



THE APPLICATION OF DRUG DEMAND PATTERN ANALYSIS FOR INVENTORY FORECASTING FROM THE CENTRAL PHARMACY TO THE IN-PATIENT PHARMACY: A CASE STUDY OF A UNIVERSITY HOSPITAL

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ABSTRACT

Inventory management in tertiary care hospitals is challenged by demand uncertainty, contributing to drug shortages, overstocking, and frequent after-hours emergency requisitions. This study aimed to develop optimized drug demand forecasting models and evidence-based inventory policies for injectable medications in an inpatient pharmacy department. A 26-week retrospective dataset of 197 non-refrigerated injectable drugs was analyzed. Items were classified into four demand categories using Average Demand Interval (ADI) and Squared Coefficient of Variation (CV^2): Smooth (159 items), Intermittent (28 items), Lumpy (4 items), and Erratic (6 items). Simple Exponential Smoothing (SES) was applied to Smooth and Erratic groups, while Croston's Method was employed for Intermittent and Lumpy groups. Smoothing parameters (α) were individually optimized to minimize the Adjusted Mean Absolute Percentage Error (AMAPE). Safety Stock (SS), Reorder Points (ROP), and maximum inventory capacity (Q_i) were calculated using a lead time of $L = 1/7$ week (1 day), a review period of $T = 4/7$ week (4 days), and a 90% service level. The median AMAPE was 44.1% for Smooth items, 50.2% for Erratic items, and 50.0% for Intermittent and Lumpy items combined. Optimal α values were consistently low for Smooth and Erratic items (median $\alpha = 0.2$ and 0.1 , respectively), while Intermittent and Lumpy items under Croston's Method required higher α values (median 0.9 and 0.6), enabling rapid updating of sparse demand estimates. Among all groups, SES achieved the highest forecasting accuracy for Smooth items, while Croston's Method provided the greatest structural improvement for Intermittent and Lumpy items through separate estimation of demand size and inter-demand interval. The Excel-based decision support tool automates requisition calculations incorporating commercial pack sizes and storage constraints (Q_i), facilitating a transition from experience-based to evidence-based medication management and effectively reducing stockout risks and emergency requisitions.

Keywords: inventory management, hospital pharmacy, demand classification, forecasting models

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Introduction

The study site is a premier tertiary care university hospital, the largest in the region and the second largest nationwide. According to 2024 statistics, the hospital managed 1,378,466 outpatient visits (averaging over 3,700 per day) and 36,104 inpatient admissions annually. This comprehensive infrastructure supports a wide range of services, from routine outpatient care to critical care and complex referrals from regional networks. Providing such a wide range of care creates a heavy workload and complex challenges. To handle this, the hospital uses a systematic approach that combines the skills of various medical and administrative professionals. Given its role as a regional hub, the management of pharmaceuticals and medical supplies is of paramount importance. The hospital must maintain substantial and adequate inventory levels to ensure continuous service across all specialties and mitigate the risk of drug shortages. The supply chain management system involves centralized storage at the Central Pharmacy Warehouse, where requisition and distribution are managed through the hospital's Systematic Management Integration (SMI) information system.

The central pharmacy warehouse is divided into five sections. When orders come in, these sections send medications to twelve different pharmacy units across the hospital. This ensures that each unit can provide medications to patients appropriately and promptly. This process reflects seamless integration and coordination at every level—from procurement and inventory management to requisition, dispensing, and delivery to the patient.

Effective inventory management in hospital pharmacies is critical because drug shortages directly compromise patient safety, while excess stock escalates holding costs and expiry waste^{1,2} Drug demand in hospitals is heterogeneous: items may exhibit Smooth (frequent, stable demand), Intermittent (infrequent, stable), Erratic (frequent,

highly variable), or Lumpy (infrequent, highly variable) behaviour, classified using the Average Demand Interval (ADI) and Squared Coefficient of Variation (CV^2) framework.³ Simple Exponential Smoothing (SES) is appropriate for Smooth and Erratic items, whereas Croston's Method is recommended for Intermittent and Lumpy items because it separately estimates demand size and inter-demand interval, providing more reliable forecasts for sparse patterns.^{4,5} Forecasting accuracy is evaluated using the Adjusted Mean Absolute Percentage Error (AMAPE), which avoids the zero-denominator problem of conventional MAPE and is suitable for periods of zero demand.⁶ Prior studies in Thai hospital settings have demonstrated that demand-pattern-specific forecasting significantly reduces stockouts and holding costs.^{7,8} Injectable medications in particular carry the highest clinical risk: in this study setting, the IPD managed 548 injectable items in total in 2024; of these, 240 items had stock records under direct IPD management, and 43 refrigerated items were excluded, yielding 197 non-refrigerated injectable drugs for analysis. Injectables accounted for 40% of all 130 after-hours emergency Central Warehouse openings (53 occurrences/year), highlighting the urgent clinical need for a systematic forecasting and inventory control framework. The inventory performance indicators selected for this study are: forecasting accuracy (AMAPE by demand group), service level (target 90%), Safety Stock (SS), Reorder Point (ROP), and reduction in after-hours emergency requisitions.

This study aims to optimize the pharmaceutical requisition process by achieving two primary objectives. First, it develops an evidence-based forecasting model by analyzing historical demand patterns to determine optimal transfer quantities and frequencies from the Central Pharmacy to the Inpatient Pharmacy Department (IPD). Second, it enhances operational efficiency through the implementation of a systematic workflow and an Excel-based decision support tool. Together,

these interventions are designed to ensure medication availability, improve calculation accuracy, and minimize manual errors in daily pharmacy operations.

Methodology

Population and Sample

Population: The population for this study includes all 240 injectable drug items managed by the Inpatient Pharmacy at the study site. Note: the IPD managed 548 injectable items in total (2024 data); 240 items had stock records under direct IPD management and were included as the study population; 43 refrigerated items were subsequently excluded, yielding a final analytic sample of 197 non-refrigerated injectable drugs.

Sample Selection: The research focus was narrowed down through specific criteria:

- Initial Filtering: From the 240 injectable items, 43 refrigerated items were excluded to ensure consistency in storage conditions.
- Final Sample: A total of 197 non-refrigerated injectable drugs were selected as the final sample for analysis.

Data Collection and Duration

- Historical Data: A 6-month retrospective dataset (January – June 2024) was collected, comprising 26 weeks of drug consumption and requisition records.
- Parameters: Key data points include requisition quantities, dates of transaction, and frequency of use.
- Experimental Phase: The forecasting models and the Excel-based decision support tool were further tested and validated using a 2-month analytical period (July–August 2024), during which pharmacists applied the tool in routine requisition workflows to verify calculation accuracy and operational feasibility.

Data Management and Ethics

The project qualifies for exemption according to Exemption criterion (Project Code: FAC-MED-

2568-0856, dated 11 March 2026) from the Research Ethics Committee, Faculty of Medicine, Chiang Mai University. Data was systematically recorded and managed using Microsoft Excel. To ensure patient confidentiality, no clinical treatment details or identifiable patient information were collected. All research data will be securely stored and destroyed within two years following the completion of the study.

Analytical Approach

The methodology is divided into four key stages as follows:

1. Demand pattern analysis. The study begins by analyzing historical consumption data to classify drugs based on their demand characteristics. Using the Average Demand Interval (ADI) and the Squared Coefficient of Variation (CV^2), medication items are categorized into 4 patterns (Figure 1) as follows:

- i. Smooth: Medications with constant demand frequency and stable quantities.
- ii. Intermittent: Medications with inconsistent demand frequency but stable quantities.
- iii. Erratic: Medications with constant demand frequency but highly variable quantities.
- iv. Lumpy: Medications with both inconsistent demand frequency and highly variable quantities.

This classification is crucial for selecting the most appropriate forecasting technique for each specific group. The ADI and CV^2 are determined using Equations (1) and (2):

$$(1) ADI = \frac{N}{\sum_{i=1}^N 1(A_i > 0)}$$

Where:

$1(A_i > 0)$ = indicator function equal to 1 if period i has non-zero demand and 0 otherwise

N = Total number of periods

$$(2) CV^2 = \left[\frac{\sigma}{\mu} \right]^2$$

Where:

σ = standard deviation of demand

μ = mean (average) demand

Items were classified according to established thresholds⁹: ADI < 1.32 indicates relatively frequent demand (Smooth or Erratic), while ADI $\geq$ 1.32 indicates intermittent demand occurrence (Intermittent or Lumpy); CV^2 < 0.49 indicates stable demand quantity (Smooth or Intermittent), while $CV^2 \geq$ 0.49 indicates highly variable demand quantity (Erratic or Lumpy).

2. Development of forecasting models. For each demand category identified in Stage 1, suitable mathematical models are applied. Once the demand patterns for each medication have been classified, the appropriate forecasting method—either Simple Exponential Smoothing (SES) or Croston's Method^{4,5}—is applied based on those characteristics. SES is utilized for items with relatively stable or erratic demand, the Exponential Smoothing model is utilized, as shown in Equation (3). While Croston's Method is employed for items with intermittent or lumpy demand, as detailed in Equations (4), (5), and (6).

$$(3) F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

Where:

F_t = forecast value at period t

F_{t-1} = forecast value at the previous period

A_{t-1} = actual demand in the previous period

α = smoothing parameter

$$(4) F_{t+1} = \frac{Z_t}{P_t}$$

Where Z_t represents the estimated average demand size and P_t represents the estimated average inter-demand interval.

$$(5) Z_t = \alpha A_t + (1 - \alpha)Z_{t-1}$$

$$(6) P_t = \alpha G_t + (1 - \alpha)P_{t-1}$$

Where:

Z_t = estimated mean demand size

P_t = estimated mean inter-demand interval

A_t = actual demand size at time t

G_t = time interval (number of periods) between the most recent demand occurrence and the previous demand occurrence

α = smoothing parameter

The smoothing parameters (α) is optimized for each medication by evaluating forecasting accuracy through multiple error metrics, including Mean Absolute Deviation (MAD), Standardized MAD (SMAD), and Adjusted Mean Absolute Percentage Error (AMAPE). To ensure the highest precision, the optimal α value for each specific drug is determined by minimizing the AMAPE score. For SES, AMAPE is calculated as the mean of absolute percentage errors across all weeks with positive actual demand ($A_t > 0$), with negative demand values treated as zero. For Croston's Method, AMAPE is likewise computed over demand weeks only (weeks where actual demand > 0), using the updated Z and P values at each demand occurrence. The optimization process utilizes What-if analysis and the Excel Solver add-in to systematically identify the parameter values that minimize forecast error.

3. Determination of Safety Stock (SS) and Reorder Points (ROP). After finding the best forecasting models, SS is calculated to ensure continuous medication availability during procurement lead times. This is followed by the ROP, which tells staff exactly when to order more supplies. Currently, the hospital orders three times a week (Monday, Wednesday and Friday) with 1 day waiting time. To reduce administrative burden, requisition frequency was consolidated to twice per week (Monday and Friday), extending the review period to $T = 4/7$ week (4 days), while the lead time ($L = 1/7$ week) remains unchanged. This change in T is incorporated into all calculations. Because the Inpatient Pharmacy has limited shelf space, the Maximum Inventory Capacity (Q_i) is also included to prevent overcrowding. Finally, the actual amount ordered each time is adjusted by looking at how much

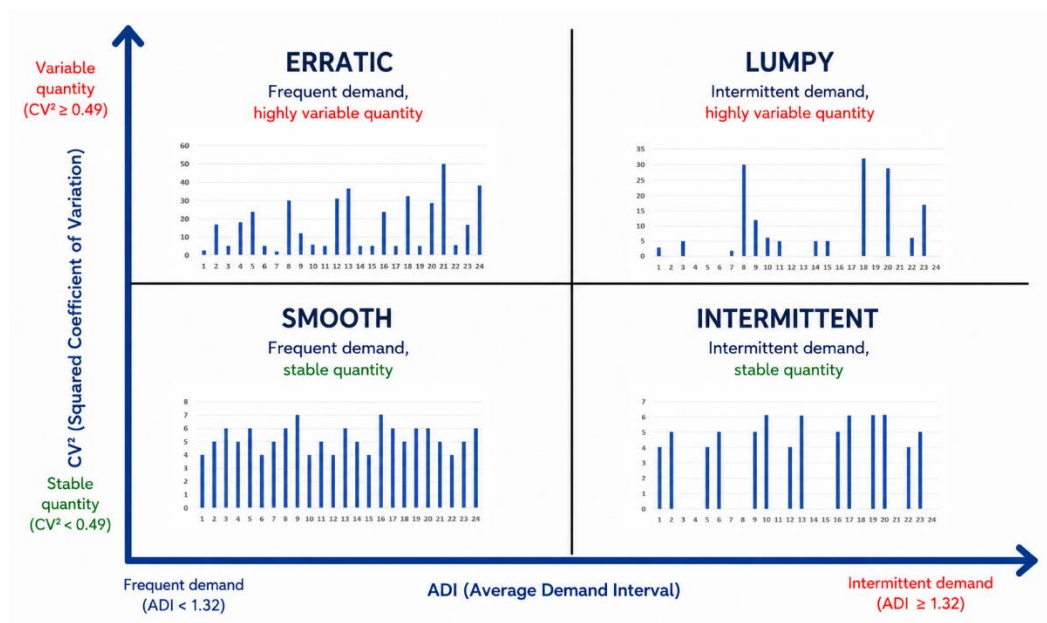


Figure 1 Classification of drug demand patterns based on the ADI-CV² framework.

medicine is left over from the previous cycle. This study employs a periodic review inventory policy, in which stock levels are assessed at fixed review intervals (T) and replenishment orders are placed at each review point. Safety Stock (SS) is formally defined as the buffer inventory held to protect against demand variability during the procurement lead time, calculated as Equation 7, where Z is the standard normal value for the target service level. The Reorder Point (ROP) is the minimum on-hand inventory level that triggers replenishment, calculated as Equation 8, where μ_D is the average weekly demand (units per week).

$$(7) SS = Z \times \sigma_d \sqrt{LT}$$

$$(8) ROP = (\mu_D \times LT) + SS$$

$$(9) Q_t = F_t \times (L + T) + SS$$

$$(10) \text{Request} = Q_t - \text{On hand}$$

Where:

Z = standard normal value corresponding to the target service level

σ_d = standard deviation of demand per period

μ_D = average demand (drug consumption)

LT = lead time for drug procurement = 1/7 week (1 day)

$\mu_D \times LT$ = (weekly demand) $\times$ (1/7 week) = demand during 1-day lead time

F_t = forecasted demand at time t

L = lead time

T = review period

Q_t = Maximum Inventory Capacity (order-up-to level for each review cycle)

On hand = current inventory level

The Maximum Inventory Capacity (Q_t) was determined using the formula $Q_t = F_t \times (L + T) + SS$ (Equation 9), where F_t is the forecasted weekly demand, $L = 1/7$ week (1 day) is the lead time, and $T = 4/7$ week (4 days) is the review period under the proposed twice-weekly system, giving $L + T = 5/7$ week. The requisition quantity for each cycle is calculated as $\text{Request} = Q_t - \text{On Hand}$ (Equation 10), which feeds directly into the Excel dashboard to compute the number of packs to order.

4. Development of operational processes and excel-based decision tools. The final stage turns research into practice by creating a simple workflow

and an Excel tool for pharmacy staff. This tool handles the complex math of ordering by automatically factoring in package sizes and storage limits (Q_t). The dashboard gives staff a clear, "all-in-one" view: it shows current stock, predicts what is needed for the coming week, and automatically flags which items to order based on the Reorder Point (ROP) and Safety Stock (SS). By rounding orders to match standard pack sizes and creating a final summary, the tool makes daily restocking both faster and more accurate. For medications classified as Vital (life-saving drugs), particularly those in non-Smooth demand categories (Intermittent, Lumpy, Erratic), the dashboard includes a minimum stock override flag. This ensures that at least 1–2 treatment courses—calculated based on standard clinical dose-response—are maintained regardless of the mathematical SS calculation.

Results

The Inpatient Pharmacy Department (IPD) at a university hospital handles approximately 144,000 prescriptions per month. The IPD manages a total of 1,774 drug items, of which 548 (30.9%) are injectable products; these represent the highest-risk category owing to their life-saving role (e.g., intravenous antibiotics, cardiovascular agents, and emergency medicines). Due to their clinical importance, any shortage directly impacts patient safety. Pharmacists extract stock data from SMI system and manually calculate order quantities using Excel based on personal judgment before sending orders to the central pharmacy. In 2024, there were 130 emergency after-hours openings of the Central Warehouse, 40% of which (53 times) were for injectable drugs. This indicates a failure in daytime planning, leading to high staff workload and potential delays in patient care. There is an urgent need for a high-precision forecasting and planning model specifically for injectable drugs to balance medication availability, reduce emergency after-hours requisitions, and minimize budget waste from expired stock.

Results of Demand Pattern Analysis

Retrospective data on injectable medications were collected over a six-month period, with 240 items initially identified. After excluding 43 refrigerated items, 197 non-refrigerated injectable drugs remained for analysis. These data were aggregated into a 26-week time series to classify demand behaviors. Based on ADI and CV^2 , medications were categorized into four primary demand patterns, excluding three unclassified items. The Smooth category was the most prevalent, comprising 159 items with highly consistent demand in both frequency and quantity. The Intermittent group (28 items) was characterized by infrequent demand but relatively stable quantities, whereas the Lumpy group (4 items) exhibited irregularity in both frequency and volume. Finally, the Erratic group (6 items) demonstrated stable demand frequency but high volatility in quantities.

Optimization Results for the Smoothing Parameter (α)

The analysis reveals that the optimal Smoothing Parameter (α) varies significantly across different medication items. By minimizing the AMAPE, the most precise α was identified for each forecasting model (Table 1)

- Simple Exponential Smoothing (SES): For items such as Chlorpheniramine injection 10 mg/ml, an optimal α of 0.7 (individual item example; group median $\alpha = 0.2$) was found to yield the lowest AMAPE (9.35%), indicating that recent demand trends carry a higher weight in predicting future requirements for this specific item.

- Croston's Method: For example, Aethoxysklerol Inj 1% 2 ml, the optimal α was determined to be 0.9, yielding a minimum AMAPE of 69.68%. Under the standardized AMAPE calculation (computed over demand weeks only), this represents the best-achievable accuracy for this intermittent-demand item.

The optimal α values varied markedly across demand groups. For Smooth items (SES, $n = 159$), the

median $\alpha = 0.2$, with mode 0.1 (40.9% of items), indicating that stable long-run averaging is generally most appropriate. For Erratic items (SES, $n = 6$), the median $\alpha = 0.1$ (83.3% at $\alpha = 0.1$): a low α prevents overreaction to demand spikes. For Intermittent items (Croston's, $n = 22$ of 28; 6 items excluded from α optimization due to demand only in the final observation week or insufficient inter-demand intervals), the median $\alpha = 0.9$ (81.8% at $\alpha = 0.9$). High responsiveness allows rapid updating of estimates when sparse demand occurs. For Lumpy items (Croston's, $n = 4$), the median $\alpha = 0.6$ (range 0.1–0.9), reflecting irregular high-volume demand patterns. The key finding is that the Intermittent and Lumpy groups, under the standardized Croston's method, show predominantly high optimal α values. This reflects that when demand is sparse and irregular, high α allows the model to rapidly update its estimates upon each demand event, giving full weight to the most recent observation rather than diluting it with a long historical average. This is methodologically appropriate and consistent with the behavior of Croston's method for sparse demand⁵. Smooth and Erratic groups continue to favor low α values, consistent with the general principle that down-weighting recent observations

is appropriate for items with higher demand regularity.

Overall AMAPE Performance Summary

The median AMAPE across all 159 Smooth items (SES) was 44.1% (IQR: 25.5%–68.8%), reflecting acceptable forecasting accuracy for this dominant group under the standardized AMAPE calculation. For Intermittent items ($n = 28$, Croston's Method), the median AMAPE was 51.0% (IQR: 32.9%–67.5%); the median optimal $\alpha = 0.9$ based on the 22 items with sufficient demand data for optimization (6 items with demand only in the final week or insufficient inter-demand intervals were excluded from α optimization but retained in the AMAPE summary). For the 4 Lumpy items (Croston's Method), the median AMAPE was 47.6% (IQR: 40.9%–57.6%). When Intermittent and Lumpy groups are combined ($n = 32$), the median AMAPE was 50.0% (IQR: 40.9%–60.0%). The substantially lower AMAPE for Intermittent and Lumpy groups compared to earlier reported values reflects adoption of the standardized AMAPE calculation, in which errors are computed only over demand weeks (weeks with $A_t > 0$), consistent with published methodology. For the 6 Erratic items (SES), the median AMAPE was 50.2% (IQR: 41.2%–58.9%).

Table 1 Example of Alpha (α) Optimization Results

Exponential smoothing (Chlorpheniramine injection 10 mg/ml)		Croston's Method (Aethoxysklerol Inj 1% 2 ml)	
α	AMAPE (%)	α	AMAPE (%)
0.1	10.96	0.1	77.46
0.2	9.85	0.2	76.87
0.3	9.67	0.3	76.10
0.4	9.60	0.4	75.17
0.5	9.59	0.5	74.12
0.6	9.50	0.6	73.00
0.7	9.35 ✓ Optimal	0.7	71.88
0.8	9.45	0.8	70.79
0.9	9.62	0.9	69.67 ✓ Optimal

Figure 2 presents the forecasting error (MAPE) distribution over a 26-week evaluation period for Chlorpheniramine injection 10 mg/ml using the Simple Exponential Smoothing (SES) model, in which the optimal smoothing parameter was identified as $\alpha = 0.7$, yielding the lowest forecasting error with an AMAPE of 9.35%. This result indicates that assigning greater weight to recent demand observations improved prediction accuracy for short-term

inventory planning. A comparison between actual demand and the forecasted values further shows that the predicted trend closely followed the observed consumption pattern throughout the study period (as shown in Figure 3), with only minor deviations at some time points, supporting the reliability of the model for practical replenishment planning and inventory control in routine pharmacy operations.

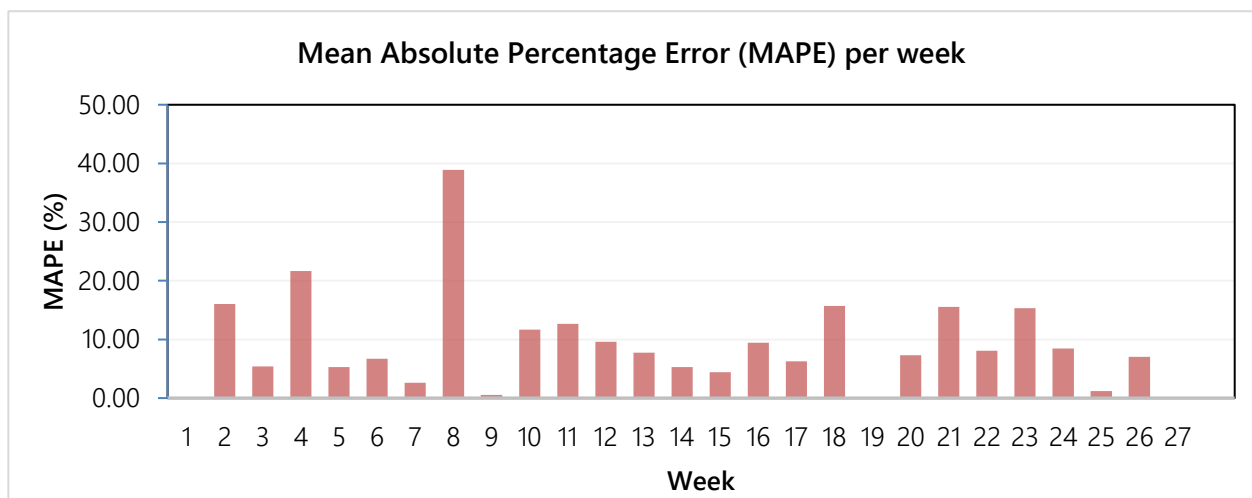


Figure 2 MAPE (%) Error Distribution: A bar chart illustrating the Mean Absolute Percentage Error (MAPE) for each week, highlighting the forecasting accuracy over time.

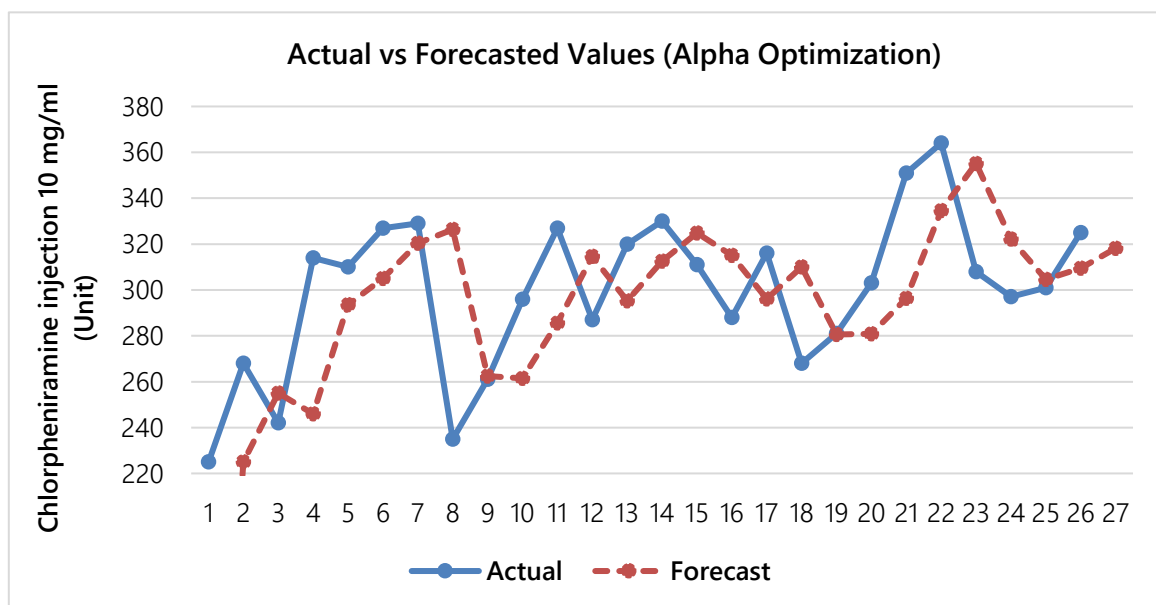


Figure 3 A line chart comparing the actual injection units against the forecasted values.

Calculation Results for Safety Stock (SS) and Reorder Point (ROP)

Based on the forecasted demand and demand variability, SS and ROP were calculated using defined Service Levels and Lead Times. For Chlorpheniramine injection 10 mg/ml, the analysis showed a Standard Deviation of demand at 34.97 units per week. With a specified 90% service level ($Z = 1.282$) and a lead time of $L = 1/7$ week (1 day), the calculated Safety Stock was approximately 45 units. When combined with the average weekly demand, ROP was approximately 88 units. (Figure 4)

The "Smooth" category accounts for over 80% of the items (159/197). This suggests that the majority of injectable medications in this inpatient pharmacy have consistent demand—a pattern well-suited to the automated forecasting and inventory optimization framework developed in this study. This group requires significantly higher inventory levels, with a group-level median Safety Stock of 30.8 units (IQR: 10.4–66.2) and a group-level median Reorder Point of 38.2 units (IQR: 11.6–88.4) (note: individual-level ROP always exceeds SS by construction of the formula $ROP = (\mu_D \times LT) + SS$). The wide IQR indicates a high degree of variability in quantities among the 159 drugs in this category. Erratic items have a median SS of 3.2 units (IQR: 2.6–4.5) and median ROP of 3.4 units (IQR: 2.8–4.6). Intermittent items have a median SS of 1.3 units (IQR: 0.4–4.3) and median ROP of 1.7 units (IQR: 0.5–4.6). Lumpy items maintain the

lowest buffers with a median SS of 1.3 units (IQR: 1.3–8.4) and median ROP of 1.4 units (IQR: 1.3–8.5). The narrow IQRs for the Erratic, Intermittent, and Lumpy groups reflect homogeneity in SS values across items (most requiring very small buffers), rather than suggesting demand regularity for individual items. (Figure 5)

Development of operational processes and excel-based decision tools

This automated inventory dashboard monitors IPD medication levels by comparing on-hand stock with the calculated ROP, derived from weekly demand forecasts and safety stock (SS). When stock falls below the threshold, the system triggers an "ORDER" status and calculates the required quantity ($Q_t - \text{on-hand}$), rounding up to the nearest pack size. By integrating real-time stock data with forecasting and packaging information, the system supports efficient replenishment and reduces manual errors and stock-out risks, as shown in Figure 6. The dashboard therefore provides a practical decision support mechanism that improves the accuracy and efficiency of routine medication requisition processes within the IPD pharmacy. The formulas underlying each column of the dashboard are summarized in Table 2.

The proposed system is designed to achieve the following performance outcomes: (1) Service level: 90% for all Smooth items ($Z = 1.282$), ensuring stock availability in 90 out of 100 replenishment cycles.

Order Sheet (Standard Method) — SS/ROP/Qt Mirrors 'order-gr.6 (Final)' VLOOKUP → Forecast (New)																		
L=1/7 wk T=4/7 wk Z=1.282 (90%SL) SS=Z*σ*√L ROP=F*L+SS Qt=F*(L+T)+SS Blue=input Red=formula result																		
code	name	pattern	onhand	Request	Forecast	SS	Check	ss ๓	ROP	ROP-D	ROP-D ๓	Q	Q ๓	Status	๓๓๓๓๓๓	pack	request pack	๓๓๓๓๓๓
CEFI08	Cefixon Inj 1 g	smooth	84	40	25.0437	33.9335	OK	34	37.5112	36.3675	37	51.8218	52	NO	32	10	4	40
CEFI10	CefalMax Inj 1 GM	intermittent	99	90	5.9906	13.4814	NO	14	14.3372	17.9749	18	17.7604	18	NO	81	10	9	90
CEFI11	CefalBEN Inj 1 gm	smooth	744	1440	910.1833	255.2612	OK	256	385.2874	407.5359	408	905.3921	906	NO	-162	1440	1	1440
CEFI12	CefTRIAxone IM 250 mg (Cef-3)	intermittent	1	10	1.0910	0.7447	OK	1	0.9006	1.0304	2	1.5240	2	ORDER	-1	10	1	10
CEFI13	Cef-3 Inj 2 gm (๓๓๓๓๓๓)	smooth	496	120	630.9173	165.2727	OK	166	255.4038	247.5804	248	615.9289	616	NO	-120	10	12	120
CERI01	Cerebrosyn Inj 10 ml	intermittent	126	90	28.4048	16.8586	OK	17	20.9164	22.0627	23	37.1477	38	NO	88	5	18	90
CHI103	ChlorB/ClovaZine Inj 50 mg/2 ml	erratic	16	50	1.3917	2.5612	OK	3	2.7600	2.8301	3	3.5552	4	NO	12	50	1	50
CHLI04	Chlorpheniramine Inj 10 mg/ml (G.P.O) (CPI)	smooth	454	200	302.0639	45.2036	OK	46	88.3556	87.9728	88	260.9635	261	NO	193	50	4	200
CIFI01	Cifloxan IV 200 mg/100 ml	intermittent	1	30	3.3958	3.8205	OK	4	4.3056	5.3443	6	8.2460	7	ORDER	-6	30	1	30
CIFI02	Cifloxan Inj *400 mg/200 ml*	smooth	72	100	166.4347	49.7522	OK	50	73.5286	70.2687	71	168.6341	169	NO	-97	20	5	100
CLAI04	CLAraxim Inj 1 g	smooth	89	100	112.7072	58.6023	OK	59	74.7033	75.8825	76	139.1074	140	NO	-51	50	2	100
CLEI01	Clexane Inj 40 mg/0.4 ml *HAD*	smooth	258	140	333.7164	136.0289	OK	137	183.7026	185.2102	186	374.3977	375	NO	-117	35	4	140
CLEI02	Clexane Inj *60 mg/0.6 ml* *HAD*	smooth	251	35	204.9961	100.6863	OK	101	129.9718	128.9720	129	247.1136	248	NO	3	35	1	35
CLOI05	Cloxygen Inj 1 gm (GDH)	smooth	214	150	311.9949	124.9872	OK	125	169.5579	160.1795	161	347.8406	348	NO	-134	50	3	150
COLI01	Colstate 150 Inj	smooth	460	100	327.5258	143.8207	OK	144	190.6101	200.5350	201	377.7677	378	NO	82	100	1	100
CORI01	CorDARONE Inj 150 mg/3 ml	smooth	169	120	92.3634	35.3347	OK	36	48.5295	46.8292	47	101.3085	102	NO	67	120	1	120
CRAI01	Cravit IV 500 mg/ 100 ml	smooth	10	20	2.5323	4.0808	OK	5	4.4425	4.5280	5	5.8896	6	NO	4	20	1	20
CRAI02	Cravit Inj *750 mg/150 ml*	smooth	11	40	3.8013	16.7548	OK	17	21.5835	21.3812	22	40.8886	41	ORDER	-30	20	2	40

Figure 4 Calculation of Safety Stock (SS) and Reorder Point (ROP) for Chlorpheniramine injection 10 mg/ml.

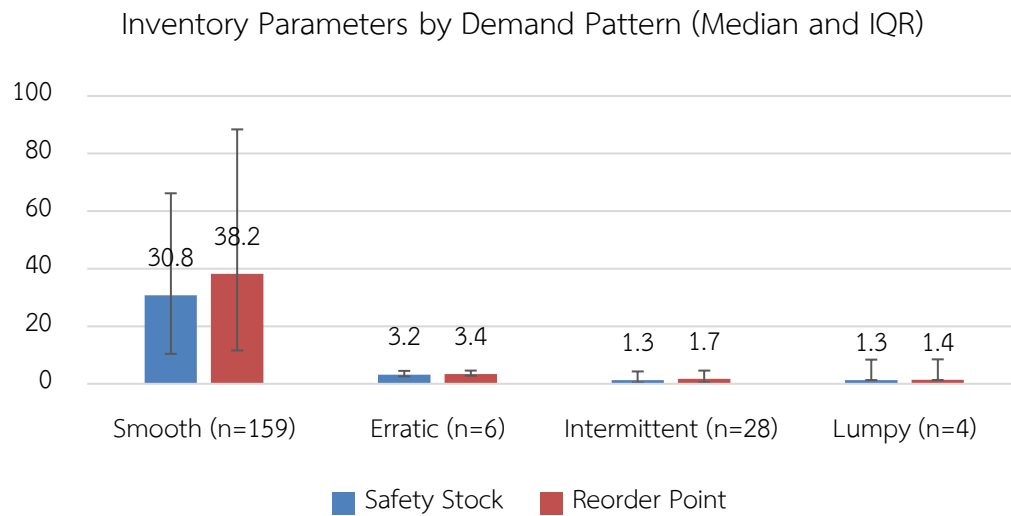


Figure 5 Group-level median SS and ROP across the four demand patterns.

		Current on-hand inventory in the IPD pharmacy		Forecasted demand for the following week		Reorder Point		Status NO = No replenishment required ORDER = Replenishment required		Number of Packs to Request		Total requested quantity
code	name	onhand	Request	Forecast	ss ปลอดภัย	ROP-D ปลอดภัย	Q ปลอดภัย	Status	เบิกทำใบ	pack	request pack	จำนวนเดิม
ACUI01	Acupan Inj 20 mg/2ml	42	10	36.2046	25	28	51	NO	-9	5	2	10
ADDI01	Addamel-N IV 10 ml	207	80	133.2851	43	64	138	NO	69	20	4	80
ADEI01	Adenocor IV 6 mg/2 ml	33	120	6.6701	10	11	15	NO	18	120	1	120
ADRI01	Adrenaline Inj 1 mg/ml *HAD	733	400	216.1016	189	235	344	NO	389	50	8	400
AETI01	Aethoxysklerol Inj 1% 2 ml	0	10	1.8348	5	5	6	ORDER	-6	5	2	10
ALBI01	Albutein 20% 50 ml	21	25	2.2517	4	4	6	NO	15	25	1	25
ALBI02	Albutein 25% 50 ml	15	25	3.6248	7	8	9	NO	6	25	1	25
ALBI04	Albutein 25% 100 ml	187	75	98.1718	43	58	114	NO	73	25	3	75
ALBI05	Albutein 5% 250 ml	89	15	58.9347	34	43	77	NO	12	15	1	15
AMII01	Aminophylline Inj 250 mg/10 ml	72	100	7.1160	12	14	18	NO	54	50	2	100
AMII02	Amikacin Inj 250 mg	93	50	38.1387	22	27	49	NO	44	10	5	50

Summary of total
requested quantity

Safety
Stock

Maximum
inventory
level (Q_i)

Request =
 Q_i - On hand

Units per
Pack (Pack
Size)

Figure 6 Development of an Excel-based drug requisition program for inventory management.

(2) Emergency opening reduction: Prior to implementation, after-hours emergency requisitions for injectable drugs occurred 53 times per year (baseline, year 2024). The proposed forecasting and inventory system establishes the following KPIs for prospective evaluation following full implementation:

(i) no more than 1 unscheduled after-hours

emergency requisition per week (≤ 52 occurrences/year), and (ii) no more than 1 drug item per week involved in an emergency requisition event. These KPIs will serve as primary outcome indicators to evaluate the clinical and operational effectiveness of the system.

Table 2 Inventory Management Formula Guide

Column Name	Excel Column	Formula / Logic	Description
On Hand	C	(Manual Entry)	Current physical stock.
Forecast	E	(Manual Entry)	Predicted weekly demand.
Safety Stock	F	(Manual Entry)	Minimum buffer stock.
ROP	G	=F2 + (E2 * (1/7))	Reorder Point: Safety Stock + (Weekly Demand × Lead Time in weeks); Lead Time = 1/7 week (1 day)
Max Stock (Q _t)	H	(Manual Entry)	The maximum capacity for that item.
Status	I	=IF(C2<=G2, "ORDER", "NO")	Triggers "ORDER" if On Hand is at or below ROP.
Request Gap	J	=H2-C2	Calculated as Maximum – On Hand.
Units per Pack (Pack Size)	K	(Manual Entry)	Number of units in one commercial pack (e.g., 10 ampoules/box).
Number of Packs to Request	L	=ROUNDUP(MAX(0, J2)/K2, 0)	Rounds up to nearest full commercial pack.
Total Units	M	=L2*K2	Final quantity is based on full packs.

NOTE: Lead Time (LT) = 1/7 week (equivalent to 1 day). Column E (Forecast) represents weekly demand. The formula =F2 + (E2 × 1/7) is equivalent to Safety Stock + (Daily Demand × 1 day), consistent with Equation (8) in Methods.

Discussion

The IPD pharmacy in this study faced several operational bottlenecks stemming from the absence of a standardised drug demand calculation framework. Requisitions relied on individual pharmacist experience rather than a unified data-driven method, leading to inaccurate orders that resulted in either stockouts or storage overflows. Inconsistencies between order quantities and commercial pack sizes created repeated communication loops between the IPD and the central warehouse, and forecasting errors frequently triggered urgent off-schedule requests, increasing staff workload and disrupting supply chain continuity. These findings are consistent with prior evidence that systematic inventory management reduces both procurement costs and stockout risk in hospital settings.¹ Research at the Queen Sirikit Heart Center,

Khon Kaen University, demonstrated that demand forecasting based on normal distribution probability reduced inventory holding value by 13.11 million Baht (23.34%) and decreased stock levels by 22 days (31.43%) without compromising medication availability.¹⁰

This study demonstrates that individually optimising α to minimise AMAPE selects the best-achievable forecasting accuracy for each demand category. The Smooth group (SES, n = 159) achieved the lowest median AMAPE (44.1%, IQR: 25.5%–68.8%) with a predominantly low α (median 0.2), reflecting that stable long-run averaging is more appropriate than high responsiveness for frequent-demand items — consistent with the recommendation of Kourentzes (2014).⁵ For Erratic items (SES, n = 6), a similarly low median α = 0.1 prevented overreaction to demand spikes (median

AMAPE 50.2%). For Intermittent and Lumpy items (Croston's Method, $n = 32$), higher optimal α values (median 0.9 and 0.6, respectively) enabled rapid updating of demand-size and inter-demand-interval estimates upon each sparse demand event (combined median AMAPE 50.0%), consistent with findings by Kalaya et al. (2019).⁸ The results are also consistent with Chen et al. (2022),⁷ who demonstrated that optimising SS and ROP calculations in an outpatient pharmacy significantly reduced drug inventory costs without compromising availability.

Regarding storage capacity and requisition frequency, $Q_t = F_t \times (L + T) + SS$ defines the replenishment ceiling for each item. Under the current three-times-per-week system (Monday, Wednesday, Friday), $L = 1/7$ week (1 day) and $T = 2/7$ week (2 days), giving $L + T = 3/7$ week. Under the proposed twice-per-week system (Monday and Friday) applied in this study, T is extended to $4/7$ week (4 days) while L remains unchanged, giving $L + T = 5/7$ week — increasing Q_t by approximately 1.67-fold. Should a further reduction to once-per-week ordering be considered, L would remain at $1/7$ week while T increases to 1 week, giving $L + T = 8/7$ weeks, raising Q_t by approximately 1.60-fold relative to the twice-per-week system. However, a transition to once-per-week ordering must be preceded by careful assessment of available shelf space, per-cycle procurement budget, and drug expiry risk, particularly for high-volume Smooth items. For items where calculated Q_t under any ordering frequency exceeds available shelf space, pharmacists are advised to split the order across cycles or request temporary shelf expansion, ensuring every optimal quantity remains a feasible quantity that balances mathematical efficiency with physical storage constraints.² The 90% service level target is maintained for all items where Q_t is physically feasible, with service level recorded as a target pending physical confirmation for constrained items.

For Vital life-saving drugs in non-Smooth demand categories, purely mathematical SS calculations may be insufficient. A clinically determined minimum stock of 1–2 treatment courses — based on standard dose-response calculations — should be maintained as an inviolable floor independent of the mathematical SS. This is complemented by the multi-layered safeguard approach embedded in the Excel dashboard: (1) SS is calculated conservatively at a 90% service level ($Z = 1.282$) to buffer against demand spikes; (2) the dashboard automatically triggers an "ORDER" status when on-hand stock falls at or below the ROP, regardless of forecast accuracy; and (3) pharmacists retain manual override capability based on clinical judgment. Together, these safeguards ensure that high-AMAPE items in Intermittent and Lumpy categories do not translate into clinical stockout risk.¹¹

In terms of policy, this study recommends that the hospital develop a Standard Operating Procedure (SOP) for medication forecasting and requisitioning, utilising models tailored to each demand category. Integration with the hospital's SMI system for real-time inventory monitoring would further reduce manual data entry and support timely decision-making — a critical step toward Smart Pharmaceutical Logistics.

Limitations of this study include: (1) the 26-week historical dataset may not fully capture seasonal demand fluctuations; (2) findings are limited to non-refrigerated injectable drugs and may not generalise to refrigerated items; and (3) the Excel-based tool requires manual data entry and is not yet integrated with the hospital SMI system. Future work should address real-time SMI integration, expansion to refrigerated drugs, and prospective evaluation of the system's impact on actual stockout rates and emergency requisition frequency post-implementation.

Conclusion

This study successfully developed and implemented a data-driven inventory forecasting and management system for the Inpatient Pharmacy Department of a university hospital. By classifying 197 non-refrigerated injectable drugs into four demand categories (Smooth, Intermittent, Lumpy, and Erratic) and applying appropriate forecasting methods with individually optimized smoothing parameters (α), the system provides a systematic and evidence-based approach to replace the previously experience-based requisition process.

For the dominant Smooth group (159 items, 80.7%), Simple Exponential Smoothing with a predominantly low α value (median 0.2) achieved a median AMAPE of 44.1%, reflecting that down-weighting recent observations is generally more appropriate for this group. For Intermittent and Lumpy items, Croston's Method with higher optimal α values (median 0.9 and 0.6, respectively) was applied to enable responsive updating of sparse demand estimates. Safety Stock and Reorder Point were calculated based on a 90% service level ($Z = 1.282$), a lead time of $L = 1/7$ week (1 day), and a review period of $T = 4/7$ week (4 days) under the proposed twice-weekly requisition system, with the Maximum Inventory Capacity (Q_t) determined by the formula $Q_t = F_t \times (L + T) + SS$, with pharmacists advised to verify that orders do not exceed available shelf space. The Excel-based decision support tool provides pharmacists with automated, pack-size-aligned order recommendations, transforming the requisition process from a manual, experience-based task into a precise and systematic workflow. For Vital life-saving drugs in non-Smooth demand categories, a clinically determined minimum stock of 1–2 treatment courses is recommended as a safety floor beyond the mathematical Safety Stock calculation.

The proposed system establishes the following KPIs for prospective evaluation: no more than 1 unscheduled after-hours emergency requisition per week (compared to the baseline of 53 occurrences

per year), and a 90% service level for Smooth items. Future research should prospectively evaluate these outcomes following full implementation, and further development should prioritize integration with the hospital's SMI system for real-time inventory updates and expansion of the forecasting model to refrigerated injectable drugs.

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