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Average-based fuzzy time series for forecasting blood bag availability: Implications for health resilience and emergency preparedness in Banda Aceh, Indonesia

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Abstract

Background: Blood availability remains a major challenge in healthcare systems, particularly in developing countries where the demand for blood often exceeds the available supply. Accurate forecasting of blood collection is therefore important to support effective blood inventory management at blood transfusion units.
Aims: This study aims to apply the Average-Based Fuzzy Time Series method to forecast the number of collected blood bags at the Blood Transfusion Unit (UTD) of the Indonesian Red Cross in Banda Aceh, both in total and by blood type.
Method: Monthly blood collection data from January 2016 to September 2020 were analyzed using the Average-Based Fuzzy Time Series model. The forecasting procedure involved constructing fuzzy intervals using the average-based approach, forming fuzzy logical relationships, and performing defuzzification. Model performance was evaluated using Mean Squared Error (MSE) and Average Forecasting Error Rate (AFER).
Result: The second-order model provided the best forecasting performance with an AFER value of 13.67% and an accuracy of approximately 86.33%, producing a prediction of 2054 blood bags for October 2020. Forecasting by blood type yielded predictions of 529 (A), 702 (O), 738 (B), and 154 (AB) blood bags.
Conclusion: The results indicate that the Average-Based Fuzzy Time Series method is effective for forecasting blood bag availability and can support planning and management of blood supply at blood transfusion units. Furthermore, the proposed approach has potential applications in defense and emergency contexts by supporting medical logistics planning, improving preparedness, and enhancing the resilience of blood supply systems during military operations and disaster response.

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INTRODUCTION

Globally, the availability of blood remains a major challenge for many countries. The World Health Organization (WHO) reports that anemia affects approximately 1.62 billion people worldwide, representing about 24.8% of the global population. To support healthcare services, WHO recommends that the minimum national blood supply should reach approximately 2% of the total population. However, blood availability in Indonesia has not yet met the national demand. Data indicate that the national blood requirement is estimated to reach around 5.1 million bags per year, while the available supply is only about 4.2 million bags, resulting in a significant shortage (Media Indonesia, 2019). This condition highlights the importance of more effective blood supply management and planning to ensure that the demand for blood transfusion services can be adequately fulfilled.

Blood availability is also recognized as a critical component of a resilient healthcare system, particularly in responding to public health emergencies and large-scale disasters. Disruptions in blood supply can significantly reduce the capacity of healthcare systems to respond effectively to crises, making preparedness and resource planning essential (Blanchet et al., 2017; Kruk et al., 2015; World Health Organization, 2021). Blood availability is not only a healthcare issue but also a critical component of national health resilience and health security. Disruptions in blood supply systems can significantly undermine a nation's ability to respond effectively to mass casualty incidents, natural disasters, and public health emergencies. In such situations, the timely availability of adequate blood supplies is essential for life-saving medical interventions and for maintaining the operational readiness of healthcare systems (Yazer & Spinella, 2018). Therefore, ensuring a stable and well-managed blood supply is a strategic priority that supports both civilian healthcare services and emergency preparedness at the national level.

In Indonesia, blood availability is maintained through the Blood Transfusion Unit (Unit Transfusi Darah, UTD), which is responsible for organizing blood donation activities, blood collection, and distribution to healthcare facilities. In Aceh Province, one of the institutions responsible for providing blood supply is the UTD of the Indonesian Red Cross (PMI) in Banda Aceh. Based on data from UTD PMI Banda Aceh, during the period 2017–2018 the number of collected blood bags reached 50,588, while the total demand amounted to 114,083 bags (Indonesian Red Cross (PMI) Banda Aceh, 2020). The considerable gap between blood demand and supply indicates the need for better planning and forecasting of future blood availability.

One approach that can be used to predict the number of available blood bags is the fuzzy time series method. This method is a time series forecasting technique that utilizes fuzzy set theory to capture patterns in historical data and project them into the future. Fuzzy concepts have been widely used in decision-making systems and uncertainty modeling due to their ability to represent ambiguity and uncertainty in real-world data (Klir & Yuan, 1995; Zimmermann, 2010). The fuzzy time series method was first introduced by (Song & Chissom, 1993) and has since been further developed to improve forecasting accuracy for various types of time series data.

One of the early developments in fuzzy time series was proposed by (Chen, 1996), who introduced an efficient approach for handling forecasting problems using fuzzy logical relationships. This approach was later extended through the development of high-order and multi-factor fuzzy time series models to improve forecasting accuracy and flexibility (Lee et al., 2006). Another important advancement is the average-based interval approach introduced by (Huarng, 2001), which determines interval lengths based on the average variation of data. This approach produces more representative intervals and enhances forecasting performance.

The average-based fuzzy time series method has since been widely applied in various forecasting domains, including stock index prediction (Xihao & Yimin, 2008), electricity consumption forecasting (Ekananta et al., 2018), traffic density forecasting (Wiguna, 2015), and tourist arrival prediction (Vivianti et al., 2020). Furthermore, fuzzy time series methods have been utilized in broader applications such as financial forecasting (Bose & Mali, 2019), short-term electricity load forecasting (Kazim et al., 2026), tourism demand prediction (Wang, 2004), and various economic and business indicators (Chen & Chung, 2006; Lucas et al., 2022; Nishad & Aggarwal, 2023; Wang & Liu, 2025; Wu et al., 2025; Zhu et al., 2023). These studies demonstrate that fuzzy time series approaches are effective in handling uncertainty and fluctuations in time series data, making them widely used in modern forecasting applications (Chen et al., 2025). In general, forecasting methods play a crucial role in supporting decision-making processes across various fields, particularly when dealing with time-dependent data (Box et al., 2015).

Although various forecasting methods have been developed to support blood supply chain management, accurately predicting blood availability remains a significant challenge for blood transfusion institutions. Recent studies indicate that time series forecasting methods can help anticipate imbalances between blood demand and supply (Chideme et al., 2024). Several studies have also employed machine learning approaches such as Long Short-Term Memory (LSTM) models to predict the number of blood donors or blood demand (Shokouhifar & Ranjbarimesan, 2022). However, most of these studies focus on modeling blood demand at a macro level, while the application of fuzzy time series methods to directly predict blood bag availability at the blood transfusion unit level remains relatively limited.

Therefore, this study applies the Average-Based Fuzzy Time Series method to forecast the number of collected blood bags at the UTD PMI Banda Aceh. Unlike previous studies, this research not only predicts the total number of blood bags but also performs forecasting based on blood types (A, B, O, and AB). The average-based approach is used to determine interval lengths adaptively based on the average variation of historical data, which is expected to improve forecasting accuracy and provide more detailed information for blood bank managers in planning blood availability. In addition, this approach has potential applications in the defense sector, particularly in supporting military medical logistics, improving preparedness for mass casualty situations, and enhancing the resilience of blood supply systems during emergency and disaster response operations.

METHOD

Dataset

This study uses secondary data obtained from the Blood Transfusion Unit (Unit Transfusi Darah, UTD) of the Indonesian Red Cross (PMI) in Banda Aceh. The dataset consists of monthly time series data of the number of collected blood bags, both in total and by blood type (A, B, O, and AB). The data period spans from January 2016 to September 2020, comprising a total of 57 observations. These data are used as the primary variable to forecast the number of collected blood bags for the subsequent period, namely October 2020.

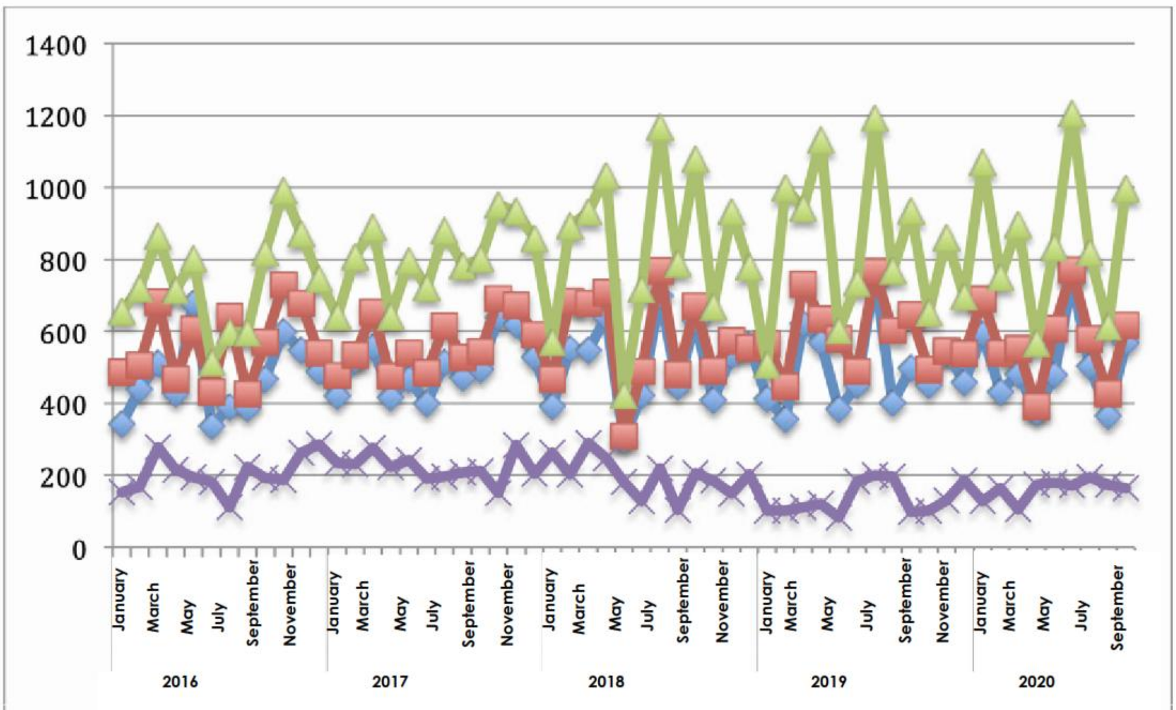

Figure 1. Time series plot of collected blood bags by blood type (A, B, O, and AB) at UTD PMI Banda Aceh, January 2016-September 2020.

Figure 1 presents the time series data of collected blood bags by blood type (A, B, O, and AB) at UTD PMI Banda Aceh from January 2016 to September 2020. The blue line represents blood type A, the red line represents blood type B, the purple line represents blood type O, and the green line represents blood type AB. As shown in Figure 1, the data for each blood type exhibits a seasonal pattern, indicated by recurring variations in the data across different years.

Average-Based Fuzzy Time Series Method

The forecasting method employed in this study is the Average-Based Fuzzy Time Series (FTS), which is an extension of the conventional FTS method designed to improve forecasting accuracy through interval determination based on the average variation of the data. FTS models time series data using fuzzy set theory, where numerical values are transformed into linguistic variables, allowing temporal relationships within the data to be analyzed more flexibly (Song & Chissom, 1993).

The first step is to determine the universe of discourse based on the minimum and maximum values of the historical data:

$$U = [D_{\min}, D_{\max}] \tag{1}$$

Next, the interval length is determined using the average-based approach. This method calculates the absolute differences between two consecutive observations and then computes their average. Half of this average value is used as the basis for determining the interval length, which is subsequently adjusted according to a predefined interval base as suggested in previous studies (Xihao & Yimin, 2008).

The universe of discourse U is then partitioned into several subintervals u_i with interval length r as follows:

$$u_i = [D_{\min} + (i-1)r, D_{\min} + ir] \tag{2}$$

Each subinterval is represented as a linguistic fuzzy set $A_1, A_2, \dots, A_n$. The historical data are then fuzzified by mapping each value to its corresponding interval.

After the fuzzification process, relationships between consecutive time periods are established using Fuzzy Logical Relationships (FLR). If the data at time period t belong to fuzzy set A_i and the data at time period t + 1 belong to fuzzy set A_j, the relationship is expressed as

$$A_i \rightarrow A_j$$

FLRs that share the same antecedent are then grouped into Fuzzy Logical Relationship Groups (FLRG). The forecasting process is performed based on the established FLRG, where the predicted value is obtained through defuzzification by taking the midpoint of the corresponding interval or the average of the midpoints of the related intervals.

Evaluation Metrics

The forecasting accuracy is evaluated using two error measures: Mean Squared Error (MSE) and Average Forecasting Error Rate (AFER). The MSE is calculated as

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2 \tag{3}$$

while the AFER is defined as

$$AFER = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{4}$$

where A_t represents the actual value and F_t represents the forecasted value at time period t. Smaller values of MSE and AFER indicate better forecasting accuracy. The proposed method consists of several stages as shown in Figure 2.

Figure 2. Research design of the proposed Average-Based Fuzzy Time Series method.

RESULTS AND DISCUSSION

Data Analysis and Fuzzy Set Construction

Based on the initial analysis of the historical data, the number of collected blood bags shows fluctuating patterns over time with varying values each year. The minimum value recorded is 1214 bags in May 2018, while the maximum value is 2894 bags in May 2020. These minimum and maximum values are used to determine the universe of discourse as follows,

$$U = [1214,2894].$$

The interval length is determined using the average-based method, which produces an average absolute difference of 481.89. Half of this value is used as the basis for determining the interval length, resulting in an interval size of 240. The universe of discourse is then partitioned into seven fuzzy intervals as shown in Table 1.

Table 1. Fuzzy subsets and interval midpoints.

Interval	Subset	Midpoint
1	(1214, 1454)	1334
2	(1454, 1694)	1574
3	(1694, 1934)	1814
4	(1934, 2174)	2054
5	(2174, 2414)	2294
6	(2414, 2654)	2534
7	(2654, 2894)	2774

Each interval is represented as a linguistic fuzzy set $A_1, A_2, \dots, A_7$. Based on the fuzzification of historical data, Fuzzy Logical Relationships (FLR) are constructed and subsequently grouped into FLRG, as presented in Table 2.

Table 1. Fuzzy logical relationship group.

Current State	Next State
A_1	A_3
A_2	A_3, A_4, A_5
A_3	A_2, A_4, A_5, A_6, A_7
A_4	A_2, A_3, A_5, A_6, A_7
A_5	A_1, A_3, A_4, A_6
A_6	A_1, A_2, A_3, A_5, A_6
A_7	A_4

Forecasting Results Using Average-Based FTS

Based on the constructed FLRG, the defuzzification process is carried out using the midpoint values of each interval. The resulting defuzzification values are $A_1 = 1814, A_2 = 2054, A_3 = 2259, A_4 = 2198, A_5 = 2054, A_6 = 1901$, and $A_7 = 1938$. The last observed data point is September 2020 with an actual value of 1638 bags, which belongs to fuzzy set A_2.Based on the established FLRG, the prediction for the next period follows the defuzzification value of A_2.Therefore, the predicted number of collected blood bags for October 2020 is,

$$\widehat{Y}_{Oct2020} = 2054.$$

To improve forecasting accuracy, further testing is conducted using higher-order Average-Based Fuzzy Time Series models. In the second-order model, the FLR construction uses two previous observations, namely $F(t-2)$ and $F(t-1)$, to predict $F(t)$. The evaluation results show that the second-order method produces an MSE value of 135.820 and an AFER value of 13.67%, corresponding to an accuracy level of approximately 86.53%.

Further experimentation is conducted using a third-order model that utilizes three previous observations. However, the combination of linguistic values in the last three periods does not appear in the FLRG, resulting in the inability to obtain a forecast value. Therefore, the third-order model is not used in the prediction process.

Model Performance Comparison

The comparison of forecasting model performance is conducted using Mean Squared Error (MSE) and Average Forecasting Error Rate (AFER). The comparison results are presented in Table 3.

Table 3. Comparison of forecasting model performance.

Method	MSE	AFER
FTS Order 1	306.389	25.56%
FTS Order 2	135.820	13.67%
FTS Order 3	–	–

The results indicate that the second-order Average-Based Fuzzy Time Series model provides the best performance, yielding smaller error values compared with the first-order model. Meanwhile, the third-order model fails to produce a forecast because the combination of the most recent linguistic values is not found in the constructed FLRG.

Forecasting Model Based on Blood Types

In addition to forecasting the total number of collected blood bags, this study also analyzes forecasting based on blood types A, B, O, and AB.

Based on the analysis of historical data, the minimum and maximum values for each blood type are used to determine the universe of discourse. The resulting universes of discourse for each blood type are presented in Table 4.

Table 4. Universe of discourse of collected blood bags by blood type.

Blood Type	Universe of Discourse
A	[301, 756]
B	[309, 771]
O	[422, 1206]
AB	[83, 290]

The interval length is determined using the average-based method. Based on the average absolute differences of the historical data, the interval lengths obtained are 65 for blood type A, 66 for blood type B, 112 for blood type O, and 23 for blood type AB. These intervals are used to construct fuzzy subsets and perform the fuzzification process on the historical data. Subsequently, Fuzzy Logical Relationships (FLR) are established and grouped into FLRG, which serve as the basis for the defuzzification and forecasting processes.

Based on the first-order Average-Based Fuzzy Time Series model, the predicted number of collected blood bags for October 2020 is presented in Table 5.

Table 5. Forecasting results of collected blood bags for October 2020.

Blood Type	Forecast (Bags)
A	529
B	527
O	702
AB	181

The results indicate that the highest predicted number of collected blood bags comes from blood type O, while the lowest prediction is associated with blood type AB.

To improve forecasting accuracy, the model was further developed using the second-order Average-Based Fuzzy Time Series, which utilizes two previous historical observations as the basis for constructing fuzzy relationships. The forecasting results obtained using the second-order model for October 2020 are presented in Table 6.

Table 6. Forecasting results of collected blood bags by blood type using second-order FTS.

Month	A	B	O	AB
October 2020	-	738	–	279

The forecasting results show that the second-order model produces predictions of 738 bags for blood type B and 279 bags for blood type AB. Meanwhile, predictions for blood types A and O cannot be obtained because the combination of the most recent linguistic values does not appear in the constructed FLRG. This finding indicates that higher-order models do not always guarantee the availability of predictions under all data conditions.

Evaluation and Analysis of Model Performance

The forecasting accuracy is evaluated using the Mean Squared Error (MSE) and the Average Forecasting Error Rate (AFER). The evaluation results for the first-order model are presented in Table 7.

Table 7. Forecasting error values by blood type.

Blood Type	MSE	AFER
A	9.557	17.52%
B	9.422	14.39%
O	29.112	18.30%
AB	2.106	23.43%

Based on the AFER values, the forecasting accuracy for blood types A, B, and O falls within a good category, while blood type AB shows relatively lower accuracy. The evaluation is also conducted for the second-order model as shown in Table 8.

Table 8. Forecasting error values by blood type (second-order).

Blood Type	MSE	AFER
A	-	-
B	6424	11%
O	-	-
AB	836	23.43%

The error values for blood types A and O cannot be calculated because the forecasting values are not defined in the second-order FLRG. Meanwhile, the forecasting accuracy for blood types B and AB reaches approximately 89% and 90.13%, respectively. These results indicate that the Average-Based Fuzzy Time Series method provides relatively good forecasting performance for most blood types and has the potential to be used as a decision-support tool for planning blood supply management at UTD PMI.

In cases where the second-order FTS model does not produce a valid forecast due to the absence of matching fuzzy logical relationships, practitioners may consider using the first-order model as a fallback approach. The first-order model generally provides more stable and consistent predictions because it relies on simpler relationships and requires less data complexity. In addition, alternative strategies can be applied to address this limitation. For instance, smoothing techniques or hybrid approaches can be used to improve model robustness. Another possible approach is to expand the dataset or adjust the interval partitioning to increase the likelihood of forming complete fuzzy relationships. Therefore, rather than relying solely on higher-order models, a flexible modeling strategy that combines multiple approaches is recommended for practical implementation.

Comparison Between Total Forecasting and Blood-Type-Based Forecasting

In addition to forecasting the total number of collected blood bags, this study also performs forecasting based on blood types. Conceptually, the total number of blood bags is the sum of the number of bags collected for each blood type, namely A, B, O, and AB. For example, in January 2016, the number of collected blood bags consisted of 342 bags of blood type A, 486 bags of blood type B, 656 bags of blood type O, and 154 bags of blood type AB, resulting in a total of 1638 bags.

Based on the forecasting results using the Average-Based Fuzzy Time Series method, the total number of collected blood bags for October 2020 is predicted to be 2054 bags. Meanwhile, the forecasting results based on blood types produce predictions of 529 bags for blood type A, 738 bags for blood type B, 702 bags for blood type O, and 259 bags for blood type AB. When all blood-type predictions are summed, the total reaches 2228 bags, which differs from the total forecast of 2054 bags. This discrepancy is caused by variations in the data patterns of each blood type, which affect the formation of fuzzy logical relationships and the resulting forecasts.

Compared to previous studies that generally focus on aggregate forecasting (Bose & Mali, 2019; Lucas et al., 2022), this study provides a more detailed forecasting framework by incorporating blood-type-based predictions. This approach enhances the granularity of forecasting results and offers additional insights that are not captured by total forecasting alone. Furthermore, the use of the average-based interval method improves the adaptability of interval formation, which contributes to better handling of data fluctuations, as also highlighted in previous fuzzy time series studies (Huarng, 2001; Nishad & Aggarwal, 2023).

From an application perspective, the ability to forecast both total and blood-type-specific availability has important implications for emergency and defense-related contexts. In military medical logistics and disaster response scenarios, different blood types are required in varying proportions. Therefore, more granular forecasting can support strategic planning, improve resource allocation, and enhance preparedness in handling mass casualty situations. This highlights the potential contribution of the proposed method in strengthening the resilience and effectiveness of blood supply systems in both civilian and defense sectors.

Furthermore, forecasting results represent estimated values that approximate the actual values. Therefore, differences between the total forecast and the aggregated blood-type forecasts are reasonable in time series forecasting. Consequently, evaluating forecasting accuracy through error calculations becomes an important step in assessing the performance of the applied method.

Implications for Health Resilience, Emergency Preparedness, and Blood Supply Management

Accurate forecasting of blood availability plays a critical role in supporting surge capacity planning for disaster response, particularly in situations such as natural disasters and mass casualty incidents where demand increases rapidly. Reliable predictions enable healthcare providers to anticipate demand, optimize inventory, and ensure timely blood availability, thereby improving the effectiveness of emergency medical response. In addition, blood availability is essential in military medicine and defense health systems, where adequate supply supports treatment of injured personnel and enhances operational readiness in crisis situations.

From a practical perspective, the forecasting results can support procurement planning, staff scheduling, and targeted donor recruitment at blood transfusion units such as UTD PMI Banda Aceh. For instance, anticipated shortages in specific blood types can guide focused donor campaigns, while predicted demand levels can improve resource allocation and operational efficiency. The accuracy achieved of approximately 86% is sufficiently reliable for decision-making in dynamic environments, providing a useful approximation to reduce uncertainty in blood supply management.

The proposed method can also be extended to forecast other critical medical resources, such as oxygen, vaccines, and medical equipment, thereby supporting integrated planning in emergency healthcare systems. To maintain reliability, forecasting models should be updated regularly as new data become available to capture evolving patterns and unexpected events.

In disaster-prone regions such as Aceh Province, accurate blood supply forecasting plays a critical role in strengthening healthcare system resilience and emergency preparedness. The forecasting results can be integrated into disaster management systems to support pre-disaster stockpiling, optimize distribution, and enhance coordination among blood banks, hospitals, and emergency response agencies. In addition, predicted demand can guide the allocation of blood reserves across multiple locations to ensure rapid availability during crises. This approach also has the potential to be scaled across other blood transfusion units in Indonesia, thereby improving coordination and reinforcing the resilience of the national blood supply chain while enabling more proactive and effective responses to large-scale emergencies.

One limitation of this study is that the actual data for the forecasted period (October 2020) were not available at the time of analysis, so direct validation of the predicted values could not be performed. Future research should incorporate updated datasets to compare forecasting results with actual observations, which would allow for a more comprehensive evaluation of model performance and reliability.

CONCLUSION

This study applies the Average-Based Fuzzy Time Series method to predict the number of collected blood bags at UTD PMI Banda Aceh. The results show that the second-order FTS model provides the best forecasting performance, producing a prediction of 2054 blood bags for October 2020 with an accuracy level of approximately 86.33% based on the AFER metric. Forecasting by blood type produces predictions of 529 bags for type A, 702 bags for type O, 738 bags for type B, and 154 bags for type AB, with accuracy levels ranging from 81.70% to 90.13%. These findings indicate that the Average-Based Fuzzy Time Series method is effective for forecasting blood bag availability and can support decision-making in planning blood supply management.

For future research, several directions can be considered to further improve forecast performance. First, the proposed method can be extended by incorporating higher-order or hybrid models, such as combining fuzzy time series with machine learning approaches to enhance accuracy. Second, future studies may include additional variables, such as seasonal factors, donor behavior, or external events, to better capture complex data patterns. Third, the model can be applied and validated on larger datasets or different regions to assess its generalizability. Finally, further research may explore the integration of the proposed method into real-time decision support systems, particularly for emergency and defense-related medical logistics.

AUTHOR CONTRIBUTIONS

I.M.: Conceptualization, investigation, methodology, supervision, and writing-review & editing. N.A.: Conceptualization, data curation, visualization, software, and writing-original draft. R.R.: Conceptualization, methodology, investigation, and supervision. V.A.: Investigation and validation. S.: Investigation, visualization, and validation.

CONFLICT OF INTEREST

The authors declare that have no conflict of interest.

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