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Logistics Efficiency Improvement and Waste Reduction using the Appropriate Forecasting Techniques Analysis for Hospital Pharmaceutical Demand Forecasting Error Reduction

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Abstract

Effective waste management is guided by the 7R framework (Refuse, Reduce, Reuse, Repair, Repurpose, Recycle, and Recover). This study emphasizes the first two most important principles (Refuse and Reduce) by improving pharmaceutical demand forecasting to reduce waste and enhance logistics efficiency. The objective of this research was to analyze the appropriate forecasting techniques for the case study hospital important pharmaceutical demand forecasting error reduction. Using ABC analysis, 219 products were classified, with Group A items (70.95% of total inventory value) selected for analysis. These were further categorized into cyclical/seasonal demand (31 SKUs) and demand without seasonality (188 SKUs). Randomized Complete Block Design (RCBD) was applied in the Design of Experiments (DOE) using the Analysis of Variance (ANOVA) and multiple comparisons test for the appropriate forecasting techniques analysis in order to reduce the important pharmaceutical demand forecasting error. The forecasting technique was the main factor and Mean Absolute Deviation (MAD) served as the response variable. According to the class A cyclical/seasonal demand pharmaceutical products, the most appropriate forecasting technique was the 12-month seasonal length Winters' method. The average of MAD obtained by the yearly seasonal length Winters' method decreased by 7.04 units per month comparing to the 3-month moving average which was the current forecasting method because of the seasonality of pharmaceutical demand. For the class A drugs without seasonality, the most appropriate forecasting technique was single exponential smoothing. The MAD of single exponential smoothing decreased by 38.47 units per month comparing to the 3-month moving average which was the as-is forecasting method of the case study hospital. It can be concluded that Winters' method with 12-month seasonal length was suitable for cyclical/seasonal demand drugs, reducing MAD by 11% compared to the traditional 3-month moving average. For pharmaceutical demand without seasonality, single exponential smoothing was the most appropriate forecasting method, reducing MAD by 17.5%. The findings demonstrated that selecting appropriate forecasting methods could significantly improve logistics efficiency, reduce pharmaceutical waste, and enhance hospital supply chain performance.

Keywords : Logistics Efficiency; Demand Forecasting; Pharmaceuticals; Forecasting Techniques

Introduction

Effective waste management involves the practice of 7R (Refuse-Reduce-Reuse-Repair-Repurpose-Recycle-Recover). Amongst these 7Rs, the first two important principles (Refuse and Reduce), relate to the non-creation of waste by refusing unsustainable products, avoiding excess of production over consumption, and reduce nonconforming products and production wastes in the manufacturing process [1]. The next two (Reuse and Repair) refer to increasing the usage of the existing product. There are numerous products commonly perceived as single use, can be reused multiple times. Repairing nonconforming products and fixing broken items can reduce waste generation. Repurpose and Recycle involve maximum usage of the materials used in the product, and Recover involves the recovery of embedded energy in the waste material [2]. Refuse and Reduce are the most critical because they directly address overproduction and unnecessary resource consumption, which are key drivers of inefficiency in logistics and supply chain operations. Efficient logistics management plays a vital role in reducing costs, eliminating waste, improving service quality, and ensuring the sustainable use of resources.

In the healthcare sector, pharmaceutical logistics presents a particular challenge. Hospitals must balance the need for reliable pharmaceutical availability with the risk of overstocking and wastes. Excessive pharmaceutical demand forecasting leads to surplus inventory, higher inventory carrying cost, and drug expiration, whereas underestimation results in shortages and treatment delays. These inefficiencies not only increase costs but also have significant effects on patient safety and healthcare quality [3].

Accurate pharmaceutical demand forecasting is therefore essential for hospital logistics efficiency improvement [4]. However, the as-is forecasting method of the case study hospital, which is the 3-month moving average, often fails to account for the cyclical and seasonal patterns in pharmaceutical demand. Recent studies highlight the importance of applying more advanced forecasting techniques to minimize forecasting errors and improve inventory management in healthcare supply chain [5, 6]. Despite these insights, limited research has examined the comparative effectiveness of different forecasting methods in reducing pharmaceutical demand forecasting errors for the important hospital drugs in Thailand.

To address this gap, this research investigated forecasting techniques for high-value hospital pharmaceutical products classified as Group A using the ABC analysis. Specifically, the objectives of the research were: (1) to analyze the effects of forecasting techniques on pharmaceutical demand forecasting errors, and (2) to identify the most appropriate forecasting method for reducing demand forecasting errors in essential (Group A) drugs. By focusing on error reduction, this study aimed to improve logistics efficiency, minimize pharmaceutical wastes, and strengthen hospital supply chain performance.

Methodology

The design of experiments was applied in this research for planning and conducting experiments, as well as for analyzing and interpreting the resulting data [7]. DOE is used in scientific research to study systems, processes, or products by analyzing independent variables (Xs) and their effects on measurable response variables (Y) [8]. DOE is a powerful statistical tool widely used across various industries [9], not only in engineering and product/ process development [10] but also in fields as follows: management, marketing, healthcare, tourism, food [11], pharmaceuticals, energy [12], and architecture [13].

This study applied the Design of Experiments (DOE) framework to plan, conduct, and analyze the research. A Randomized Complete Block Design (RCBD) was employed to minimize variability among pharmaceutical products, while Analysis of Variance (ANOVA) was used to evaluate the effects of forecasting techniques on demand forecasting error, measured by Mean Absolute Deviation (MAD). Then the main effects plot and multiple comparisons test were conducted to determine the most appropriate forecasting method for the MAD reduction.

1. Population and Sample

The ABC analysis was performed to classify pharmaceutical products into three inventory categories:

Group A: Top 70% of inventory value
Group B: Next 20%
Group C: Remaining 10%

Stock keeping units or SKUs for short are item codes of pharmaceutical products. This study focused on Group A pharmaceutical products, comprising 219 SKUs (12% of all hospital drug SKUs), which represented 70.95% of the total inventory value (THB4,433,258,336).

These were further divided into two subgroups based on demand patterns:

(1) Cyclical or seasonal demand (31 SKUs): for example, Molnupiravir and Favipiravir used in COVID-19 treatment, Oseltamivir (Tamiflu) for influenza, and Clotrimazole for fungal infections, which show seasonal variations, especially during the rainy season.

(2) Demand without seasonality (188 SKUs): for example, Atorvastatin (Xarator), a cholesterol lowering drug with consistently high demand throughout the year.

The classification of Group A pharmaceutical products by demand characteristics is illustrated in **Figure 1**.

The time series analysis forecasting techniques were evaluated as the independent variable [14]:

(1) 3-month moving average
(2) single exponential smoothing
(3) double exponential smoothing
(4) 9-month seasonal length Winters' Method
(5) yearly seasonal length Winters' Method

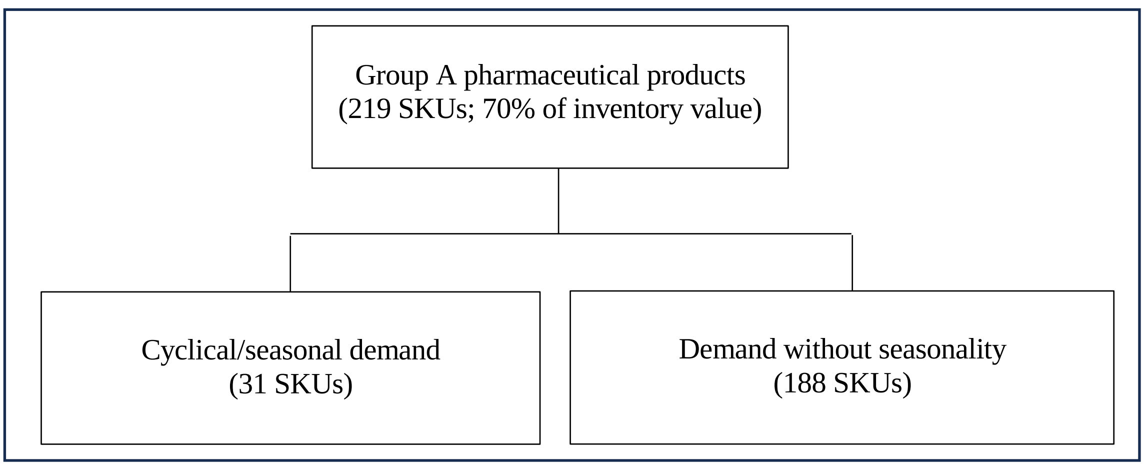

Figure 1 Classification of Group A pharmaceutical products by demand characteristics

In the additive Winters' method, the seasonal variations are assumed to be constant in magnitude, regardless of the level of the series. That is, the effect of seasonality is added to the base level and trend. The seasonal variations are assumed to be proportional to the level of the series in the multiplicative Winters' method. The seasonal effect is multiplied by the base level and trend [14]. Since (1) the pharmaceutical seasonal pattern was proportional to series level (not constant magnitude), (2) pharmaceutical demand seasonality grew or shrank with trend, and (3) the pharmaceutical demand variance was not constant and increased with level, the multiplicative Winters' method was applied in the pharmaceutical demand forecasting of the case study hospital.

The 9-month seasonal length Winters' Method was selected based on the observed demand pattern pharmaceutical products such as drugs used in the treatment of RSV infection. Respiratory Syncytial Virus (RSV) season typically lasts around 6-9 months. The yearly seasonal length Winters' Method was also selected based on the observed demand pattern pharmaceutical products. For example, the seasonality of drugs used in the treatment of seasonal influenza (Oseltamivir) was 12 months, generally with a peak during the rainy season. The response variable was the Mean Absolute Deviation (MAD), chosen for its reliability and interpretability in measuring pharmaceutical demand forecasting error.

2. Experimental Design

Time Series Analysis demand forecasting techniques was used in the experiment to determine the appropriate forecasting techniques [15]. The Analysis of Variance (ANOVA) was applied to experiment the five forecasting techniques (5 levels) effects and the blocking factor, which was the pharmaceutical products as follows: (1) pharmaceutical products with cyclical or seasonal demand (31 SKUs) and (2) drugs without cyclical or seasonal demand (188 SKUs). To control drug SKUs heterogeneity, a Randomized Complete Block Design (RCBD) was implemented, with the blocking factor defined as pharmaceutical product SKUs.

Analysis of Variance was applied to test for significant differences among forecasting methods, and the multiple comparisons test was conducted to identify the forecasting method that minimized the Mean Absolute Deviation (MAD), which served as the response variable. The smaller the MAD, the more desirable the forecasting method. Therefore, the pharmaceutical logistics efficiency was increased.

3. Data Collection

Monthly demand for Group A drugs were collected from hospital records covering a 60-month period (January 2020 – December 2024). The data were separated into the two demand categories identified earlier (seasonal demand vs. demand without seasonality).

4. Data Analysis

ANOVA was applied to test the effects of forecasting methods on demand forecasting error (MAD). Multiple comparisons tests were then conducted to determine which forecasting method produced significantly lower error. For benchmarking purposes, the hospital's existing forecasting method, the 3-month moving average, was included as a reference.

5. Validity and Reliability

Model adequacy checking was performed to confirm the appropriateness of applying ANOVA [16]. The assessment focused on three key assumptions: normality, equality of variance, and independence of residuals.

- Normality assumption: The distribution of the residuals was examined to ensure it followed a normal distribution, which was assessed using a normal probability plot.
- Equality of variance: Homogeneity of variances across groups was tested to confirm that error variances were consistent.
- Independence assumption: Residuals were examined to verify that residuals were independent.

Results and Discussion

1. Seasonal or cyclical demand drugs (31 SKUs)

From the analysis of variance (ANOVA) with Mean Absolute Deviation (MAD) as a response variable in **Table 1**, it was found that forecasting techniques had a significant effect on the MAD since the P-Value was less than the significance level of 0.05.

Table 1 ANOVA table for seasonal or cyclical demand drugs (31 SKUs)

General Linear Model: MAD versus Forecasting Method, Pharmacy

Analysis of Variance for MAD, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Forecasting Method	4	1803	1803	451	17.03	0.000
Pharmacy	30	371954	371954	12398	468.69	0.000
Error	120	3174	3174	26		
Total	154	376931				

S = 5.14329 R-Sq = 99.16% R-Sq(adj) = 98.92%

According to the Randomized Complete Block Design (RCBD), the pharmaceutical products SKUs variable was a blocking factor [17]. It was not a factor to be analyzed in this research.

Multiple comparisons test was conducted as displayed in **Figure 2**. As shown in Figures 3, the main effects plot [18] for MAD was used to analyze and determine the most appropriate forecasting technique for pharmaceutical demand forecasting error reduction. According to the multiple comparison test, the adjusted P-Value of pairwise comparisons was less than 0.05, which was the significance level, as shown in the red rectangles in **Figure 2**. Therefore, it was concluded that the average of MAD obtained by the yearly seasonal length Winters' method was significantly smaller than the average of MAD obtained by (1) the 3-month moving average, (2) double exponential smoothing and (3) the 9-month seasonal length Winters' method.

Bonferroni Simultaneous Tests
Response Variable MAD
All Pairwise Comparisons among Levels of Forecasting Method
Forecasting Method = Double Exponential Smoothing subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Moving Average (MAL= 3)	-2.164	1.306	-1.657	1.0000
Single Exponential Smoothing	-7.461	1.306	-5.711	0.0000
Winters' Method (SL = 12)	-9.211	1.306	-7.051	$\boxed{0.0000}$
Winters' Method (SL = 9)	-3.274	1.306	-2.506	0.1354

Forecasting Method = Moving Average (MAL= 3) subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Single Exponential Smoothing	-5.297	1.306	-4.055	0.0009
Winters' Method (SL = 12)	-7.047	1.306	-5.394	$\boxed{0.0000}$
Winters' Method (SL = 9)	-1.110	1.306	-0.850	1.0000

Forecasting Method = Single Exponential Smoothing subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Winters' Method (SL = 12)	-1.750	1.306	-1.340	1.0000
Winters' Method (SL = 9)	4.187	1.306	3.205	0.0173

Forecasting Method = Winters' Method (SL = 12) subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Winters' Method (SL = 9)	5.937	1.306	4.545	$\boxed{0.0001}$

Figure 2 Multiple comparison test for seasonal/cyclical demand pharmaceutical products (31 SKUs)

From the main effects plot to analyze the most suitable forecasting method in **Figure 3**, it was found that the average of Mean Absolute Deviation (MAD) obtained by the 12-month seasonal length Winters' Method was the smallest value. The average of MAD using the yearly seasonal length Winters' method decreased by 7.04 units per month or 11% comparing to the 3-month moving average which was the current forecasting method because of the seasonality of pharmaceutical demand.

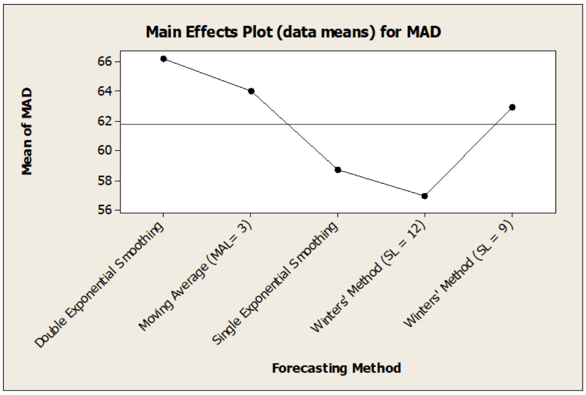

Figure 3 Main effects plot for seasonal demand

2. Non-cyclical or non-seasonal demand drugs (188 SKUs)

To control drug SKUs heterogeneity, a Randomized Complete Block Design (RCBD) was implemented. According to the Randomized Complete Block Design (RCBD), the pharmaceutical products SKUs variable was a blocking factor.

For the demand without seasonality of Class A pharmaceutical products, the ANOVA table in **Table 2** displayed that forecasting techniques had a significant effect on the MAD since the P-Value was less than the significance level of 0.05.

Table 2 ANOVA table for non-cyclical or non-seasonal demand drugs (188 SKUs)

General Linear Model: MAD versus Forecasting Method, Item Code

Analysis of Variance for MAD, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Forecasting Method	4	324185	324185	81046	12.52	0.000
Item Code	187	392488453	392488453	2098869	324.31	0.000
Error	748	4840894	4840894	6472		
Total	939	397653532				

S = 80.4474   R-Sq = 98.78%   R-Sq(adj) = 98.47%

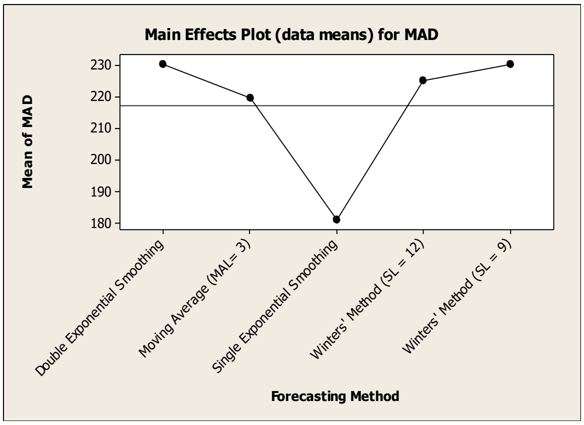

Figure 4 Main effects plot for non-seasonal demand

From **Figures 4**, the main effects plot for pharmaceutical demand without seasonality was used to analyze and determine the most suitable forecasting method for pharmaceutical demand forecasting error reduction. Multiple comparisons test was conducted as shown in **Figure 5**.

According to the main effects plot to analyze the most suitable forecasting method in **Figure 5**, it was found that the average of Mean Absolute Deviation (MAD) obtained by the single exponential smoothing was the smallest value. The average of MAD using the single exponential smoothing decreased by 38.47 units per month or 17.5% comparing to the 3-month moving average which was the as-is forecasting method. According to the multiple comparison test, the adjusted P-Value of pairwise comparisons was less than 0.05, which was the significance level, as shown in the red rectangles in **Figure 5**. Therefore, it could be concluded that the average of MAD obtained by the single exponential smoothing was significantly smaller than the average of MAD obtained by (1) the 3-month moving average, (2) double exponential smoothing, (3) the 9-month seasonal length Winters' method and (4) 12-month seasonal length Winters' method. Since most of non-cyclical or non-seasonal demand pharmaceutical products demand patterns were not increasing trend or decreasing trend, the double exponential smoothing was inappropriate to apply. Additionally, the Winters' method was also unsuitable because of the demand without seasonality.

Bonferroni Simultaneous Tests
Response Variable MAD
All Pairwise Comparisons among Levels of Forecasting Method
Forecasting Method = Double Exponential Smoothing subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Moving Average (MAL= 3)	-10.79	8.298	-1.300	1.0000
Single Exponential Smoothing	-49.26	8.298	-5.936	0.0000
Winters' Method (SL = 12)	-5.00	8.298	-0.602	1.0000
Winters' Method (SL = 9)	0.11	8.298	0.013	1.0000

Forecasting Method = Moving Average (MAL= 3) subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Single Exponential Smoothing	-38.47	8.298	-4.636	0.0000
Winters' Method (SL = 12)	5.79	8.298	0.698	1.0000
Winters' Method (SL = 9)	10.90	8.298	1.313	1.0000

Forecasting Method = Single Exponential Smoothing subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Winters' Method (SL = 12)	44.26	8.298	5.334	0.0000
Winters' Method (SL = 9)	49.37	8.298	5.950	0.0000

Forecasting Method = Winters' Method (SL = 12) subtracted from:

Forecasting Method	Difference of Means	SE of Difference	T-Value	Adjusted P-Value
Winters' Method (SL = 9)	5.109	8.298	0.6157	1.000

Figure 5 Multiple comparison test for non-seasonal demand pharmaceutical products (188 SKUs)

Table 5 Appropriate forecasting method for pharmaceutical products with cyclical or seasonal demand

MAD of 3-month moving average	MAD of yearly seasonal length Winters' method	MAD Difference	% MAD Difference
64.01 unit per month	56.97 unit per month	7.04 unit per month	11%

Table 6 Suitable forecasting method for pharmaceutical demand without seasonality

MAD of 3-month moving average	MAD of single exponential smoothing	MAD Difference	% MAD Difference
219.52 unit per month	181.05 unit per month	38.47 unit per month	17.5%

- For cyclical or seasonal demand pharmaceutical products (31 SKUs), such as Molnupiravir (for adult COVID-19 patients), Favipiravir (for pediatric COVID-19 patients), Oseltamivir (Tamiflu, used for influenza A and B), and Clotrimazole (an antifungal agent frequently required during the rainy season), the most effective method was 12-month seasonal length Winters' method. The proposed forecasting method significantly outperformed the 3-month moving average, double exponential smoothing, and 9-month seasonal length Winters' method, achieving an 11% reduction in MAD (7.04 units per month) at the 0.05 significance level. The improvement reflects the ability of the forecasting model to capture cyclical and seasonal demand fluctuations.
- For pharmaceutical demand without seasonality (188 SKUs), such as Atorvastatin (Xarator), a cholesterol-lowering agent with consistent demand across all seasons, and other similar pharmaceutical products, the single exponential smoothing method was the most appropriate. It reduced MAD by 17.5% (38.47 units per month) compared to the current hospital forecasting method, which was the 3-month moving average, and also outperformed double exponential smoothing and Winters' methods with 9-month and 12-month seasonal lengths, with 0.05 significance level.

Limitation

- The scope of the data: a 60-month dataset from the case study hospital was used to analyze in this research.
- The study did not include external factors such as supply shocks that may influence pharmaceutical demand patterns.

Conclusions

This research employed the ANOVA to examine factors influencing the Mean Absolute Deviation (MAD) of the time series forecasting methods. Five forecasting techniques were evaluated: (1) 3-month moving average, (2) single exponential smoothing, (3) double exponential smoothing, (4) 9-month seasonal length Winters' Method and (5) 12-month seasonal length Winters' Method. The analysis focused on high inventory value Group A drugs, which were divided into two subgroups: cyclical/seasonal demand (31 SKUs) and non-cyclical or non-seasonal (188 SKUs). According to the class A cyclical/seasonal demand pharmaceutical products, the most appropriate forecasting technique was the 12-month seasonal length Winters' method. The average of MAD obtained by the yearly seasonal length Winters' method decreased by 7.04 units per month comparing to the 3-month moving average which was the current forecasting method because of the seasonality of pharmaceutical demand. For the class A drugs without seasonality, the most appropriate forecasting technique was single exponential smoothing. The MAD of single exponential smoothing decreased by 38.47 units per month comparing to the 3-month moving average which was the as-is forecasting method of the case study hospital. It can be concluded that

Winters' method with 12-month seasonal length was suitable for cyclical/seasonal demand drugs, reducing MAD by 11% compared to the traditional 3-month moving average. For pharmaceutical demand without seasonality, single exponential smoothing was the most appropriate forecasting method, reducing MAD by 17.5%.

These findings confirm that pharmaceutical demand forecasting methods should be tailored to demand seasonality and patterns rather than applied uniformly which are consistent with the research results of Merkuryeva et al. (2019) and Rathipriya et al. (2023). The present findings and previous studies are consistent as follows: the time series analysis methods are applied, and the multiplicative Winters' method is selected because of the pharmaceutical demand seasonality growth with trend. In practice, hospitals adopting suitable forecasting techniques can improve logistics efficiency, reduce inventory carrying cost, and minimize pharmaceutical wastes from overstocking and expiration. The results provide both theoretical evidence and practical guidance for hospital supply chain optimization.

The MAD reduction in pharmaceutical demand forecasting is a quantitative enabler of the 7R waste management. It prevents redundant pharmaceutical procurement through accurate forecasting, and reduces pharmaceutical inventory levels and expired stock to minimize resource use and waste generation. (Refuse and Reduce), enhances circular use of pharmaceutical products (Reuse, Repair, Repurpose and Recycle), and minimizes end-of-life losses (Recover). Reduction in MAD typically yields reduction in pharmaceutical waste, demand accuracy increase and improvement in hospital logistics efficiency, while strengthening environmental sustainability and patient care reliability.

Future research may extend this analysis to other measures of demand forecasting error as follows: Mean Absolute Percentage Error (MAPE) and Mean Squared Deviation (MSD). Future research may explore the combined impact of forecasting methods and inventory control policies to further strengthen hospital logistics performance.

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