21.4285	20.903
10	9.5265	13.038	22.7765	8.493	11.9945	14.9385	14.203
11	8.8865	13.058	20.7165	8.513	12.4445	16.3885	14.223
12	6.3765	9.128	17.1865	4.973	8.8045	10.7485	10.683
13	9.3365	13.678	20.2865	9.133	10.3045	13.2485	14.843
14	5.5465	8.108	15.7965	4.553	7.9845	12.9285	10.263
15	9.5165	13.798	20.7065	9.253	12.0445	14.9885	14.963
16	9.5665	13.048	20.6165	7.503	11.3645	14.3085	14.213
17	9.9565	14.198	20.3665	9.653	11.6845	14.6285	15.363
18	5.8565	7.478	16.4965	4.573	8.5545	13.4985	11.243
19	10.0565	12.468	17.7865	8.923	12.3345	11.2785	14.633
20	9.4265	11.668	18.6065	7.053	11.9945	14.9385	14.763

Table B2. Reorder Points for RBCs under The Seasonal Blood Shortage

Hospital	MON	TUE	WED	THU	FRI	SAT	SUN
1	92.0023	91.7293	85.6053	101.1573	41.7308	48.5773	120.4743
2	66.8003	66.3823	62.0208	73.7743	28.1423	34.0208	84.5343
3	100.9643	100.7668	89.9018	116.868	35.9013	43.9928	130.6538
4	60.5758	57.8018	54.3563	65.7963	25.9768	31.7163	70.6063
5	80.9453	80.6228	71.8163	89.3123	30.8703	38.1158	101.8313
6	28.2758	27.588	27.1178	33.8978	18.738	24.8818	27.2338
7	17.4313	15.4403	15.8373	23.2358	16.0223	21.8223	11.6748
8	41.9583	41.3793	39.5328	47.5448	21.2753	27.3703	46.2113
9	49.3258	46.6543	45.718	58.6443	23.3478	29.5818	57.7643
10	49.8518	47.2298	46.2173	57.6263	23.4908	29.5963	47.0028
11	29.4163	28.7153	28.1523	35.2078	19.1558	25.0258	28.8798
12	3.658	2.2298	3.4003	5.6868	12.5643	18.2678	4.5623
13	58.1458	54.3853	49.4623	62.1503	23.8778	31.2408	63.1343
14	29.8708	27.548	27.0663	33.8413	18.883	24.908	25.5238
15	66.3108	62.6128	60.1038	76.3223	27.5868	33.4488	76.5363
16	31.668	29.3038	28.6678	35.8893	19.2988	25.413	28.0778
17	26.0438	23.6318	22.0288	29.5028	18.0378	24.1748	21.6643
18	14.6563	13.7808	13.8788	18.4158	15.1958	21.2763	6.8418
19	27.2848	27.3958	24.5898	33.2923	18.4523	24.4673	22.5238
20	4.4803	3.0523	4.2418	7.0808	12.7608	18.4808	11.5453

Table B3. Inventory Strategy Parameters for Platelets under The Seasonal Blood Shortage

Hospital	Q	S	(T,S)	EWA-base
1	29.43921	31.08571	(1,31.0857)	31.08571
2	31.56779	33.21429	(1,33.2142)	33.21429
3	51.93207	53.57857	(1,53.5785)	53.57857
4	31.33207	32.97857	(1,32.9785)	32.97857
5	29.16064	30.80714	(1,30.8071)	30.80714
6	30.69636	32.34286	(1,32.3428)	32.34286
7	28.36064	30.00714	(1,30.0072)	30.00714
8	29.76779	31.41429	(1,31.4142)	31.41429
9	56.16779	57.81429	(1,57.8142)	57.81429
10	31.06779	32.71429	(1,32.7142)	32.71429
11	30.53921	32.18571	(1,32.1857)	32.18571
12	11.73207	13.37857	(1,13.3785)	13.37857
13	28.11064	29.75714	(1,29.7571)	29.75714
14	9.789214	11.43571	(1,11.4357)	11.43571
15	31.28207	32.92857	(1,32.9285)	32.92857
16	27.96064	29.60714	(1,29.6071)	29.60714
17	31.69636	33.34286	(1,33.3428)	33.34286
18	11.58921	13.23571	(1,13.2357)	13.23571
19	25.71779	27.36429	(1,27.3642)	27.36429
20	26.41064	28.05714	(1,28.0571)	28.05714

Table B4. Inventory Strategy Parameters for RBCs under The Seasonal Blood Shortage

Hospital	Q	S	(T, S)	EWA-base
1	193.1834	212.7657	(1,220.7657)	214.7657
2	182.494	200.9543	(1,208.9542)	202.9543
3	245.87	272.5143	(1,280.5142)	274.5143
4	152.1185	171.3543	(1,179.3542)	173.3543
5	202.5104	226.0857	(1,234.0857)	228.0857
6	79.93277	87.94857	(1,95.9485)	89.94857
7	53.25584	58.41714	(1,66.4171)	60.41714
8	107.3717	119.76	(1,127.76)	121.76
9	124.1313	138.4171	(1,146.4171)	140.4171
10	131.3396	145.6914	(1,153.6914)	147.6914
11	88.32656	96.62286	(1,104.6228)	98.62286
12	28.41414	30.43714	(1,38.43714)	32.43714
13	148.2171	166.4629	(1,174.4628)	168.4629
14	78.12849	87.79429	(1,95.79428)	89.79429
15	163.8178	183.5486	(1,191.5485)	185.5486
16	82.31486	92.42286	(1,100.4228)	94.42286
17	69.28263	77.99143	(1,85.99142)	79.99143
18	45.7037	50.04	(1,58.04)	52.04
19	77.60949	85.39429	(1,93.3942)	87.39429
20	35.30613	37.43143	(1,45.4314)	39.43143