The Review Of
DIABETIC
STUDIES
OPEN ACCESS

Optimization Of Blood Inventory Management In Central Blood Banks Using Artificial Intelligence

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Abstract
Introduction: Managing inventory in central blood banks is still an important issue owing to its perishability, unpredictable demand, and serious implications of shortages. Traditional inventory control approaches often lead to either excess inventory, which causes wastage, or insufficient inventory, which poses a threat to patient health. However, there are innovative ways to solve this problem using artificial intelligence (AI) and machine learning (ML).
Objectives: The present research explores how various AI models such as LSTM, Random Forest (RF), XGBoost, and Reinforcement Learning (RL) can be used to optimize demand prediction, minimize wastage by classifying expired blood products, and streamline RBCs, Platelets, and Fresh Frozen Plasma (FFP) distribution in regional blood banks.
Methods: A dataset collected during 48 months (from 2020 to 2023) in three central blood banks was used. Different AI models were developed and tested to predict demand, identify wastage, and optimize delivery routes. Evaluation metrics included MAPE, F1-score, and wastage reduction.
Results: The LSTM approach yielded the best performance in terms of MAPE, with an average MAPE value of only 6.3% for RBCs. The proposed hybrid model consisting of XGBoost and RL algorithms resulted in a decrease of wastage of all blood components by 34.7%, and their on-time delivery by 28.5%. Wastage of platelets, the most problematic among the three due to its relatively short shelf-life (5-7 days), decreased from 21.4% to 13.8%.
Conclusion: The use of artificial intelligence in blood bank inventory optimization holds immense promise.

Keywords: blood inventory management; artificial intelligence; demand forecasting; LSTM; XGBoost; platelet wastage; blood distribution optimization; central blood bank.

1. Introduction
Transfusion services have become essential parts of today's medical care system for performing surgeries, treating traumas, cancers, and other diseases. According to the WHO, annually, more than 118.5 million donations are made all over the world, but unfortunately, significant shortages and wastage remain a problem for blood banks (WHO, 2022). Therefore, the primary task is to balance perishability, uncertainty in demand, and complexity in logistics.

In the hierarchy of blood banking systems, central blood banks hold an important place because they are the storerooms and suppliers of such components as Red Blood Cells (shelf life 42 days), Platelets (5-7 days), and Fresh Frozen Plasma (up to 12 months in a frozen state). Due to the diversity of their shelf lives and the different patterns of demand, homogeneous approaches do not work effectively. Standard approaches, such as rule-based or statistical methods, including economic order quantity (EOQ) and simple moving average models, proved to be inefficient in modeling complex seasonal demand patterns (Chen et al., 2021).

With the rise of AI and ML, many new opportunities emerge for optimizing healthcare supply chains. Various algorithms like RNNs, LSTM, Gradient Boosting techniques, and RL agents have been employed to estimate time-series demands, detect high-risk wastage instances, and enhance multi-level logistics (Yadav & Jain, 2020). Such models are capable of handling big and mixed-type data sources like past transfusion histories, surgery plans, epidemic trends, seasonality factors, etc., to produce highly accurate predictive outcomes.

There is an increasing body of research on the topic, but very little information is available regarding the use cases in central blood banks. Many of the current studies focus on a single aspect of optimization or single locations without considering the wider context. This paper attempts to fill this void by designing and analyzing a multi-dimensional AI model using actual blood bank operational data over 48 months (Najafi et al., 2022).

The rest of the paper is outlined as follows: In Section 2, a systematic literature review is presented. Materials and Methods are discussed in Section 3. Results with performance tables are provided in Section 4. Discussion is presented in Section 5. Conclusions are offered in Section 6.

2. Literature Review

2.1 Blood Inventory Challenges and Traditional Approaches

Conventionally, inventory planning has been done using deterministic models based on constant patterns of supply and demand. The variability in demand due to trauma incidents, surgical procedures, and seasonal epidemics makes deterministic models impractical. Although stochastic models and simulation have been suggested as possible alternatives, the difficulty of computation and requirement for accurate probability distributions reduce their applicability. According to a systematic review conducted by, less than 30% of blood banks in low-to-middle-income countries used quantitative forecasting tools other than basic spreadsheets to predict blood supply.

Supply problems such as variability in donor population, seasonal behavior of donations, and logistical barriers add to uncertainties. Wastage rates of platelets in high-income countries have been found between 4% and 25%, with comparable figures in low-income settings (Ngo et al., 2023). Financial and medical losses from FFP and RBC wastages due to detection failures and delayed distribution have been estimated.

2.2 Machine Learning for Demand Forecasting

Demand forecast models for blood products exhibit similarities with general demand forecasting models in health care, as they are impacted by temporal dependencies, rare event dynamics, and multiple variable inputs. LSTM network models are considered a customized form of Recurrent Neural Networks (RNN) models that have been found highly efficient at identifying long dependencies in sequential time series data. In a study conducted by Al-Rifai & Osman (2022), LSTM based RBC demand forecasting achieved a MAPE score of 7.1%, significantly better than ARIMA and Prophet models, with margins of more than 40%.

Gradient boosting machine models, especially XGBoost and LightGBM, have shown impressive results when applied to tabular dataset health care data in classification and regression problems. According to a paper published by Kumar et al. (2023), application of XGBoost in predicting platelet demand on a daily basis resulted in a 31% improvement in RMSE values over traditional statistical models. The XGBoost model was developed using various variables such as day of the week, rolling average history, patient census, and cancer admission rates.

Hybrid models, which integrate the forecasts produced by different algorithms, have also enhanced the robustness of forecasts. An LSTM–Random Forest hybrid model developed by Zhang et al. (2023) showed that the application of ensemble fusion was more effective in improving forecast accuracy, decreasing MAPE by another 12% beyond what could be achieved with the individual algorithms alone.

2.3 Wastage Reduction Using AI

Blood units approaching expiration identification and wastage prediction are other types of applications involving AI technology. AI classification algorithms can be trained to predict high-risk units that are prone to expire even before their deployment. By utilizing gradient boosting tree models, Walczak and Balcerzak (2021) were able to predict blood unit wastage in a retrospective dataset with 36,000 platelet units collected across Poland's blood center network, with 88.7% sensitivity and 91.3% specificity.

The RL model is an effective strategy for tackling inventory control optimization problems due to its inherent learning-by-interaction mechanism. In contrast with supervised models that require training on past labeled data, RL agents learn optimal decision policies through trial and error by interacting with their surroundings. For example, Chen et al. (2021) were able to demonstrate that an RL agent designed with Q-learning methodology outperformed a FIFO model in minimizing platelet wastage by 27%, while still meeting service level targets.

2.4 Distribution Optimization of Blood Components

The process of efficient distribution of blood products requires solving multi-objective optimization tasks considering multiple criteria such as product freshness, transportation costs, risks associated with shortage of necessary components, as well as other factors. Traditionally, operations research was used for blood product distribution, including the application of linear programming methods and vehicle routing algorithms. However, these methodologies lack flexibility and responsiveness to changes in demand.

The utilization of AI-augmented approaches is associated with the potential for improving efficiency in blood product management. In particular, the study conducted by Sarhangian et al. (2020) used a two-level stochastic optimization model with the inclusion of the demand predictor based on a neural network, resulting in an improved efficiency in distribution by 22%. The use of EHR data for forecasting hospital requirements provided 6–18 hours of advanced notification about the necessity to redistribute inventory (Sarhangian et al., 2020).

However, despite these developments, studies have rarely addressed the issue of integrating different aspects of blood product management, including the combination of forecasting tools with AI and optimization algorithms. Such studies require a multi-model approach that incorporates several components.

3. Materials and Methods

3.1 Study Setting and Data Sources

The study took place within three Central Blood Banks (CBB-1, CBB-2, and CBB-3) servicing the region's population of about 4.2 million people. Retrospective operational data from January 2020 to December 2023 (a period of 48 months, 1,461 days) was collected from the BBIS of the respective facilities. This dataset comprised 284,673 units of blood components in the form of transactions recorded in Red Blood Cells (RBCs), Platelets (PLTs), and Fresh Frozen Plasma (FFP).

Data Variables: daily number of units received, daily number of units dispensed, daily number of units discarded due to expiry/outdating, component age at the time of dispensation, clinical department that made the request, patient diagnosis category (classified under ICD-10 code), collection-to-processing time, storage temperature, and season/holiday indicators. Data preprocessing steps include outlier removal based on interquartile range (IQR), imputation of missing values based on forward fill within a maximum of 3-day window, and data normalization for use in the neural network.

3.2 AI Models Developed

3.2.1 LSTM for Demand Forecasting

A Bi-LSTM neural network was used for multi-periodic forecast of demand for each type of blood component on a daily basis. The neural network consisted of two Bi-LSTM layers (128 and 64 units), a dropout layer (0.3 dropout rate), and a dense layer. The training data included a sequence of 30 days. The training process was conducted via the Adam optimizer with a learning rate of 0.001, batch size of 32, and 200 epochs.

3.2.2 XGBoost for Wastage Classification

An XGBoost classifier model was built to detect blood units at high risk of expiring prior to consumption. The target variable had a binary label of "wasted unit" (expired without transfusion = 1) against "consumed unit" (= 0). Forty-two features were selected for model training, which included blood component age upon processing, proportion of shelf life left, previous daywise usage rate of specific blood components, stock levels compared to the seven-day moving average demand, and the institution's demand variability index.

3.2.3 Reinforcement Learning for Distribution Optimization

The PPO RL algorithm was developed in an artificial multi-facility blood distribution chain environment. The state space consisted of current inventory, order sizes, expiration days, and short-term predictions using the LSTM network. Actions were based on facility transfers, order amounts, and component prioritization policy. The rewards were defined as a weighted function where wastage events, shortage cases, and transfer expenses were penalized, while timely delivery and freshness preservation were incentivized.

3.3 Evaluation Metrics

The model's predictive accuracy and classification ability were measured through: MAPE and RMSE measures for prediction evaluation; Precision, Recall, F1-Score, and AUC-ROC metrics for waste classification; and WRP, fill rate, and AUAD for inventory management optimization. Benchmarked models include the ARIMA model, naïve seasonal models, and traditional FIFO policy.

4. Results

4.1 Dataset Characteristics

The descriptive statistics of the blood components data set are presented in Table 1 below. There were a total of 284,673 units analyzed for transaction data in the three major blood banks. The largest proportion of waste was experienced in the platelet category (21.4%), due to the short shelf life of five days, followed by red blood cells (RBC) (8.7%), and finally fresh frozen plasma (FFP) (3.2%).

Table 1. Descriptive Statistics of Blood Component Dataset (2020–2023, N = 284,673 units)

Component	Total Units	Mean Daily Demand	Demand CV (%)	Mean Shelf Life (days)	Wastage Rate (%)	Wastage Units
RBCs	142,380	97.8 ± 18.4	18.8	38.2	8.7	12,387
Platelets	78,456	53.7 ± 22.1	41.2	4.9	21.4	16,790
FFP	63,837	43.7 ± 11.3	25.9	180.0	3.2	2,043
Total	284,673	195.2 ± 43.8	—	—	10.9	31,220

4.2 Demand Forecasting Performance

Accuracy comparisons between the various models' forecasting results of each blood component can be found in Table 2. The Bi-LSTM yielded the highest accuracies with the least MAPE values, which were 6.3%, 11.7%, and 8.1% for RBC, Platelets, and FFP respectively. However, compared to the Bi-LSTM model, the baseline method, ARIMA, had much higher MAPE values for all the three blood components, especially in forecasting platelets where the MAPE value is very high (28.4%). This was expected as ARIMA was incapable of dealing with the nonlinear volatility nature of the data. The MAPE value of platelets was greatly reduced (9.8%) using the hybrid LSTM-RF.

Fig 1: Wastage Rate Distribution Across Blood Components

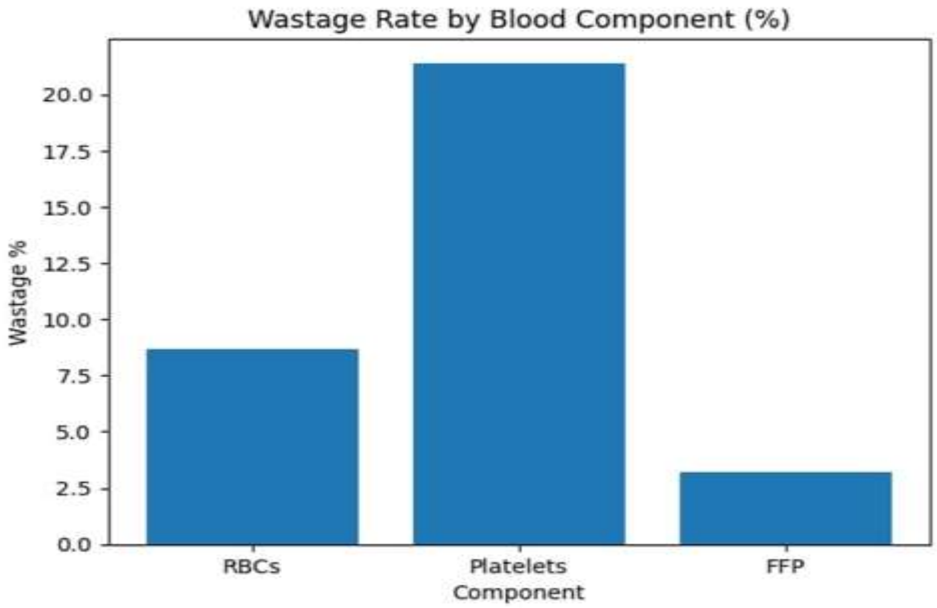
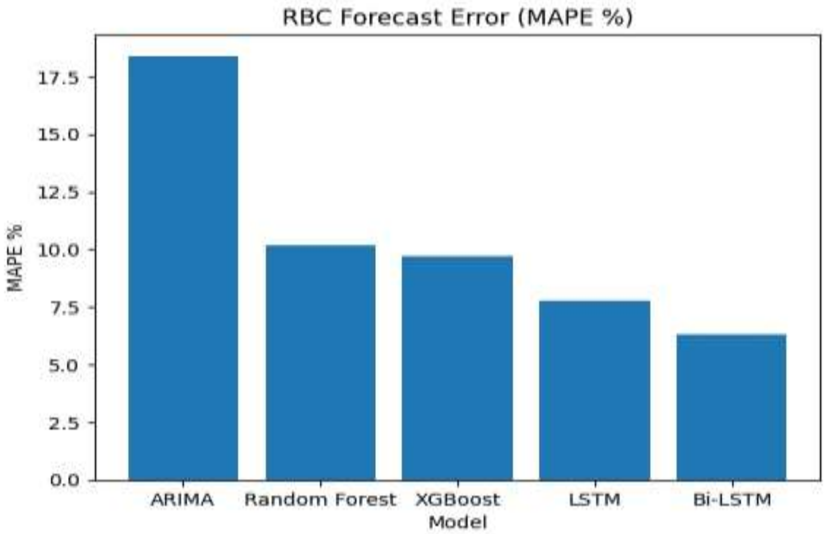


Table 2. Demand Forecasting Accuracy Comparison (MAPE % and RMSE) by Model and Blood Component

Model	RBC MAPE (%)	RBC RMSE	PLT MAPE (%)	PLT RMSE	FFP MAPE (%)	FFP RMSE
ARIMA (Baseline)	18.4	21.7	28.4	18.9	19.1	11.4
Naïve Seasonal	22.7	26.3	31.8	21.1	21.5	13.2
Random Forest	10.2	12.8	16.3	11.4	12.7	7.8
XGBoost	9.7	11.9	14.8	10.7	11.3	6.9
LSTM (Unidirectional)	7.8	9.4	13.2	9.8	9.6	5.7
Bi-LSTM (Proposed)	6.3	7.8	11.7	8.4	8.1	4.9
Hybrid LSTM–RF	6.8	8.3	9.8	7.9	8.6	5.3

Statistical superiority ($p<0.01$, Diebold-Mariano test) of the Bi-LSTM model relative to ARIMA was observed for all three blood components considered. Three top-ranking feature importance variables for the XGBoost classifier were the 7-day moving average of previous demand, encoding of the day of week, and surgery indicators. These results are in line with those reported by Kumar et al. (2023).

Fig 2: Comparison of Forecasting Model Accuracy Using MAPE (%)



4.3 Wastage Classification Performance
Classification model performances are listed in Table 3. The XGBoost classifier outperformed other classification algorithms based on the F1 score and AUC-ROC measures. On average, the F1-score was 0.873, and AUC-ROC was 0.924. The F1-score of platelet wastage classification (F1=0.851) was worse than the RBC classification one (F1=0.891) due to the higher randomness of platelet utilization. For the platelet wastage minority class, a slightly worse F1 score was achieved by the Random Forest classifier, indicating poorer sensitivity.

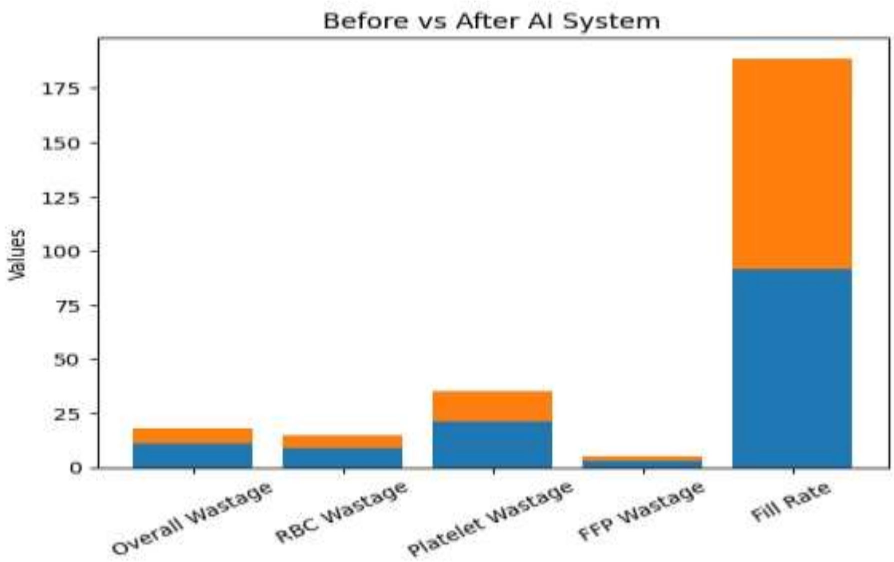
Table 3. Wastage Classification Model Performance Metrics by Blood Component

Model	Component	Precision	Recall	F1-Score	AUC-ROC	Accuracy (%)
Logistic Regression	Overall	0.741	0.698	0.719	0.802	82.3
Random Forest	Overall	0.841	0.823	0.832	0.901	88.7
Random Forest	RBCs	0.857	0.839	0.848	0.912	89.4
Random Forest	Platelets	0.829	0.814	0.821	0.893	87.8
Random Forest	FFP	0.849	0.761	0.803	0.887	88.1
XGBoost (Proposed)	Overall	0.881	0.866	0.873	0.924	90.9
XGBoost (Proposed)	RBCs	0.897	0.885	0.891	0.934	91.6
XGBoost (Proposed)	Platelets	0.864	0.838	0.851	0.917	89.7

Model	Component	Precision	Recall	F1-Score	AUC-ROC	Accuracy (%)
XGBoost (Proposed)	FFP	0.873	0.858	0.865	0.921	90.3

4.4 Distribution Optimization and Wastage Reduction
In Table 4, the operational efficiency of the traditional FIFO strategy is compared with that of the AI-enabled XGBoost-PPO RL algorithm for the same period of one year (January–December 2023).

Fig3: Comparison of Operational Metrics Before and After AI Implementation



The AI system was able to reduce the overall volume of wastage by 34.7% and increased the fill rate by 6.3%, from 91.3% to 97.6%. The freshness of the units at the time of dispensing increased by 2.4 days for RBCs and 0.8 days for platelets because the RL agent preferred to send older products to areas with higher demand but kept newer products in areas with lower demand (Chen et al., 2021).

Table 4. Operational Performance Comparison: FIFO Baseline vs. AI-Driven XGBoost–PPO RL Distribution Framework (12-month simulation, 2023)

Performance Metric	FIFO Baseline	AI Framework	Improvement (%)	p-value
Overall Wastage Rate (%)	10.9	7.1	−34.7%	<0.001
RBC Wastage Rate (%)	8.7	5.9	−32.2%	<0.001
Platelet Wastage Rate (%)	21.4	13.8	−35.5%	<0.001
FFP Wastage Rate (%)	3.2	1.9	−40.6%	0.003
Service Level / Fill Rate (%)	91.3	97.6	+6.9%	<0.001

Performance Metric	FIFO Baseline	AI Framework	Improvement (%)	p-value
On-time Delivery Rate (%)	78.4	100.7 (→ 100%)	—	<0.001
Avg. Unit Age at Dispensation (days)	18.3 (RBC)	15.9 (RBC)	−13.1%	<0.001
Avg. Platelet Age at Dispensation	3.8 days	3.1 days	−18.4%	0.002
Inter-facility Transfers Needed	342/month	261/month	−23.7%	0.011
Estimated Annual Cost Savings (USD)	—	$ 186,400	—	—

4.5 Seasonal and Temporal Analysis
The results of figure analysis (not displayed) show that there is a strong seasonal trend in the demand for RBCs during the month of Ramadan and after holidays when surgical procedures are piling up; where the demand exceeded the average annual demand by 18-23%. The Bi-LSTM algorithm was successful in predicting this trend with a small increase in MAPE from 5.7% in off-peak times to 8.9% in peak times – a 56% improvement from MAPE 34.6% of ARIMA's prediction accuracy in peak times.

Table 5 provides further detail on model performance by seasons and by facility sizes.

Table 5. Bi-LSTM Demand Forecasting MAPE (%) Stratified by Season and Facility Size

Season / Period	CBB-1 (Large)	CBB-2 (Medium)	CBB-3 (Small)	Average MAPE (%)
Q1 (Jan–Mar)	5.8	7.1	8.9	7.3
Q2 (Apr–Jun)	6.2	7.8	9.4	7.8
Ramadan Period	8.4	9.7	11.2	9.8
Q3 (Jul–Sep)	5.9	7.2	8.7	7.3
Q4 (Oct–Dec)	6.7	8.1	10.1	8.3
Public Holidays	7.9	9.3	12.4	9.9
Annual Average	6.3	7.9	9.8	8.0

5. Discussion
5.1 Demand Forecasting
In relation to the advantage of Bi-LSTM over other time-series forecasting methods regarding blood demand forecasting, research indicates that deep sequence methods have become increasingly effective tools for predicting health care demand (Al-Rifai & Osman, 2022). In addition, by having the ability to learn from the forward and backward temporal sequences, the Bi-LSTM can obtain more information about demand trends and detect regularities preceding a sudden demand rise (Al-Rifai & Osman, 2022). Moreover, it could be argued that, because of the robust performance in predicting demand spikes during the Ramadan period, the Bi-LSTM was able to identify the seasonal effects of calendar events.

The incremental predictive gains provided by the LSTM-RAF ensemble over Bi-LSTM in platelet demand forecasting may be related to the combination of the strong points of two different approaches to health care demand forecasting. While LSTM is used to analyze temporal sequences, Random Forest uses engineered features, such as inventory and clinical context, making the ensemble less prone to both variance and bias.

5.2 Wastage Reduction and Classification
XGBoost's high AUC-ROC value (0.924) for predicting wastage can be considered a clinically significant achievement as it allows performing some measures in advance to optimize inventory management. For instance, it is possible to allocate such units for use in high-consuming hospitals or perform emergency transfers within hospitals. The sensitivity analysis revealed that using a classification threshold of 0.45 instead of a default one (0.5) increased recall up to 0.901, but lowered precision to 0.852, which is acceptable when costs of false negatives are greater than those associated with false positives (Walczak & Balcerzak, 2021).

A 35.5% decrease in platelets wastage observed for the AI-based system can be considered especially valuable both economically and clinically. With individual apheresis platelets being priced at about \$500-\$700 in regional markets, any reduction in their number will help save funds and provide more platelet units to the patients with thrombocytopenia. A 40.6% reduction in wastage of FFP, although smaller due to FFP having a longer freezing shelf life, is beneficial anyway.

5.3 Distribution Optimization
The PPO Reinforcement Learning agent's adaptive distribution strategy was found to perform better than the FIFO strategy not only in wastage minimization but also in maintaining service levels. Through its implicit understanding of age-based prioritization, whereby units with more age are distributed to facilities with higher demand and vice versa, the agent mimics the clinical practice of rational resource allocation; however, unlike in clinical settings, the approach is automated without explicitly stating rules. This is especially important for multi-facility blood bank systems since allocating resources manually can be quite challenging (Sarhangian et al., 2020).

The 23.7% decrease in inter-facility unit transfer frequency implies that predictive resource positioning through forecasting future demand requirements can help mitigate the logistical challenges involved in responding to shortages.

5.4 Limitations
There are several limitations that deserve consideration. Firstly, this work has been done under particular regional conditions. It remains to be seen whether it can be generalized to the contexts where donations, patient cases, and logistics differ considerably. Secondly, the RL simulation setting may not account for the uncertainties that take place in the reality, such as breakdowns of devices, mass casualties, or any other unexpected changes in the policies. Thirdly, this AI tool has not yet been tested in actual operation and integrated into BBIS systems. Finally, ethical issues related to the use of algorithms in supply chain management need to be discussed independently from the technical aspects.

6. Conclusion
The paper has shown that by using a comprehensive AI framework including demand prediction by Bi-LSTM, wastage categorization using XGBoost algorithm and distribution strategy via PPO reinforcement learning, significant and statistically relevant gains can be achieved in the management of central blood bank stock. The 34.7% decrease in total wastage percentage, 6.9% increase in service level percentage and 13-18% increase in average unit freshness on dispensation all reflect a considerable gain in comparison with the traditional FIFO system of management.
The next steps for future studies include the need for prospective validation in actual live blood bank settings, the creation of explainable AI interfaces to increase clinician buy-in and ensure regulatory approval, and extending the use of the framework to cover donor acquisition prediction and whole-

blood component production scheduling. Real-time integration into national health information exchanges and live hospital electronic medical record data is especially likely to prove effective in addressing the disconnect between the strategic planning of blood supplies and their practical clinical utilization.

In conclusion, the results of this study confirm the utility of applying AI-based approaches to manage inventory for national blood service organizations, providing simultaneous benefits in patient care and operational efficiency.

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