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AN INTEGRATIVE MODEL FOR DRUG INVENTORY OPTIMIZATION IN PHARMACIES USING WMA AND EOQ CONTINUOUS

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ABSTRACT

Efficient drug inventory control is essential for pharmacies to maintain service quality, prevent stockouts, and reduce financial losses caused by excessive inventory. This study develops an integrative inventory optimization model combining ABC analysis, Weighted Moving Average (WMA) forecasting, and the Economic Order Quantity (EOQ) Continuous Review approach. ABC analysis identifies high-priority drugs requiring strict control, WMA forecasts demand for Category A items, and the EOQ model determines optimal order quantity, safety stock, and reorder point. Results show that the integration of forecasting and continuous review improves accuracy in estimating demand fluctuations and reduces total inventory costs compared with existing ordering practices. The originality of this work lies in formalizing the integration of WMA forecasting into EOQ Continuous Review, specifically for pharmaceutical inventory systems. Study limitations include the use of a single-pharmacy dataset, fixed lead-time assumptions, and reliance on only one forecasting method. This integrated approach provides a novel and more responsive solution for pharmaceutical inventory management, as the use of WMA enhances forecast accuracy by emphasizing recent demand shifts, while the EOQ Continuous Review model ensures optimal ordering decisions in real time. Together, these methods create a more adaptive framework that reduces uncertainty, improves stock availability, and minimizes overall inventory costs.

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1. INTRODUCTION

Pharmacies play a vital role in ensuring the timely availability of medications for the public by implementing effective inventory management strategies [1]. Drug inventory control aims to prevent issues such as overstocking, understocking, stockouts, damage, expiration, loss, and order returns. Due to the large number and variety of medications, it is essential to identify which drugs should be prioritized to ensure budget efficiency [2]. Additionally, the increasing complexity of healthcare needs requires pharmacies to adopt data-driven approaches in order to maintain optimal stock levels. Moreover, effective inventory management contributes not only to operational efficiency but also to improved patient safety and service quality.

Due to the quantity and variety of pharmaceutical items, an analytical method is required to determine stock management priorities. The ABC (Always Better Control) analysis provides a classification technique for inventory items based on their investment value. Hence, the ABC analysis is applied to classify and prioritize drugs based on investment value. This method ranks items from highest to lowest investment and groups them into three categories: A, B, and C [2]. In practice, this categorization helps pharmacies allocate resources more strategically, ensuring that high-value and fast-moving items receive greater attention. The method also supports more structured decision-making, particularly when dealing with limited inventory budgets.

Fluctuations in demand data can be addressed through forecasting future demand values. Forecasting methods help analyze past behavioral patterns in the data, offering structured approaches for interpretation and resolution, while increasing confidence in the accuracy of predictions [4]. One such technique is the Weighted Moving Average (WMA), a time series forecasting method that applies weighted factors to historical data [5]. It is commonly used for short-term predictions, assigning greater weight to the most recent data, which is considered most relevant [6]. Because WMA adapts to shifts in recent demand trends, it is particularly suitable for pharmacy environments where consumption patterns may change rapidly. As a result, the method improves the reliability of demand estimation before inventory control decisions are made.

Inventory refers to idle resources awaiting further processing [8], whether through manufacturing, distribution, or consumption systems. The Economic Order Quantity (EOQ) method helps organizations optimize inventory by balancing ordering costs and holding costs [9]. A variant, the EOQ Continuous Review model, incorporates fluctuating demand levels to avoid stock shortages or surpluses in pharmacies [10]. This study builds upon insights from the article [10] by introducing drug classification to focus inventory control efforts on prioritized medications. Additionally, it includes demand forecasting, an aspect often overlooked in prior studies, to estimate future demand levels and minimize the risks of stockouts and overstocking.

This study aims to enhance pharmaceutical inventory management in pharmacies through a structured approach. The first objective is to classify drugs based on investment value using ABC Analysis, allowing pharmacies to prioritize key items that significantly impact inventory costs. The second goal is to forecast the demand for drugs in category A—those deemed most critical—by applying the Weighted Moving Average (WMA) method, which emphasizes recent data trends for more accurate short-term predictions. The third objective is to determine the optimal ordering quantity for drugs in category A using the Economic Order Quantity (EOQ) Continuous Review model, with the aim of balancing ordering and holding costs while ensuring timely restocking. Collectively, these methods support more precise, cost-efficient, and responsive inventory decisions in pharmacy settings. Previous studies [10] on pharmaceutical inventory management predominantly rely on traditional techniques such as ABC Analysis without incorporating forecasting models, or apply EOQ solely within periodic review systems. These approaches are limited in their ability to anticipate short-term fluctuations in drug demand and often fail to support timely restocking decisions in dynamic pharmacy environments.

This study introduces a novel inventory strategy for medium-scale pharmacies by integrating the Weighted Moving Average (WMA) method for short-term demand forecasting with the EOQ Continuous Review model for real-time inventory control. The combination produces a more adaptive and precise decision-making framework that responds effectively to changes in demand, reduces inventory-related costs, prevents overstocking or product expiry, and ultimately improves overall service efficiency.

2. RESEARCH METHODS

2.1 Preliminaries

2.1.1 Category

The first objective is to classify drugs in the pharmacy based on investment value using ABC Analysis [11]. This method divides inventory items into three categories—A, B, and C—based on the proportion of total investment costs [2].

1. Category A includes drugs that account for approximately 70% of the total inventory cost,
2. Category B about 20%,
3. Category C roughly 10%. This classification helps prioritize control efforts on high-investment items for more efficient inventory management.

2.1.2 Forecasting Category A Drug Demand Using Weighted Moving Average in Pharmacies

1. Data Patterns in Forecasting

Forecasting often faces uncertainty due to varying data patterns, ranging from simple to complex [12]. Identifying the correct pattern is essential to selecting the most suitable forecasting method. One type of time series pattern is the stationary pattern, in which the data remains relatively stable over time.

2. Stationarity Testing with Augmented Dickey-Fuller (ADF)

The Augmented Dickey-Fuller (ADF) test was applied in this study to examine whether the drug demand data exhibited stationarity before conducting forecasting. Stationarity testing is essential because the Weighted Moving Average (WMA) method assumes that the underlying time series has a stable mean and variance over time; non-stationary data may produce biased or misleading forecasts. The ADF test extends the basic Dickey-Fuller procedure by including lagged differences to address autocorrelation and reliably detect the presence of unit roots—an indication of non-stationarity.

By confirming stationarity through the ADF test, the dataset was verified as suitable for short-term forecasting using WMA. This step ensures that patterns in the historical data are consistent enough for weighted smoothing to perform effectively. The use of the ADF test therefore strengthens the validity of the forecasting results and prevents model inaccuracies due to underlying structural instability in the demand series.

3. Weighted Moving Average (WMA) Method

The Weighted Moving Average (WMA) is a time series forecasting method that assigns weights to historical data values [5]. It is commonly used for short-term predictions [6], with greater emphasis placed on recent observations, which are considered more relevant to current trends [16]. This characteristic makes WMA particularly suitable for forecasting drug inventory demand, as pharmacies typically manage stock on a short replenishment cycle and rely on recent usage patterns to guide ordering decisions. Because drug consumption can fluctuate due to seasonal illnesses or prescription changes, a method that responds quickly to recent variations, such as WMA, provides a more accurate and practical basis for determining short-term inventory need.

The method results in smoother trend-cycles, as data values do not shift abruptly—their influence gradually decreases with time. Unlike equal-weight methods, WMA offers flexibility through various weighting schemes, allowing modelers to fine-tune predictions based on data behavior [17].

Forecast values are calculated using the following formulas [18]:

$$F_t = W_1X_{t-1} + W_2X_{t-2} + \cdots + W_nX_{t-n} + e, \tag{1}$$

$$W_n + W_n + \cdots + W_n = 1. \tag{2}$$

This equation represents the core forecasting formula of the Weighted Moving Average (WMA), where each historical data point X_{t-k} is multiplied by a corresponding weight W_k. More recent data typically receives larger weights, making the forecast more responsive to recent demand fluctuations. The term e represents the forecast error, capturing the deviation between the predicted value and the actual observation.

Eq. (2) is a normalization constraint for the weights. It ensures that the total weight assigned across all historical observations equals 1. This condition is essential because it keeps the scale of the forecast consistent with the scale of the data and prevents inflation or deflation of the predicted values.

Together, Eqs. (1) and (2) define how the WMA method constructs forecasts: Eq. (1) specifies how the weighted historical data is combined, while Eq. (2) ensures that the weights are proportionally valid within the forecasting model. Below are the descriptions of Eqs. (1) and (2).

F_t	= forecast for period t;
$W_1, W_2, \dots, W_n$	= weights assigned to each historical data point;
$X_{t-1}, X_{t-1}, \dots, X_{t-n}$	= actual values of previous periods;
n	= number of periods used;
e	= error term.

4. Forecast Accuracy with MAPE

MAPE (Mean Absolute Percentage Error) is the most commonly used method for measuring the accuracy of forecasting models. Expressed as a percentage, the MAPE value indicates the extent of deviation between the model's predictions and the actual data. The actual data used is drawn from a test dataset. Its main advantages are ease of interpretation and the ability to compare across different models [19]. The formula for calculating MAPE is as follows [17]:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left(\frac{Y_t - F_t}{Y_t}\right) \times 100\,. \tag{3}$$

5. Model Reliability: Underfitting vs Overfitting

Underfitting: Model too simple, fails to capture data patterns—high error on training and test data. Overfitting: Model too complex, adapts too closely to training data—low training error but high-test error. Both can distort prediction quality and must be managed in time series modeling. As a result, the model exhibits low error accuracy on training data but high error on testing data [20].

2.1.3 Determining the Optimal Order Quantity for Category A Drugs Using the EOQ Continuous Review Method in Pharmacies.

The Economic Order Quantity (EOQ) method is used to determine optimal inventory cycles by calculating the order quantity that minimizes total annual ordering and holding costs [11]. This method is based on several key assumptions [8]:

1. Demand per period is known.
2. Ordered items are always available.
3. Lead time is constant.
4. Ordering and holding costs vary over time.
5. No backorders occur due to stockouts.

To address inventory challenges in pharmacies under fluctuating demand conditions, the traditional EOQ model needs to be adjusted [3]. Therefore, a modified EOQ method is applied to items with variable demand characteristics. This model adopts the following assumptions:

1. Demand is fluctuating.
2. Order quantity is constant, and orders are placed when inventory reaches the reorder point.
3. Item price remains constant, regardless of quantity ordered or time.
4. Ordering cost is fixed per order, independent of the quantity ordered.
5. No quantity discounts are available.
6. Shortage costs are proportional to the amount of unmet demand.
7. Expiration dates are known.
8. Expired drugs cannot be resold.

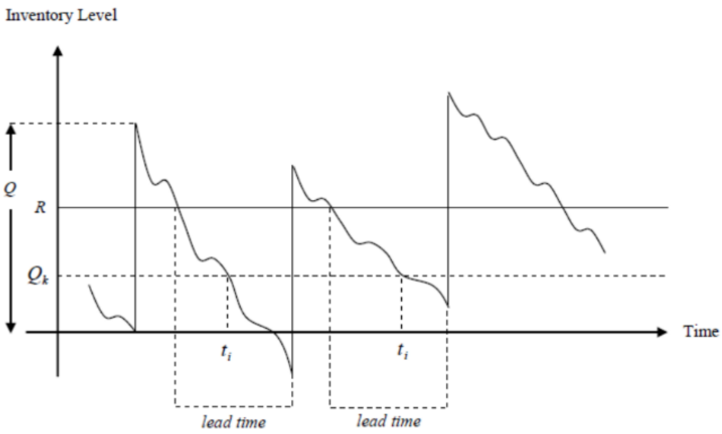

Figure 1. EOQ Graph with Fluctuating Demand Level

Fig. 1 illustrates the probabilistic EOQ graph, which depicts inventory level fluctuations throughout a single cycle. The cycle begins with the inventory at its maximum—equal to the order quantity (Q). Over time, the inventory level decreases in a fluctuating manner until it reaches zero, indicating a stockout. Once a new order arrives, the inventory is replenished to Q, marking the completion of one cycle. The graph also highlights that the demand level often exceeds the reorder point.

For items where demand follows a probability distribution during the lead time, the EOQ model is redesigned to account for shortage costs arising from such variability [3]. Consequently, the total inventory cost will be adjusted by incorporating additional cost components as follows:

$$TIC = \frac{AD}{Q^*} + Ph\left[\frac{Q^*}{2} + R - D_L\right] + \frac{\pi D}{Q^*}\left[\int_R^\infty (x-R)f(x)dx\right] + (1-\theta)PD, \tag{4}$$

with:

P = Purchase price;
D = Average demand;
A = Ordering cost;
Q^* = Optimal order quantity;
h = Holding cost fraction;
R = Reorder point;
D_L = Average demand during lead time;
π = Shortage cost;
$f(x)$ = Probability density function of demand during lead time;
θ = Fraction of quality items;
$(1-\theta)$ = Fraction of expired items.

The optimal order quantity is obtained using the following formula:

$$Q_2^* = \sqrt{\frac{2D\left(A + \pi\int_R^\infty (x-R)f(x)dx\right)}{h}}, \tag{5}$$

where:

D = Average demand;
A = Ordering cost;
Q_2^* = Optimal order quantity considering demand fluctuations;
h = Holding cost fraction;
$f(x)$ = Probability density function of demand during lead time;
π = Shortage cost;
x = Random variable representing demand during lead time.

The integral component:

$$\int_R^\infty (x-R)f(x)dx,$$

be computed using:

$$\sigma_d\left[\varphi(Z_\alpha) - Z_\alpha\left(1 - \emptyset(Z_\alpha)\right)\right],$$

where $\varphi(Z_\alpha)$ is a probability density function and $\emptyset(Z_\alpha)$ is the survivor function [21].

The basic EOQ method has a limitation in its assumption that demand remains constant. This assumption does not reflect real-world conditions, as demand in many companies—including pharmacies—is currently fluctuating. Therefore, this method is better suited to the actual conditions of pharmaceutical inventory management, since it assumes random (stochastic) demand [8]. Under this method, inventory is ordered once the stock level reaches or falls below the reorder point (ROP) [22]. Ordering continues until the inventory level reaches its maximum stock level. The ROP value is determined based on shortage costs or other inventory-related probabilities [8]. The reorder point can be treated as a probability distribution, with the assumption that the inventory system does not deviate. The only risk of shortage occurs when demand exceeds available stock during the lead time.

Before determining the ROP, the value of α can be calculated using the following equation, derived from the partial derivative of Total Inventory Cost (TIC) with respect to R:

$$\left[\int_R^\infty f(x)dx\right] = \frac{Qh}{\pi D}. \tag{6}$$

Here, the probability density function of demand during lead time ($f(x)$) and the integral limits indicate the probability of demand exceeding the reorder point. This equation helps estimate the risk of stockouts, especially when demand during lead time surpasses available inventory in a pharmacy setting.

The general formula for reorder point (ROP) is:

$$ROP = R = D_L + Safety\ Stock. \tag{7}$$

Safety Stock can be calculated using:

$$Safety\ Stock = Z_\alpha \sigma_d \sqrt{L}. \tag{8}$$

Substituting Eq. (8) into Eq. (7), we obtain:

$$ROP = R = D_L + Z_\alpha \sigma_d \sqrt{L}, \tag{9}$$

with:

D_L	=	Average demand during lead time;
D	=	Demand rate;
P	=	Purchase price;
Q^*	=	Optimal order quantity;
h	=	Holding cost fraction;
R	=	Reorder point;
Z_α	=	Z-Value (from standard normal distribution);
π	=	Shortage cost;
σ_d	=	Standard deviation of demand;
L	=	Lead time.

2.2 Research Method

This research was conducted at the Industrial and Financial Mathematics Laboratory, Department of Mathematics, from March to October 2025. It is a quantitative study utilizing secondary data obtained through pharmacy records. The data were obtained from confidential company documents collected from pharmacies in Malang City. The research methodology is described as follows:

2.2.1 Problem Identification

The study begins by identifying challenges associated with products that exhibit non-constant and fluctuating data patterns, though the data remains stationary and tends to revolve around the average demand in each period. From the stationary-pattern sales data, future forecasts will be made, and the optimal order quantity will be calculated.

2.2.2 Literature Review

Relevant literature was explored to identify theories that align with the research problem. The key theoretical frameworks guiding this study include the ABC Analysis grouping method, the Weighted Moving Average (WMA) forecasting technique, and the EOQ Continuous Review inventory model.

2.2.3 Data Collection

Data was sourced from company documents containing information such as the list of drugs sold, unit selling price, unit purchase price, storage costs, one-time ordering costs, shortage costs per unit, and demand quantities.

2.2.4 Data Processing

1. Drugs were first classified based on investment value using sales and inventory records. The dataset consisted of monthly transaction data for 12 months, covering 42 drug items in various dosage forms (tablets, capsules, syrups, ointments, and injectable products). These items were selected as samples because they represent high-turnover and frequently dispensed medications in the pharmacy, making them relevant for forecasting and inventory optimization.
2. Drug demand was forecasted using the Weighted Moving Average (WMA) method, and the predictive accuracy of the model was evaluated through the Mean Absolute Percentage Error (MAPE) using historical sales quantity data.
3. Optimal order quantities for the next period were determined based on the WMA demand forecasts using the EOQ Continuous Review model, incorporating item-specific ordering costs, holding costs, and lead times.

3. RESULTS AND DISCUSSION

3.1 Drug Classification Using ABC Analysis

After identifying the demand for each drug, the total revenue per product was calculated by multiplying the unit demand by its selling price. The cumulative revenue distribution was then analyzed to determine the investment value of each drug. The analysis showed that the total annual revenue reached IDR 1,284,500,000, with the highest-revenue items contributing disproportionately to overall value. Group A consists of 42 pharmaceutical products that collectively contribute approximately 70.4% of the cumulative revenue (≈ IDR 904,000,000), as shown in Table 1. Meanwhile, Groups B and C account for 20.1% and 9.5% of the remaining investment value, respectively, confirming a clear Pareto pattern and justifying the ABC classification.

Table 1. ABC Analysis Results

No	Item Name	No	Item Name	No	Item Name	No	Item Name
1	Demacolin	12	Alpara	23	Decolgen Flu Tablet	34	Mixagrip Flu
2	Imerson Cr	13	Bronchitin Tablet	24	Grantusif	35	Paramex Tablet
3	Paratusin Tablet	14	Dextral	25	Molexflu	36	Ambroxol 30 mg
4	Amoxsan 500	15	Paracetamol Tablet	26	Decolgen FX	37	Nisagon Cr
5	Mefinal 500mg	16	Tera-F	27	Tuzalos	38	Konidin Tablet
6	Carmeson 8mg	17	Fluimucil 200mg	28	Lodecon	39	Neometor Tablet
7	Flutamol-P	18	Caviplex	29	Mucopect Tablet 30mg	40	Calortusin Tablet
8	Panadol Flu	19	Amtasida Doem Tab	30	Teosal	41	Neozep Forte Tablet
9	Flasicox 15 mg	20	Flucadex	31	Osteocare Tablet	42	Ametilson 4mg
10	Tremenza Tablet	21	Cerini	32	Omeprazole		
11	Novamox 500mg	22	Rhemafar	33	Mixagrip Flu & Batuk		

3.2 Forecasting Tablet Drug Demand Using the Weighted Moving Average (WMA) Method

The data in Table 2 includes the actual monthly demand for Category A tablet drugs.

Table 2. Demand for Category A

Period	Year	Month	Demand Quantity
1	2023	July	297
2		August	325
3		September	283
4		October	360
5		November	178
6		December	357
7	2024	January	296
8		February	271
9		March	316
10		April	256
11		May	254
12		June	249

Forecasting Steps for Category A Drug Demand

1. Plotting the data

A graph, Fig. 2, is plotted to detect patterns. The fluctuations tend to center around the mean with no significant trend or seasonality.

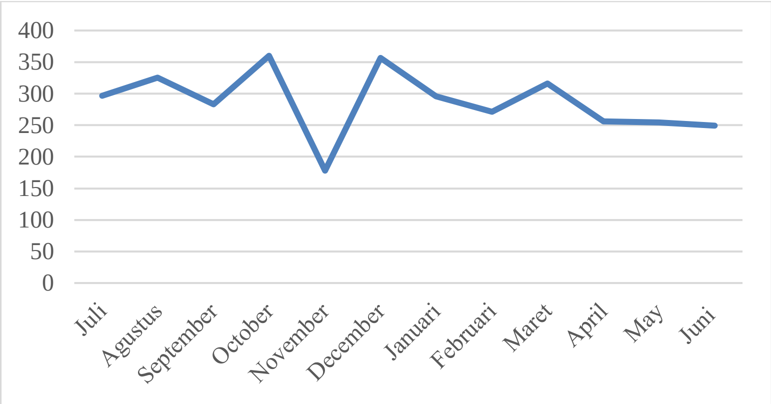

Figure 2. A Graph of Data

2. Augmented Dickey-Fuller (ADF) Test

To ensure that the data is stationary in terms of its mean, the Augmented Dickey-Fuller (ADF) test was conducted using Python programming. The results of the ADF test are shown in Table 3.

Table 3. ADF Test Result

ADF test	Result
ADF Statistic	-5.224727976552979
p-value	7.825566209345693e-06
Critical Value (1%)	-4.223238279489106
Critical Value (5%)	-3.189368925619835
Critical Value (10%)	-2.729839421487603

The ADF test yielded a very low ADF statistic, indicating a strong likelihood that the data is stationary. Furthermore, the extremely small p-value (less than 0.05) suggests that the null hypothesis (H_0) can be rejected, confirming the stationarity of the data. In addition, since the ADF statistic is lower than all the critical values at the 1%, 5%, and 10% significance levels, this further strengthens the conclusion that the data is indeed stationary. Based on the pattern analysis of the data, the most suitable forecasting method is the Weighted Moving Average (WMA). This method assigns greater weight to the most recent data, making it more responsive to pattern changes compared to the simple Moving Average approach.

3. Determining the WMA period and weight values

The selection of the WMA period and corresponding weights was carried out through an iterative process to identify the optimal model using Python programming. The criteria for determining the optimal model were based on achieving low MAPE values for both the training and testing datasets, and ensuring the model did not exhibit signs of overfitting or underfitting. Based on the results of the iteration, Table 4 was identified as optimal.

Table 4. WMA Period

WMA Period	5
Weight 1	0,4
Weight 2	0,25
Weight 3	0,25
Weight 4	0,05
Weight 5	0,05

A WMA period of 5 means that the forecasting method uses the last 5 periods of data, assigning specific weights to each. Weight 1 (the largest) corresponds to the most recent data or the period immediately preceding the forecasted period. Weight 2 applies to data from two periods prior, and so on until Weight 5, which reflects data from five periods prior. Additionally, the weights sum to a total of 1, ensuring that the calculations remain proportionally balanced.

4. Forecasting based on observed data

Forecasting was carried out on the observed data for periods that still have actual values using the formula in Eq. (1). Forecasting is carried out on observation data in the period that still has actual values by using the formula in Eq. (1). The forecast results are calculated up to Period 12 and are summarized as follows:

Table 5. Forecasts Result

t	Year	Month	X_t	Data set	F_t
1	2023	July	297	Training	-
2		August	325		-
3		September	283		-
4		October	360		-
5		November	178		-
6		December	357		263.05
7	2024	January	296		307.70
8		February	271		284.30
9		March	316	Test	298.55
10		April	256		294.90
11		May	254		281.80
12		June	249		272.95

5. Calculating MAPE (Mean Absolute Percentage Error)

The MAPE value was obtained using the formula in Eq. (2). For the training dataset, three periods were used, as forecasts were available for three time points. Therefore, the MAPE calculation for the training data uses N = 3, and is computed as follows:

Table 6. MAPE Calculation with N = 3

t	Y_t	F_t	$\left\lvert\left(\frac{Y_t - F_t}{Y_t}\right) x\ 100\right\rvert$
6	357	263.05	26.32
7	296	307.70	3.95
8	271	284.30	4.91
	Total		35.18

$$\text{MAPE} = \frac{1}{3}(35.18)$$
$$= 11.73$$

The MAPE for the test dataset was calculated with $N = 4$, as follows:

Table 7. MAPE Calculation with N = 4

t	Y_t	F_t	$\left\lvert\left(\frac{Y_t - F_t}{Y_t}\right) x\ 100\right\rvert$
9	316	298.55	5.52
10	256	294.90	15.20
11	254	281.80	10.94
12	249	272.95	9.62
	Total		41.28

$$\text{MAPE} = \frac{1}{4}(41.28) = 10.32$$

The training model produced a MAPE of 11.73%, and the test dataset yielded 10.32%. Based on Table 1, these MAPE values fall within the "good" category, as they lie in the 10%–20% range. Additionally, the model showed no indications of overfitting or underfitting, affirming its optimal performance and reliability for forecasting future periods.

6. Performing forecasts for future periods

The optimal model, using a WMA period of 5 with weights of 0.4, 0.25, 0.25, 0.05, and 0.05, will be applied to forecast demand values for Category A over the next 18 periods (from period 13 to period 30). Using the same approach, forecasting is carried out up to period 30. If historical data is no longer available for the calculation, the forecasted result from the previous period is used as input for the next period. The complete set of forecasted demand values for Category A is presented in Table 8 below.

Table 8. Forecasted Result

t	Year	Month	X_t	F_t
1	2023	July	297	-
2		August	325	-
3		September	283	-
4		October	360	-
5		November	178	-
6		December	357	263.05
7	2024	January	296	307.70
8		February	271	284.30
9		March	316	298.55
10		April	256	294.90
11		May	254	281.80
12		June	249	272.95
13		July	-	256.45
14		August	-	256.93
15		September	-	254.63
16		October	-	255.35
17		November	-	255.30
18		December	-	255.29
19	2025	January	-	255.36
20		February	-	255.29
21		March	-	255.31
22		April	-	255.31
23		May	-	255.31
24		June	-	255.31
25		July	-	255.31
26		August	-	255.31
27		September	-	255.31
28		October	-	255.31
29		November	-	255.31
30		December	-	255.31

3.3 Determining the Optimal Order Quantity using EOQ

The forecasting results using the WMA method from the demand data for category A medicines will be used to calculate the optimal order quantity. However, it is necessary to determine the forecasted demand for each medicine by multiplying the forecast results by the revenue percentage of each medicine, as shown in Table 1. The medicines selected for EOQ calculation are the five with the highest investment value. The EOQ calculation requires one year of demand data, so the total forecasted demand for category A medicines over one year is shown in Table 9.

Table 9. Forecasted Result

t	Year	Month	X_t	F_t
1	2024	July	-	256
2		August	-	257
3		September	-	255
4		October	-	255
5		November	-	255
6		December	-	255
7	2025	January	-	255
8		February	-	255
9		March	-	255
10		April	-	255
11		May	-	255
12		June	-	255
Total				3063

As an example, the medicine Demacolin has a revenue percentage of 0.072602 and a total forecasted demand over one year of 3,063 units. Therefore, the forecasted demand for one year is $3{,}063 \times 0.072602 = 222.379 \approx 222$ units. The forecasted data for the annual medicine demand is shown in Table 10.

Table 10. Forecasted Demand Data for Each Medicine

No	Medicine Name	Forecasted Demand
1	Demacolin	222
2	Imerson Cr	199
3	Paratusin Tablet	136
4	Amoxsan 500	136
5	Mefinal 500mg	94

The purchase price data for each medicine is provided in Table 11.

Table 11. Forecasted Demand Data for Each Medicine

No	Medicine Name	Purchase Price (IDR) (P)
1	Demacolin	49,500
2	Imerson Cr	69,500
3	Paratusin Tablet	259,500
4	Amoxsan 500	300,000
5	Mefinal 500mg	140,000

The medicines sold at the pharmacy are obtained through suppliers. Therefore, there are preparation costs involved during procurement, which are included as part of the ordering costs. The details of the ordering costs can be found in Table 12.

Table 12. Ordering Cost Data

Cost Type	Period Cost (Rp)
Administrative Cost	1,000.00
Employee Salary	150,000.00
Total	151,000.00

Storage costs include all expenses incurred related to medicine storage. Based on interview results, the costs involved in managing storage include electricity expenses, display shelf maintenance costs, and storage cleanliness costs. These costs amount to 20% of the purchase price of each medicine product. Therefore, the storage cost for each product is provided in Table 13.

Table 13. **Shortage Cost Data**

No	Medicine Name	Shortage Cost (IDR) (π)
1	Demacolin	9,900
2	Imerson Cr	13,900
3	Paratusin Tablet	51,900
4	Amoxsan 500	60,000
5	Mefinal 500mg	28,000

3.4 EOQ Calculation Considering Demand Fluctuation

As an example, the EOQ calculation considering demand fluctuation (Q_2) is taken from the data of the medicine Demacolin by calculating the probability of shortage when demand exceeds the reorder point.

According to Pratiwi et al. [21], the calculation of $\int_r^\infty (x-r)f(x)dx$ is equivalent to:

$$\sigma_d\left[\varphi(Z_\alpha) - Z_\alpha\left(1-\emptyset(Z_\alpha)\right)\right].$$

Based on the obtained data:

The standard deviation $(\sigma_d) = 0.04$ was obtained by calculating the variability of historical monthly demand using the standard deviation formula for time-series data. This value reflects the dispersion of demand around its mean based on the observed sample period. The probability density value $\varphi(1.46648)) = 0.136119$ was derived from the standard normal distribution, where 1.46648 represents the normalized Z-score computed from the difference between the reorder point and the average demand, divided by σ_d. The probability density was then evaluated using the standard normal probability density function, $Z_{0.92874} = 1.46648$.

Survival function value $(1-\emptyset)(1.46648) = 0.07126$, is

$$\int_r^\infty (x-r)f(x)dx = (0.04)\left[\varphi(1.46648) - (1.46648)\left((1-\emptyset)(1.46648)\right)\right]$$

$$\int_r^\infty (x-r)f(x)dx = (0.04)[0.136119 - (1.46648)(0.07126\ )] = 0.0013\,.$$

As an example, the calculation of $\boldsymbol{Q_2^*}$ for the medicine Demacolin is as follows:

$$Q_2^* = \sqrt{\frac{2(222)\left(Rp.151{,}000.00 + (Rp.51{,}500.00)(0.0013)\right)}{Rp.9{,}900.00}} = 82.31 \approx 82.$$

The same calculation was carried out for four other pharmaceutical products, and the results are presented in Table 14.

Table 14. **Value of $\boldsymbol{Q_2^*}$**

No	Medicine Name	Q_2^*
1	Demacolin	82
2	Imerson Cr	66
3	Paratusin Tab	28
4	Amoxsan 500	26
5	Mefinal 500mg	32

Next, the risk probability of stockout is calculated using the following values $Q_2 = 82$ from Table 14, $h = Rp.9{,}900.00$ from Table 14, $\pi = Rp.51{,}500.00$ from Table 15, and $D = 222$ from Table 11.

The probability of stockout is determined by:

$$\left[\int_R^\infty f(x)dx\right] = \frac{(82)(Rp.9{,}900.00)}{(Rp.51{,}500.00)(222)} = 0.07126$$

This value, $\left[\int_R^\infty f(x)dx\right] = 0.07126$, represents the probability of running out of stock. Therefore, the significance level for confidence can be calculated as:

$$\alpha = 1 - (0.07126) = 0.92874.$$

Based on the Normal Distribution Table, the value of $Z_{0.92874}$ under the normal curve is 1.46648. The safety stock for Demacolin is calculated using $\sigma_d = 0.04$ and lead time $(L) = 1$, as follows

$$\text{Safety stock} = SS_{\ 2} = (1.46648)(0.04)\sqrt{1} = 0.06,$$

$$R_2 = 19 + (1.46648)(0.04)\sqrt{1} = 19 + 0.06 = 19.06 \approx 19.$$

Since the medicines are purchased per strip, the results are rounded up. Using the same calculation method, the process was applied to four other pharmaceutical products and can be seen in Table 15.

Table 15. Safety Stock and Reorder Point (ROP)

No	Medicine Name	$SS_{\ 2}$	R_2
1	Demacolin	0.06	19
2	Imerson Cr	0.06	17
3	Paratusin Tab	0.05	11
4	Amoxsan 500	0.05	11
5	Mefinal 500mg	0.03	8

Calculation of TIC_2 considering fluctuating demand using the example of Demacolin. The required cost components are as follows:

1. Ordering Cost

$$O_p = \frac{AD}{Q_2^*} = \frac{(151{,}000)(222)}{(82)} = Rp. 408{,}804.87.$$

2. Holding Cost

$$O_s = h\left[\frac{Q_2^*}{2} + R_2 - D_L\right] = (Rp. 9{,}900.00)\left[\frac{82}{2} + 19 - 19\right] = Rp. 405{,}900.00.$$

3. Shortage Cost

$$O_k = \frac{\pi D}{Q_2^*}\ [\sigma_d[\varphi(1.46835) - (Z_{0.929})((1 - \emptyset)(1.46835))]]$$
$$= \frac{(Rp. 51{,}500.00)(222)}{(82)}\ [(0.04)[0.13575 - (1.46835)(0.07100)]]$$
$$= Rp. 175.66.$$

By adding all the individual costs, the total inventory cost for Demacolin is:

$$TIC_2 = \ Rp. 408{,}804.87 + Rp. 405{,}900\ +\ Rp. 175.66 = Rp. 814{,}880.53$$

Using the same calculation method, this process was carried out for four other pharmaceutical products, and the results are shown in Table 16.

Table 16. TIC_2 Values

No	Medicine Name	Ordering Cost (Rp)	Holding Cost (Rp)	Shortage Cost (Rp)	TIC_2 (Rp)
1	Demacolin	408,804.87	405,900	175.66	814,880.53
2	Imerson Cr	455,287.87	458,700	234.44	914,222.32
3	Paratusin Tab	733,428.57	726,600.00	555.71	1,460,584.29
4	Amoxsan 500	789,846.15	780,000.00	634.72	1,570,480.87
5	Mefinal 500mg	443,562.5	448,000.00	224.21	891,786.471

4. CONCLUSION

This model is readily implementable within ERP systems and can be integrated into existing pharmacy workflows without significant structural changes. The EOQ model, applied using demand-fluctuation approaches, resulted in identical optimal order quantities for the five highest-investment medicines; however, incorporating demand variability led to marginally higher total inventory costs, highlighting the subtle impact of uncertainty on cost efficiency. Furthermore, the forecasting results showed that WMA consistently produced low MAPE values, indicating reliable predictive performance for short-term demand. The combined application of WMA and EOQ also demonstrated improved stock continuity, reduced frequency of emergency orders, and minimized risk of stockouts, reinforcing the model's potential to support decision-making and improve operational stability in medium-scale pharmacies.

Author Contributions

Kwardiniya Andawaningtyas: Conceptualization, Funding Acquisition, Methodology, Project Administration, Formal Analysis, and Investigation. Raqqasyi Rahmatullah Musafir: Investigation, Writing—Original Draft, and Software. Nandia Primasari: Investigation, Writing—Original Draft, and Software. Rina Adhista: Data Curation, Software, and Validation. Trya Rizky Adellia: Writing—Original Draft and Software. Cornelia Yosefine Halim: Visualization and Writing—Review & Editing. Evi Ardiyani: Formal Analysis, Visualization, and Writing—Original Draft. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interests and have no conflicts of interest to report study

Declaration of Generative AI and AI-Assisted Technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement, including grammar, spelling, and clarity. The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. All final text was reviewed and approved by the authors

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