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Forecasting Blood Availability in Pontianak City using ARIMA Models to Optimize Inventory Planning at UTD PMI

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ABSTRACT

It is of utmost importance to control the blood supply in UTD PMI because if there is a requirement for blood, PMI can fulfill the necessary blood needs and keep the ideal blood availability. PMI UTD may encounter a shortfall of blood supply if increases in blood demand are not supported by an increase in the number of donors contributing blood. A forecast of the number of blood requests is essential to estimate the quantity of blood that is necessary and the number of blood donors that are required to be prepared to fulfill the needed blood requests. This study is a quantitative investigation that use the Autoregressive Integrated Moving Average (ARIMA) method in order to provide an accurate prediction regarding the quantity of blood that is required for each blood type in Pontianak City. UTD PMI Pontianak City provided the information that was used in this study. The information that was used included information on the number of blood requests for blood types A, AB, B, and O. Following this, the data was subjected to three iterative steps of Box Jenkins analysis, which included order identification, parameter estimation, and diagnostic testing. The goal was to obtain the most accurate model, which was then utilised to forecast the quantity of blood demand that will occur in the subsequent periods. Furthermore, the findings of this investigation indicate that the ARIMA (2,0,0), ARIMA (3,0,3), ARIMA (1,0,2), and ARIMA (1,0,0) models are the most accurate models for predicting the availability of blood categories A, AB, B, and O. ..UTD Pontianak City is anticipated to be able to manufacture bloodstock consisting of 73 blood bags over the next five days. The bloodstock will include 19 bags of Group A, 6 bags of Group AB, 22 bags of Group B, and 6 bags of Group O specifics. In light of the forecast results, it is envisaged that UTD PMI will be able to maximize inventory planning for blood in Pontianak City to reduce the number of instances in which there are shortages of blood availability.

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A. INTRODUCTION

As a result of factors such as rising rates of accidents, rising population growth, and shifting patterns of unhealthy lifestyles among individuals, there is a growing demand for more blood (Zhou et al., 2021). In addition, individuals suffering from specific ailments and pregnant women are contributing to the rise in the need for blood. Therefore, it is of the utmost importance for health services to ensure a sufficient blood supply (Raturi & Kusum, 2020). Because of the massive demand for blood, it might be challenging to meet the requirements of various health services. One of these services is the Blood Transfusion Unit (UTD), a component of the Indonesian Red Cross (PMI). Blood donation, blood supply, and blood distribution are some operations done by UTD, a healthcare facility (Booth et al., 2021). On the other hand, PMI is an Indonesian national association organization that operates in the health, social, and humanitarian sectors.

However, there are occasions when hospital demand for blood differs from blood availability. When it comes to blood supply management, one of the most significant challenges is the unpredictability of blood supply and demand (Shih & Rajendran, 2020). Blood supply and demand conditions need to be more consistent, resulting in many blood demands not being fully satisfied. As a result, it is necessary to take measures to predict instability in blood need (Wang et al., 2020). The demand for blood can be anticipated, for example. Forecasting is one of the instruments utilized to establish an effective and efficient plan (Hanifi et al., 2020). Forecasting is all about explaining a future event by processing data. Time series analysis is one method that can be used to forecast the demand for blood (Xie & Wang, 2020).

Numerous researchers, including Gress et al. (2021); Shokouhifar et al. (2021); Sudtachat et al. (2023), have conducted research in the field of medicine, particularly in relation to the requirement for blood components. The study of blood demand is becoming increasingly important not only in the medical field but also in the field of statistics, particularly in the field of forecasting. Recently, numerous researchers, including Ben Elmir et al. (2023); Li et al. (2021); Sarvestani et al. (2022); Shokouhifar & Ranjbarimesan (2022); Twumasi & Twumasi (2022), have conducted research on predicting the required blood volume. An essential component of medical care is the ability to accurately estimate the volume of blood that will be required, particularly in circumstances that include severe blood loss. In the process of building and evaluating prediction models for blood volume estimates, the mathematical discipline of statistics plays a significant role. The prediction of the required blood volume requires a combination of clinical judgment, modern measurement techniques, and statistical models, as stated in the previous sentence. It is vital to have a solid understanding of predictive elements such as colourimetric estimation, demographic-based estimations, and applications of machine learning in order to efficiently manage patient care and reduce issues that are related to blood loss. Healthcare practitioners can make improvements in the accuracy of blood volume forecasts through the continued development of statistical methods and their incorporation into clinical practice. It will ultimately lead to improvements in patient care and outcomes.

This study aims to analyze the significant number of blood donations made at UTD PMI Pontianak City. The UTD compiled a report in 2021 that states that 28 hospitals and clinics receive an average daily demand for blood of 120 blood bags. Of these, 17 hospitals are in Pontianak City, while 11 hospitals are located outside of Pontianak City, respectively. Consequently, based on the data provided by 12,809 volunteer blood donors, PMI Pontianak City has only been able to acquire around 83 percent of the supply. The forecasting of blood demand is therefore an essential strategic stage in the process of ensuring the availability of sufficient and timely blood, which eventually results in the saving of lives and an increase in the effectiveness of the health system in Pontianak City. Hospitals and blood banks can better manage their blood stores using forecasting, which helps to ensure that there is neither a shortage nor an excess of blood supplies. Given the short shelf life of blood, forecasting aids in minimizing blood waste. In addition, effective forecasting is helpful in preparing for emergency events such as severe accidents, natural catastrophes, or disease outbreaks, all of which have the potential to increase the demand unexpectedly and significantly for blood.

An accurate forecast of the demand for blood is absolutely necessary in order to maximize the effectiveness of inventory planning. Attempts to forecast the complex and ever-changing nature of blood demand using conventional methods, such as straightforward linear models, have been demonstrated to be insufficient. For the purpose of accurately predicting the demand for blood, time-series analysis, and more specifically the application of ARIMA (Auto Regressive Integrated Moving Average) models, has been accepted as a powerful method. To provide a more solid basis for judgments about inventory management, these models are able to incorporate seasonal fluctuations, trends, and other patterns in the data.

Based on information on the quantity of blood requests, the Autoregressive Integrated Moving Average (ARIMA) model is the forecasting technique utilized in this study. This dataset was provided by UTD PMI Pontianak City. From January 1, 2023, to December 31, 2023, a total of 365 observations were made during this study's daily observation period. There is a congruence between the research aims of this work and the overarching goals of employing statistical models such as ARIMA in order to predict and regulate blood demand efficiently. In order to contribute to the existing body of knowledge on blood inventory management, the study intends to accomplish these objectives. It will ensure that healthcare personnel are able to make well-informed decisions in order to address the needs of patients while simultaneously eliminating inefficiencies.

The utilization of ARIMA models for the purpose of providing an accurate forecast of blood demand will make it possible for UTD PMI to improve its inventory planning, hence reducing the possibility of shortages and avoiding wastage. This strategy is in line with the best practices on a global scale for managing blood inventories, which ensures that medical professionals are able to make well-informed judgments in order to satisfy the requirements of their patients efficiently. The findings of this study will contribute to the existing body of knowledge concerning blood inventory management. These findings will offer insights that may be utilized in comparable situations to enhance patient care and outcomes. This study intends to improve the efficiency and efficacy of blood inventory management in Pontianak City by utilizing sophisticated statistical approaches such as ARIMA to anticipate blood demand. The ultimate goal of this study is to increase the availability of fresh blood for patients who are in need of it.

B. METHODS

1. Data Collection

The aim of this study is to produce an accurate prediction regarding the quantity of blood that is required for each blood type in Pontianak City. This study is a quantitative investigation that makes use of the Autoregressive Integrated Moving Average (ARIMA) approach. This study uses data from the UTD PMI Pontianak City from January to December 2023, totalling 365 observations… Each blood type, specifically A, AB, B, and O, has its own daily blood demand data, which is the way the data is presented. Processes of analysis We carry out tests of the data's stationarity, both in terms of variance and average, to provide a prediction regarding the required amount of blood. To determine whether the data are stationary, a visual examination of the time series plot is required. Once the data has reached a stationary state, the next step is to identify the model by utilizing ACF and PACF plots. Afterwards, the process of parameter estimation is carried out for all the alternative models that have been acquired. The next step involves conducting a diagnostic check to determine the best model. One last thing to do is to estimate the volume of blood that will be required during the next few periods.

2. Autoregressive Integrated Moving Average (ARIMA) Model

Time series analysis involves analysing past data patterns collected over time to make quantitative forecasts (Torres et al., 2021). The data utilized in time series analysis should exhibit a stationary variance and average. When there is no discernible trend in the data and it consistently fluctuates around a stable mean and variance, it is considered stationary (Zeroual et al., 2020). In addition to utilizing the time series plot, stationarity can also be observed by examining the ACF plot, which exhibits a rapid decline to near zero (Imro'ah et al., 2024). The autocorrelation function (ACF) in time series data reflects the correlation between Z_t and Z_{t+k}, separated by a time lag k. Whenever the effect of lag $t+1, t+2, \cdots, t+k-1$ is taken into consideration independently, the Partial Autocorrelation Function (PACF) is utilized as a tool to measure the degree of proximity between Z_t and Z_{t+k} (Hewamalage et al., 2023). If $\hat{\rho}_k$ and $\hat{\phi}_k$ are the autocorrelation function and partial autocorrelation function at the k-th lag, respectively, Z_t represents the value of variable Z at the t-th time, and $\bar{Z}$ represents the average value of Z_t, then the ACF and PACF calculated from the data sample can be expressed (Gopu et al., 2021).

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} = \frac{\sum_{t=1}^{n-k}(Z_t - \bar{Z})(Z_{t+k} - \bar{Z})}{\sum_{t=1}^{n}(Z_t - \bar{Z})^2}, \qquad k = 0, 1, 2, \dots$$

and

$$\hat{\phi}_{k+1,k+1} = \frac{\hat{\rho}_{k+1} - \sum_{j=1}^{k} \hat{\phi}_{kj}\, \hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^{k} \hat{\phi}_{kj}\, \hat{\rho}_j}, \qquad j = 1, 2, \dots k$$

The Autoregressive Integrated Moving Average (ARIMA) model is one of the models that the field of time series analysis employs. In 1967, George Box and Gwilym Jenkins conducted an in-depth study on this model. Order p refers to the AR model's order, order d refers to the differencing model's order, and order q refers to the MA model's order. The ARIMA model is expressed as ARIMA (p, d, q) because it is composed of these three orders (Imro'ah et al., 2023). The following is a description of the ARIMA model in its general structure.

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) e_t$$

where $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ and $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$; B is backshift operator. A model identification process that is based on the ACF and PACF plots is used to derive the p and q orders in the ARIMA model (Imro'ah & Huda, 2022). The process continues with estimating parameters, which may be done using various approaches, including the Moment method, Ordinary Least Square (OLS), and Maximum Likelihood, in addition to other methods (Deif et al., 2021). This stage occurs after the procedure has obtained several different models that could be used. Using the least squares (OLS) method, which may be stated in the following manner, is one way to estimate parameters for linear models (Ravishanker et al., 2021).

$$Y = X\beta + e$$

Alternately, it can be written in the following matrix form.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_n \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix}$$

If Z_t is a time series dataset that adheres to the MA(q) process where $t = 1,2,\cdots,n$, then

$$Z_t = -\theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} + e_t$$

or

$$\begin{bmatrix} Z_{q+1} \\ Z_{q+2} \\ \vdots \\ Z_n \end{bmatrix} = \begin{bmatrix} -e_q & -e_{q-1} & \cdots & -e_1 \\ -e_{q+1} & -e_q & \cdots & -e_2 \\ \vdots & \vdots & \ddots & \vdots \\ -e_{n-1} & -e_{n-2} & \cdots & -e_{n-q} \end{bmatrix} \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_q \end{bmatrix} + \begin{bmatrix} e_{q+1} \\ e_{q+2} \\ \vdots \\ e_n \end{bmatrix}$$

That is, the parameter vector for the MA(q) model, which is denoted by θ_i and $i = 1,2,\cdots,q$

$$\begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_q \end{bmatrix} = \left(\begin{bmatrix} -e_q & -e_{q-1} & \cdots & -e_1 \\ -e_{q+1} & -e_q & \cdots & -e_2 \\ \vdots & \vdots & \ddots & \vdots \\ -e_{n-1} & -e_{n-2} & \cdots & -e_{n-q} \end{bmatrix}^t \begin{bmatrix} -e_q & -e_{q-1} & \cdots & -e_1 \\ -e_{q+1} & -e_q & \cdots & -e_2 \\ \vdots & \vdots & \ddots & \vdots \\ -e_{n-1} & -e_{n-2} & \cdots & -e_{n-q} \end{bmatrix} \right)^{-1} \left(\begin{bmatrix} -e_q & -e_{q-1} & \cdots & -e_1 \\ -e_{q+1} & -e_q & \cdots & -e_2 \\ \vdots & \vdots & \ddots & \vdots \\ -e_{n-1} & -e_{n-2} & \cdots & -e_{n-q} \end{bmatrix}^t \begin{bmatrix} Z_{q+1} \\ Z_{q+2} \\ \vdots \\ Z_n \end{bmatrix} \right)$$

To demonstrate that the ARIMA model that was obtained is suitable for usage, it is required to conduct diagnostic tests on the residuals of the modeling process (Zhao et al., 2021). Examining residuals that satisfy white noise assumptions (residuals are independent and normally distributed) is one of the diagnostic tests that are performed. These tests can be performed using a residual ACF plot (for residual independence) and a normal qq plot (for residual normality). Additionally, it is possible to accomplish this by employing the Ljung Box and Kolmogorov-Smirnov test statistics (Hussain et al., 2022). The residual ACF plot and the normal QQ plot were two of the diagnostic tests that were carried out in this study. There are several model accuracy metrics that are used to determine which ARIMA model is the most accurate. These criteria include Aikaike's Information Criteria (AIC), Mean Absolute Error (MAE), and Bayesian Information Criteria (BIC) (Shashvat et al., 2021).

C. RESULT AND DISCUSSION

Within the scope of this study, the data collected from the UTD PMI Pontianak City is analyzed to determine the total number of blood requests for all blood types (A, AB, B, and O). Modeling each blood group with the ARIMA model allows for the subsequent forecasting of the demand for blood types throughout numerous subsequent periods. Table 1 contains descriptive statistics derived from the data that was collected. The average demand for type O blood is the highest compared to the need for blood from other blood groups. According to the number of active blood donors documented in Pontianak City, this is according to the situation. UTD PMI Pontianak City has disclosed that there are a total of 14,597 contributors who are actively contributing. There were 4,163 donors with blood type A, 3,003 donors with blood type B, 6,219 donors with blood type O, and 1,212 donors with blood type AB. UTD PMI Pontianak City is currently responsible for meeting the blood requirements of 28 hospitals. When it comes to blood donation activities, the role of the community or institutions that carry them out must be balanced with the need for adequate blood supplies.

As can be seen from the fact that the mean is greater than the median, the shape of the distribution reveals that every blood group has a positive skewness. According to the histogram in the third column of Table 1, the data accumulates more in smaller values. While this is happening, we are to look at the fluctuations in the data and then see that the data varies around the mean (the dotted line on the time series plot) and remains constant in variance. Since this time series data is stationary, it is possible to say it is. A stationarity test was also performed on the data, and the findings showed that the data were stationary. It was in addition to the visual examination of the data. Because the data that was utilized is stationary, the analysis continues with the identification of models based on the ACF and PACF plots (the second column of Table 2), the estimation of parameters for all the feasible models (the fourth column of Table 2), and diagnostic tests. This article only includes some of the results of the diagnostic tests. Only models that satisfy the white noise assumptions are shown to have diagnostic test results provided (the fifth column of Table 2). After completing the white noise assumption test, the accuracy value of the model that satisfies these assumptions can be determined by analysing the test results. AIC, MAE, and BIC refer to the accuracy values utilized. There is a least value among the other accuracy values, which is indicated by the red text in the sixth column of Table 2.

Table 1. Descriptive Statistic of Data

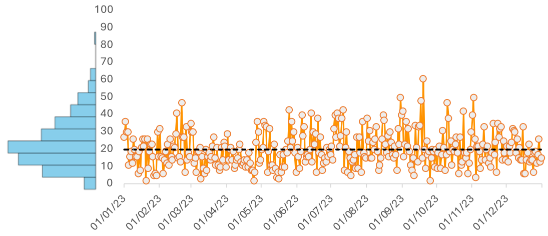
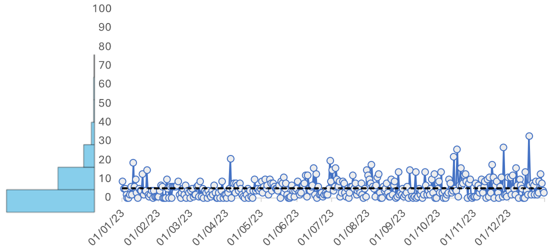
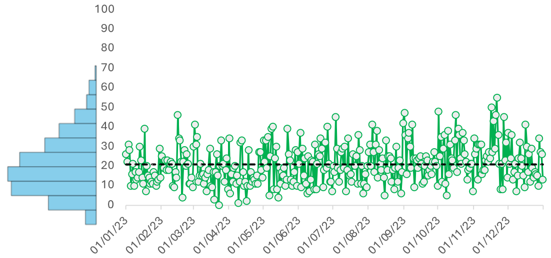
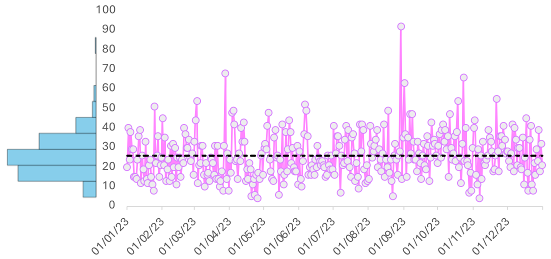
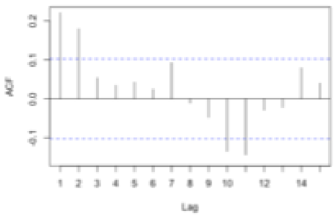
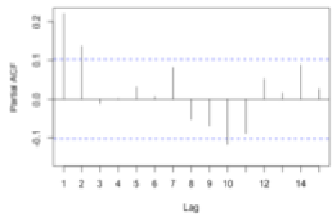
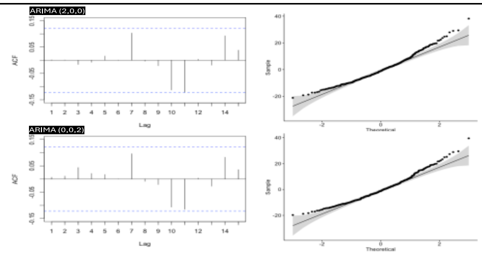
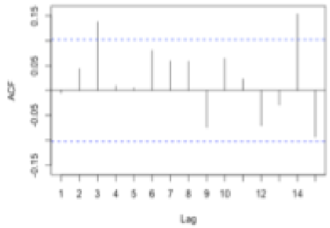
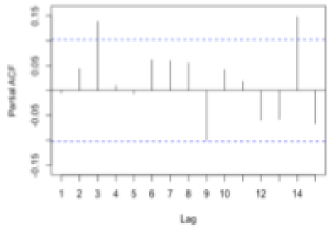
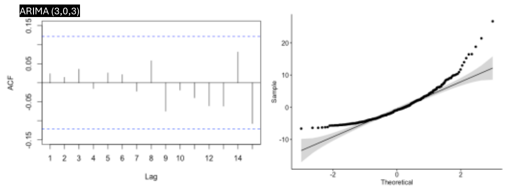
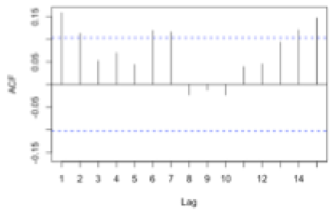
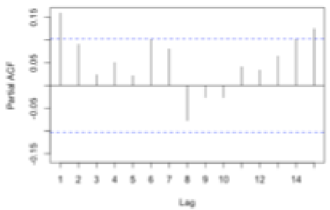
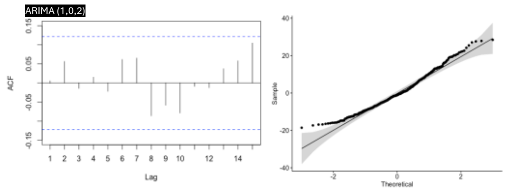
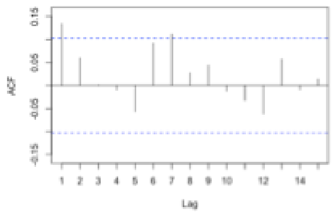
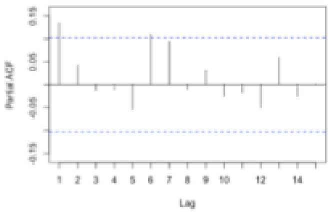
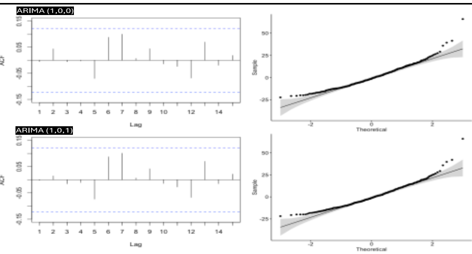
Blood Type	Descriptive Statistic			Plot
A	Min	:	2.00	
	Max	:	61.00	
	Mean	:	19.81	
	Median	:	18.00	
	Variance	:	98.35	
	Deviation Standard	:	9.92	
AB	Min	:	0.00	
	Max	:	33.00	
	Mean	:	5.21	
	Median	:	4.00	
	Variance	:	23.15	
	Deviation Standard	:	4.81	
B	Min	:	0.00	
	Max	:	55.00	
	Mean	:	20.95	
	Median	:	20.00	
	Variance	:	95.58	
	Deviation Standard	:	9.88	
O	Min	:	4.00	
	Max	:	92.00	
	Mean	:	25.90	
	Median	:	24.00	
	Variance	:	133.21	
	Deviation Standard	:	11.54	

Table 2. Results of Three Stages of Box-Jenkins Iterative (except stationarity test)

Blood Type	ACF and PACF Plot		Orde (p, d, q)	Parameter $\left(\begin{bmatrix}\mu\\ \phi_i\\ \theta_j\end{bmatrix}\times 10^{-3}\right)$	Residual plot that fulfills white noise assumptions	Model Accuration: AIC; MAE; BIC
A			(2,0,0)	$\begin{bmatrix}19,820\\ 189;138\\ 0\end{bmatrix}$		**ARIMA (2,0,0):** 2,692.41; 7.554; 2,708.01 **ARIMA (0,0,2):** 2,693.30; 7.545; 2,708.90
			(0,0,2)	$\begin{bmatrix}19,813\\ 0\\ 187;166\end{bmatrix}$		
			(2,0,2)	$\begin{bmatrix}19,819\\ 135;137\\ 57;15\end{bmatrix}$		
AB			(3,0,0)	$\begin{bmatrix}5,207\\ -12;45;138\\ 0\end{bmatrix}$		**ARIMA (3,0,3):** 2,178.79; 3.494; 2,209.99
			(0,0,3)	$\begin{bmatrix}5,206\\ 0\\ -10;49;119\end{bmatrix}$		
			(3,0,3)	$\begin{bmatrix}5,254\\ 720;-672;915\\ -764;755;-899\end{bmatrix}$		
B			(1,0,0)	$\begin{bmatrix}20,952\\ 158\\ 0\end{bmatrix}$		**ARIMA (1,0,2):** 2,699.26; 7.639; 2,718.76
			(0,0,2)	$\begin{bmatrix}20,952\\ 0\\ 140;94\end{bmatrix}$		
			(1,0,2)	$\begin{bmatrix}20,890\\ 989\\ -872;-90\end{bmatrix}$		
O			(1,0,0)	$\begin{bmatrix}25,899\\ 134\\ 0\end{bmatrix}$		**ARIMA (1,0,0):** 2,819.74; 8.903; 2,831.44 **ARIMA (1,0,1):** 2,821.24; 8.878; 2,836.84
			(0,0,1)	$\begin{bmatrix}25,901\\ 0\\ 122\end{bmatrix}$		
			(1,0,1)	$\begin{bmatrix}25,901\\ 359\\ -228\end{bmatrix}$		

Following the acquisition of the most suitable ARIMA model for each blood group, specifically ARIMA (2,0,0) for blood type A, ARIMA (3,0,3) for blood type AB, ARIMA (1,0,2) for blood type B, and ARIMA (1,0,0) for blood type O, the analysis proceeds by forecasting the overall amount of blood demand for five future periods. The forecast findings are presented in Table 3.

Table 3. Forecasting The Significant Demand For Blood Services

Period	Blood Type			
	A	**AB**	**B**	**O**
January 1, 2024	18	7	21	25
January 2, 2024	19	7	22	26
January 3, 2024	19	5	22	26
January 4, 2024	20	6	22	26
January 5, 2024	20	7	22	26

In terms of model performance and time-series analysis, the findings of the research on the use of ARIMA models for the purpose of predicting blood demand are in agreement with the findings of the former research. Nevertheless, the specificity of the current study, which focuses on various blood groups, and the precise selection of ARIMA models based on AIC and BIC criteria both contribute to the existing body of knowledge by adding another layer of value. There is a wide variety of approaches in this discipline, which is highlighted by the complexities involved in predicting as well as the possibility of hybrid models being used in other studies.

D. CONCLUSION AND SUGGESTIONS

It is well acknowledged that the blood supply at UTD PMI Pontianak City is of utmost significance. It is because if there is a demand for blood and UTD is unable to give it, there is a potential that the patient will not receive any assistance. Therefore, it is essential to make predictions regarding the blood demand to reduce the likelihood of blood supply shortages in Pontianak City. The ARIMA approach was utilized to analyze the daily blood requests made for each blood group. The ARIMA models that are used for blood groups A, AB, B, and O are referred to as ARIMA (2,0,0), ARIMA (3,0,3), ARIMA (1,0,2), and ARIMA (1,0,0). The forecast findings suggest that UTD PMI Pontianak City could create sufficient bloodstock for patients using the ARIMA approach. This stock will consist of 73 bags, with nineteen bags designated for blood type A, six bags designated for blood type AB, twenty-two bags designated for blood type B, and as many as six bags designated for blood type O. A forecast for the blood supply over the following five days is represented by this value. With any luck, future studies will use techniques in time series analysis that can predict events over an extended period so that UTD PMI can prepare for the availability of blood to reduce the number of patients in need of bloodstock.

The study did not consider external factors that could affect blood demand. These factors include shifts in population demographics, new medical technologies, and public health campaigns. Incorporating these parameters could improve the accuracy of future models. The ARIMA model performed admirably for Pontianak City; nevertheless, it is necessary to determine whether or not it is scalable to other locations that have demand patterns that are distinct from those of Poland. Various regions may have distinctive characteristics that call for forecasting models that are specifically tuned to those regions.

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