

Improving Demand Forecasting for Haemodialysis Consumables in Zambia: A Comparative Analysis of Time-Series Models

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Abstract

Background: Reliable forecasting of renal consumables is essential to prevent stock-outs and ensure uninterrupted dialysis services in Zambia's public health facilities. Recurrent shortages occur partly due to reliance on basic methods, such as the simple moving average (SMA), which struggles to capture trends and variability amid a rising burden of chronic kidney disease. This study aimed to evaluate and compare the accuracy of advanced time series predictive models against traditional forecasting methods for renal consumables at the University Teaching Hospital (UTH) in Lusaka, thereby establishing a data-driven framework for preventing stock-outs in specialised tertiary care. **Methods:** This retrospective, quantitative study analysed historical monthly consumption records (2023-2025) of key renal consumables at the University Teaching Hospital (UTH) Adult Hospital. Time series models, Weighted Moving Average (WMA), Exponential Smoothing (ES), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Dynamic Regression, were compared against the baseline SMA using rolling-origin cross-validation and error metrics, specifically Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Data analysis was conducted using Python libraries. **Results:** Analysis of historical consumption patterns revealed significant demand variability across renal consumables, with the coefficient of variation ranging from a low of 9.0% for disinfectants to a high of 47.4% for sodium bicarbonate, indicating a mix of stable and highly stochastic demand profiles. Advanced time-series models consistently outperformed the simple moving average (SMA) baseline for most stock-keeping units. At 25.80% MAPE, Exponential

smoothing resulted in 67% error reduction improvement over baseline for sodium bicarbonate while SARIMA achieved 32% error reduction improvement over baseline for disinfectants at 0.60% MAPE. Notably, no significant seasonality was detected, as demand was primarily characterised by long-term consumption trends and irregular consumption fluctuations rather than cyclical consumption patterns. **Conclusion:** The findings of this study showed that time-series models significantly outperformed the traditional simple moving average forecasting method which is currently used in the Zambian public health system. Exponential smoothing performed well for bloodline giving sets and heparin anticoagulant. SARIMA performed well for dialysis machine disinfectants, WMA for renal concentrate dialysate and sodium bicarbonate buffer. Implementing time-series models can improve forecasting accuracy and can improve prediction of demand for renal consumables. These improvements have critical implications for hospital supply chain management. Accurate prediction can improve inventory planning and would ensure the continuity of life-saving dialysis services.

Keywords

Demand Forecasting, Language Models, Renal Consumables, SARIMA, Predictive Models, Supply Chain, Time Series Models, Zambia

1. Introduction

Chronic kidney disease (CKD) is a significant global public health concern, with a steadily increasing mortality rate over recent decades (Chen et al., 2023). Globally, CKD affects approximately 10% - 13% of the population, contributing substantially to morbidity and mortality (Japiong et al., 2023). In Africa, prevalence estimates range from 4.6% to 10.1%, with a disproportionately higher burden observed in low-and middle-income countries (LMICs), particularly in sub-Saharan Africa (Hariparshad et al., 2023). A systematic review estimated the overall prevalence of CKD stages 1 - 5 in sub-Saharan Africa at approximately 17.7%. This is considerably higher than the 6.1% reported in North Africa (Ghosh & Khandoker, 2024). The elevated burden of CKD has been linked to hypertension, diabetes mellitus, and infectious diseases (Ghosh & Khandoker, 2024).

Public health interventions for CKD prevention and management remain limited in many low-income countries (Bosomprah et al., 2023). Globally, few programs exist to promote kidney health, resulting in delayed diagnosis, inadequate disease monitoring, and increased demand for tertiary healthcare services (Fatima & Rahimi, 2024). In Zambia, the rising demand for renal consumables within public health facilities reflects both the increasing incidence of CKD and ongoing challenges in forecasting demand and planning for renal care (Hariparshad et al., 2023).

The primary drivers of CKD in Zambia include diabetes mellitus, hypertension,

and chronic glomerulonephritis (Fatima & Rahimi, 2024). Despite the growing disease burden, national healthcare responses remain constrained. Evidence indicates that most CKD cases in Zambia are diagnosed at an advanced stage, often after progression to kidney failure (Bosomprah et al., 2023). Evidence suggests that increased community awareness, targeted screening of high-risk populations, and early prevention strategies can significantly improve outcomes and reduce the progression to dialysis-dependent diseases (Hariparshad et al., 2023). However, Zambia currently lacks systematic CKD prevention and early detection programs, resulting in late diagnoses and heavy reliance on limited dialysis facilities (Ong et al., 2023).

The accurate forecasting of medical supply requirements is essential for the effective functioning of healthcare services, as it ensures the timely availability of critical consumables (Chen et al., 2023; Mbuze et al., 2026; Makowane et al., 2026; Kapobe et al., 2026). In recent years, language models or predictive approaches that utilise computational techniques have demonstrated increasing value in supporting healthcare supply chain planning (Stacey et al., 2024). However, if renal consumables are not forecasted properly, consumption patterns can be severely disrupted. Shortages may lead to missed or interrupted dialysis sessions, compromising patient outcomes and increasing morbidity or mortality risks among those with end-stage kidney disease (Cohen et al., 2019). Previous evidence has found that a random forest model applied to medicines for chronic diseases achieved a training accuracy of 78% and a testing accuracy of 71% in predicting future demand trends (Ghosh & Khandoker, 2024). Similarly, empirical evidence has shown that shallow neural networks can produce lower forecasting errors, measured using root mean square error (Das et al., 2024). In contrast, the simple moving average (SMA) method, which relies solely on averaging historical consumption data, demonstrates limited capacity to account for trends, seasonality, or sudden shifts in demand patterns (Zhou et al., 2018). These limitations reduce its suitability for healthcare environments and are characterised by dynamic and time-dependent demand. Time-series models, such as autoregressive integrated moving average (ARIMA) and exponential smoothing techniques, are better equipped to capture underlying temporal structures in demand data. These models are computationally efficient, relatively easy to interpret and well suited for application in public health settings where transparency and operational feasibility are critical (Brownlee, 2018).

In many public healthcare systems, particularly in resource-constrained environments, time-series forecasting models offer a practical, interpretable, and evidence-based alternative (Stacey et al., 2024). This study applied these models and evaluated their performance relative to the simple moving average method which remains widely used in public health inventory management. The findings provide a structured framework for improving demand prediction accuracy and supporting more effective resource planning and medical supply availability at UTH in Lusaka Zambia.

2. Materials and Methods

2.1. Study Design, Site and Population

This study adopted a quantitative, comparative, and retrospective research design (Creswell, 2014). Month-to-month historical utilisation and stock records of renal consumables were analysed over a period of 36 months (January 2023 to December 2025). Graphical analysis was used to describe historical utilisation patterns, after which comparative analysis evaluated the forecasting performance of the SMA method and selected time series forecasting models using the same datasets. This study was retrospective because it relied on historical numerical data and statistical accuracy measures. Comparative because it assessed forecasting methods against each other. This study was conducted at the UTH in Lusaka, Zambia. The institution constituted the study site from which the study population and relevant data on renal consumable demand were obtained.

The study included all critical renal consumable stock keeping units at UTH that had availability of at least 36 consecutive months of historical monthly consumption data. Data completeness of at least 90% corresponding to fewer than 10% missing monthly observations was ascertained. Other considerations included routine and continued use in dialysis service delivery throughout the observation period and classification of clinically critical for dialysis treatment cases based on facility protocols and expert consultation. Monthly consumption was defined as the total quantity of each renal consumable SKU issued for use in dialysis services within a calendar month, as recorded in pharmacy stock issue records, dialysis unit consumption registers, bin cards and electronic logistics management records where available. Consumption values represented quantities physically utilised or issued for patient care during each month. The study took account of external factors such as number of dialysis sessions and patient load as predictors for the dynamic regression model. The use of external factors depended on data availability. During the study period, dialysis sessions were sometimes reduced from three times a week to twice a week because of supply shortages of consumables as evidenced by logistics and clinical records. Including these factors helped improve the forecast accuracy for the dynamic regression model. Months affected by stock-outs or rationed dialysis sessions were not excluded from analysis because they reflected operational realities influencing observed utilisation. However, these periods were identified using logistics and clinical records and interpreted cautiously since observed consumption during stock-outs may underestimate actual clinical demand. Information on reduced dialysis frequency and patient load was incorporated as external covariates in the dynamic regression model where such records were available.

This study excluded all renal consumable SKUs which had more than 10% missing or inconsistent monthly data which would render time-series modelling unreliable. Thus, only SKUs with at least 90% complete monthly observations corresponding to no more than 10% missing values were eligible for inclusion. Other exclusion parameters included discontinued SKU, substituted drugs, major for-

mulation change during the study period without continuous record linkage and items used sporadically or only during emergencies, where consumption patterns could not be meaningfully modelled.

2.2. Sample Size and Sampling Technique

The study utilised a total enumeration sampling approach, incorporating all critical renal consumables identified as essential for dialysis procedures at UTH. Critical in the sense that unavailability of any one of these consumables would result in a missed dialysis session. The critical renal consumables included, bloodlines giving sets for carrying blood from the patient to the dialyser for filtration and back to the patient, dialysers or artificial kidneys for cleaning blood by removal of waste and extra fluid, renal concentrate dialysate blood cleanser, disinfectant equipment sterilization, heparin as an anticoagulant and sodium bicarbonate for blood pH maintenance. This method ensured complete coverage of the critical stock-keeping units based on clinical relevance, consumption volume and data completeness.

A formal sample size calculation time steps were not performed because time-series forecasting models do not depend on hypothesis testing, statistical power, or predefined effect sizes (Hyndman & Athanasopoulos, 2021). Unlike inferential statistical models, forecasting approaches such as simple and weighted moving averages, SARIMA, and dynamic regression are evaluated primarily based on their ability to produce accurate out-of-sample predictions (Hyndman & Athanasopoulos, 2021). The adequacy of the data was ensured by assessing the length of the historical series relative to the model complexity and validating the model performance against out-of-sample (2025) data. Furthermore, this study encompassed all critical renal consumables recorded from 2023 to 2025, providing a comprehensive dataset for predictive analysis.

2.3. Data Analysis Using Python (SciPy)

Data from the UTH Adult Hospital were extracted using a standardised extraction tool imported into Python (SciPy) for analysis. Data analysis was performed using Python (version 3.x) with the following key libraries: pandas for data manipulation and descriptive statistics; NumPy and SciPy for numerical computations, correlation analysis, autocorrelation (ACF) plots, and paired t-tests; Matplotlib and Seaborn for visualisation of trends, scatter plots, and monthly profiles; and statsmodels for SARIMA model fitting and diagnostics. To understand the data, basic descriptive statistics were computed for each renal consumable, including the mean monthly consumption, standard deviation, minimum and maximum consumption used from 2023 to 2025, and coefficient of variation to compare variability relative to the average.

Pre-model diagnostics were conducted on the time-series data prior to model testing. Stationarity was assessed using the Augmented Dickey-Fuller (ADF) test to determine whether differencing was required. Autocorrelation function (ACF) plots were examined to identify temporal dependencies and inform model order

selection for SARIMA and related approaches.

Forecasting was undertaken using a rolling-origin cross-validation approach to assess out-of-sample predictive performance (Cerqueira et al., 2020). This method involves training models on expanding historical windows and generating forecasts for subsequent periods and simulating real-world rolling forecasts (Goodwin et al., 2024).

Model specification procedures were predefined to improve reproducibility of the forecasting comparison. The SMA model used a three-month moving window, while the weighted moving average (WMA) model applied a three-month weighted window with greater emphasis placed on the most recent observations using weights of 0.5, 0.3 and 0.2. Exponential smoothing was implemented using the Holt-Winters error, trend and seasonality (ETS) framework, with model forms selected automatically based on the lowest Akaike Information Criterion (AIC). Final SARIMA model orders for each SKU were selected after examining stationarity, ACF and partial autocorrelation function (PACF) plots together with AIC and diagnostic residual checks. The dynamic regression model incorporated external covariates including monthly dialysis sessions and patient load where records were available, with lag structures assessed using cross-correlation analysis and model fit statistics.

To determine the most suitable forecasting approach, multiple methods were compared. These included the SMA and the comparator and selected time-series forecasting models exponential smoothing, SARIMA, weighted moving average, and dynamic regression. Forecast accuracy was evaluated using two standard metrics, mean absolute error (MAE) and mean absolute percentage error (MAPE). Mean Absolute Percentage Error (MAPE) was predefined as the primary model-selection metric because it provides a scale-independent measure that allows comparison of forecasting accuracy across different renal consumables with varying utilisation volumes. Mean Absolute Error (MAE) was treated as the secondary metric to provide interpretation of forecasting deviations in original consumption units. These metrics quantify different aspects of error. MAE provides an average absolute deviation in original units, and MAPE offers a scale-independent percentage-based measure (Hyndman & Athanasopoulos, 2021). Lower values indicate better performance in healthcare supply chain contexts (Makridakis et al., 2018). MAPE values below 20% - 30% are often considered acceptable for stable demand items, while higher thresholds may apply to intermittent or variable demand (Makridakis et al., 2018; Tadayonrad & Ndiaye, 2023). Comparative statistical tests, specifically paired t-tests, were applied to assess whether the observed differences in predictive performance between SMA and the best advanced model were statistically significant. A 95% confidence interval was used and p -values < 0.05 were considered statistically significant. The followed conventional thresholds in forecasting model comparisons (Makridakis et al., 2018). This process was rigorously analysed to ensure a transparent evaluation of model performance, which was tailored to the characteristics of the renal consumable time-series data at UTH.

A paired t-test was used to determine whether the reduction in forecasting error achieved by the advanced models was statistically significant. The differences in errors were calculated for each month from January to December. The analysis was performed using Python (SciPy), and the paired t-test was run in Python (SciPy). A significance level of $p < 0.05$ was used, indicating that the results were considered statistically significant if the p -value was less than 0.05.

Dynamic regression results were analysed and reported alongside SMA, weighted moving average, exponential smoothing and SARIMA models for all SKUs where external covariate data were available. The external variables consistently available for modelling included monthly dialysis session counts and patient load records. Where external variables were incomplete or unavailable for specific SKUs or months, dynamic regression was excluded from comparative interpretation for those instances and this was clearly indicated in the results section.

The selected models, dynamic regression, exponential smoothing, SARIMA and weighted moving average, were chosen because they are widely used in time-series forecasting and capture different demand patterns such as trends and seasonality (Ajiono, 2023; Xian et al., 2023).

2.4. Data Quality Procedure

Missing data were filled in using linear interpolation. Linear interpolation estimates missing values by drawing a straight line between known points (Noor et al., 2013). This helps keep the data's trend steady without sudden changes. Linear interpolation was used instead of methods such as seasonal decomposition because it offers a balance of simplicity and transparency for small gaps in demand data which can reasonably be presumed to change gradually over time. Only datasets with no more than 10% missing monthly observations were eligible for interpolation and inclusion in the analysis. The number and proportion of interpolated observations for each SKU were documented and reported in the results section to ensure transparency regarding the extent of missing-data adjustment.

2.5. Data Governance

The study adhered to Zambia's Data Protection Act and Institutional data governance requirements. The Ministry of Health and ZAMMSA are the official data controllers and the University of Zambia kept the data legally as the academic data custodian. Only the main researcher could see the raw data. All data were made anonymous by replacing the facility name with a code to protect privacy. Data were stored safely on secure devices and were not shared openly. Data were kept only as long as needed for the study and then stored safely.

2.6. Data Reliability

To make sure the results were correct, only reliable and complete records were used. The models were tested using train-test splits and cross-validation to ensure they worked well in different cases (Qiu, 2024). Consistency was improved by fol-

lowing standard procedures and using trusted software. Additional tests checked if the models were strong across different times and product types.

The researchers first tested their methods with data from a pilot hospital to see if everything worked well. This pilot checked data quality, model setup and accuracy. The pilot needed at least 24 months of good data to ascertain accuracy. The pilot results helped improve the main study's methods. If some data was poor, replacement with better data in the final study was made.

2.7. Ethical Approval

The study upheld the highest ethical standards in accordance with recognised principles of research ethics, including respect for persons, beneficence, non-maleficence, and justice. Ethical approval was obtained from the University of Zambia Health Sciences Research Ethics Committee (UNZAHSREC) Protocol ID 2023270450 and the Zambia National Health Research Authority (NHRA) Protocol ID NHRA-2735/23/09/2025. We also got clearance UTH management to conduct the study at their institution.

The data used were historical and applied solely for forecasting and public health improvement, and not for personal purposes. Facility stock levels were anonymised and stored securely. No personal identifiers or patient-level information were collected or analysed. This approach ensured that individual privacy and autonomy were fully respected.

Finally, the study upheld scientific integrity by maintaining transparency, objectivity accountability throughout the design, analysis and reporting of the results. All data handling complied with the ethical and legal standards for data protection.

3. Results

3.1. Descriptive Statistics of Renal Consumables Utilisation at UTH-Adult Hospital

Table 1 presents the descriptive statistics of monthly consumption for the six critical renal consumables. Renal concentrate recorded the highest average consumption (mean = 664.6 units), followed by bloodlines and sodium bicarbonate. Disinfectant exhibited the lowest mean consumption (95.7 units), indicating stable use. Sodium bicarbonate demonstrated the highest relative variability (CV = 47.4%), suggesting substantial fluctuations in monthly demand. Dialysers, bloodlines, renal concentrates, and heparin exhibited moderate variability (CVs ranging from 24.9% to 33.7%). This indicated relative stable demand with occasional fluctuations.

Table 1. Descriptive statistics of renal consumables at UTH-adult hospital from 2023-2024.

Consumable	Mean	Standard deviation	Minimum	Maximum	Coefficient of variation (%)
Dialysers	309.3	104.1	118	625	33.7

Continued

Bloodlines	399.6	115.0	202	609	28.8
Renal concentrate	664.6	205.6	297	1101	30.9
Sodium carbonate	364.7	173.0	111	690	47.4
Disinfectant	95.7	8.6	60	130	9.0
Heparin	312.6	77.7	109	445	24.9

3.2. Trends of Renal Consumables at UTH-Adult Hospital from 2023-2024

Most consumables displayed gradual declining demand trends over the period under observation with varying fluctuations across the SKUs (Figure 1). Bloodlines and renal concentrates showed consistent downward patterns indicating relative demand stability. Dialysers and heparin exhibited moderate demand declines with occasional fluctuations whereas disinfectant exhibited steady demand. Sodium bicarbonate had the most irregular demand pattern. The trends indicated that most consumables had a long-term declining demand and the degree of variability differed across consumables.

Monthly Consumption Trends with Linear Trendlines

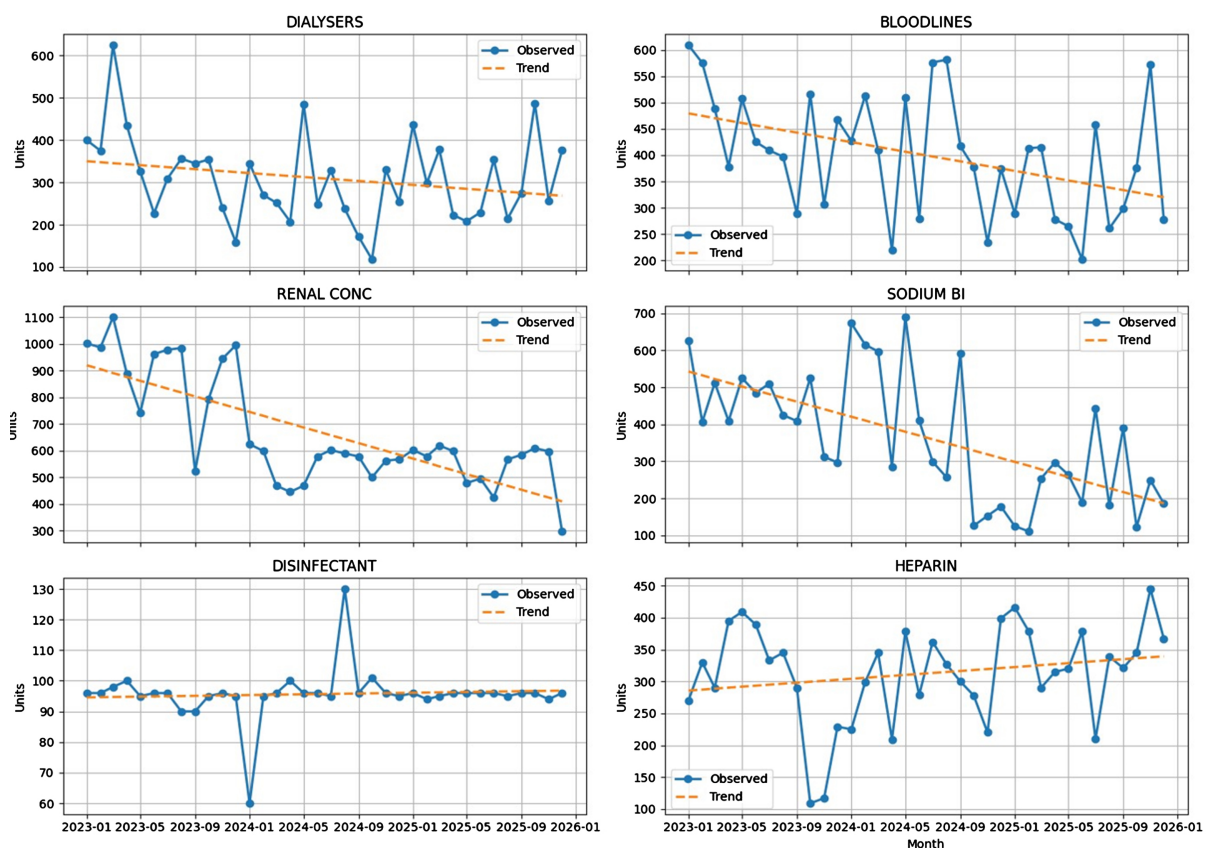


Figure 1. Monthly consumption trends for renal consumables with fitted linear trend lines, illustrating long-term usage patterns and demand variability. Bloodlines exhibited p -value < 0.0243 , heparin < 0.0045 , sodium bicarbonate < 0.0001 , disinfectant < 0.0007 whereas dialysers and renal concentrate were not significant.

3.3. Trends of Renal Consumables and Number of Dialysis Sessions at UTH-Adult Hospital

Several consumables correlated with dialysis session volumes, although the strength of this relationship differed among the SKUs (Figure 2). Dialysers and bloodlines showed a generally positive association with the number of dialysing sessions, with higher consumption often coinciding with periods of increased dialysis activity. Renal concentrate and sodium bicarbonate showed greater fluctuations in relation to dialysis session counts. Consumption of disinfectants remained remarkably stable across the study period, with minimal changes in session volume. The consistency of usage was largely unaffected by short-term fluctuations in operational activity. Heparin showed a moderate correlation with dialysis session volume. However, heparin displayed significant deviations, especially during periods of increased consumption. This did not match with corresponding rise in dialysis sessions.

Monthly Consumable Usage vs Number of Sessions (Faceted)

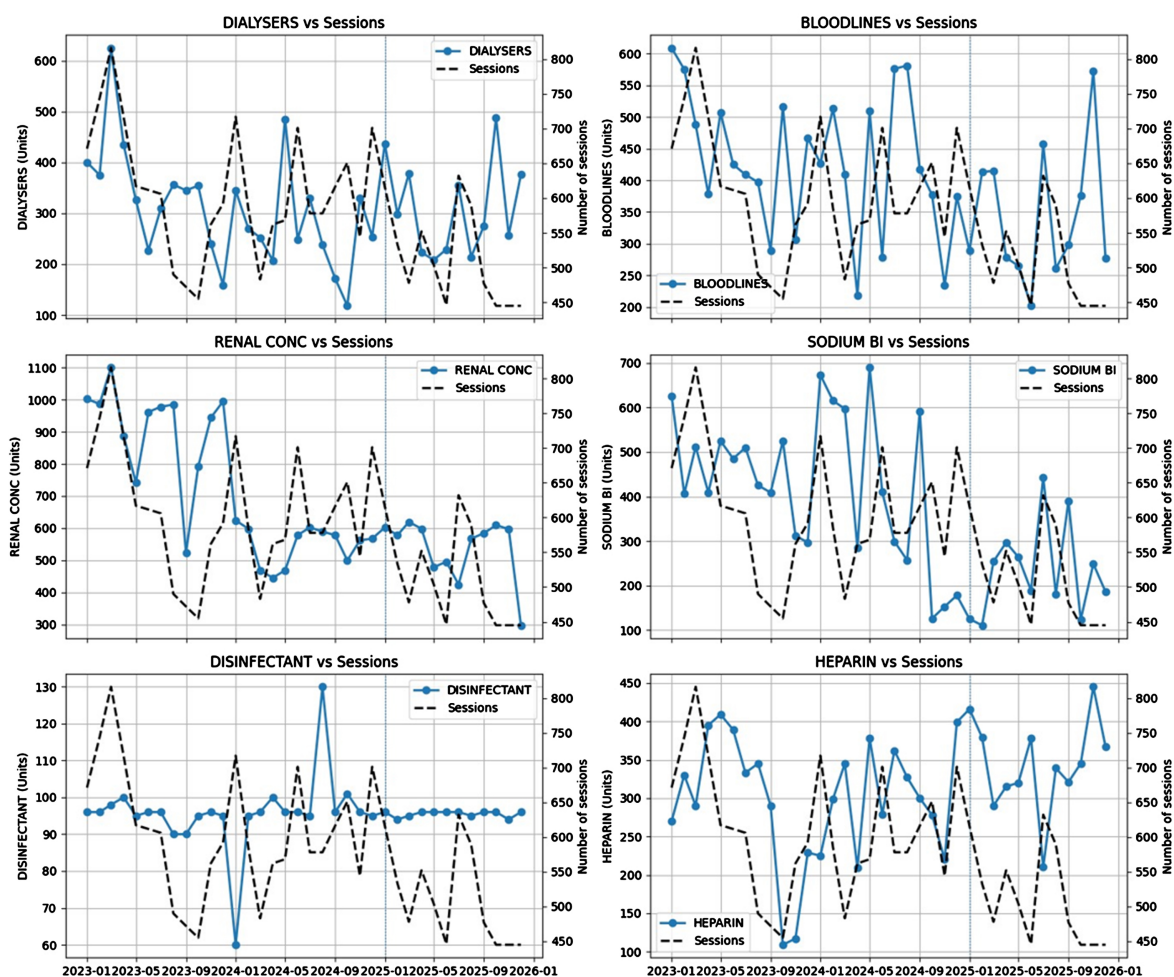


Figure 2. Faceted dual-axis plots showing monthly consumable usage (left y-axis) and number of dialysis sessions (right y-axis), highlighting varying degrees of association across consumables. Bloodlines exhibited p -value < 0.0243 , heparin < 0.0045 , sodium bicarbonate < 0.0001 , disinfectant < 0.0007 whereas dialysers and renal concentrate were not significant.

3.4. Python-Assessed Relationship between Consumption of Renal Consumables and Number of Dialysis Sessions

The data was analysed using Python to plot a faceted scatter plot graph to compare and assess an observable relationship between renal consumables and the number of dialysis sessions at UTH. Dialysers, bloodlines, renal concentrates, and sodium bicarbonate showed positive associations with dialysis session volume, as indicated by upward-sloping trend lines (Figure 3). Renal concentrates and sodium bicarbonate showed the steepest trends, indicating stronger sensitivity to changes in renal service volume. Disinfectants displayed a flat trend, with usage remaining largely constant across a wide range of session volumes. Heparin showed a weak association with session volume, with a near-horizontal trend and considerable scatter, suggesting that factors, such as dosing practices, play an important role in determining usage.

Relationship Between Consumable Usage and Number of Sessions

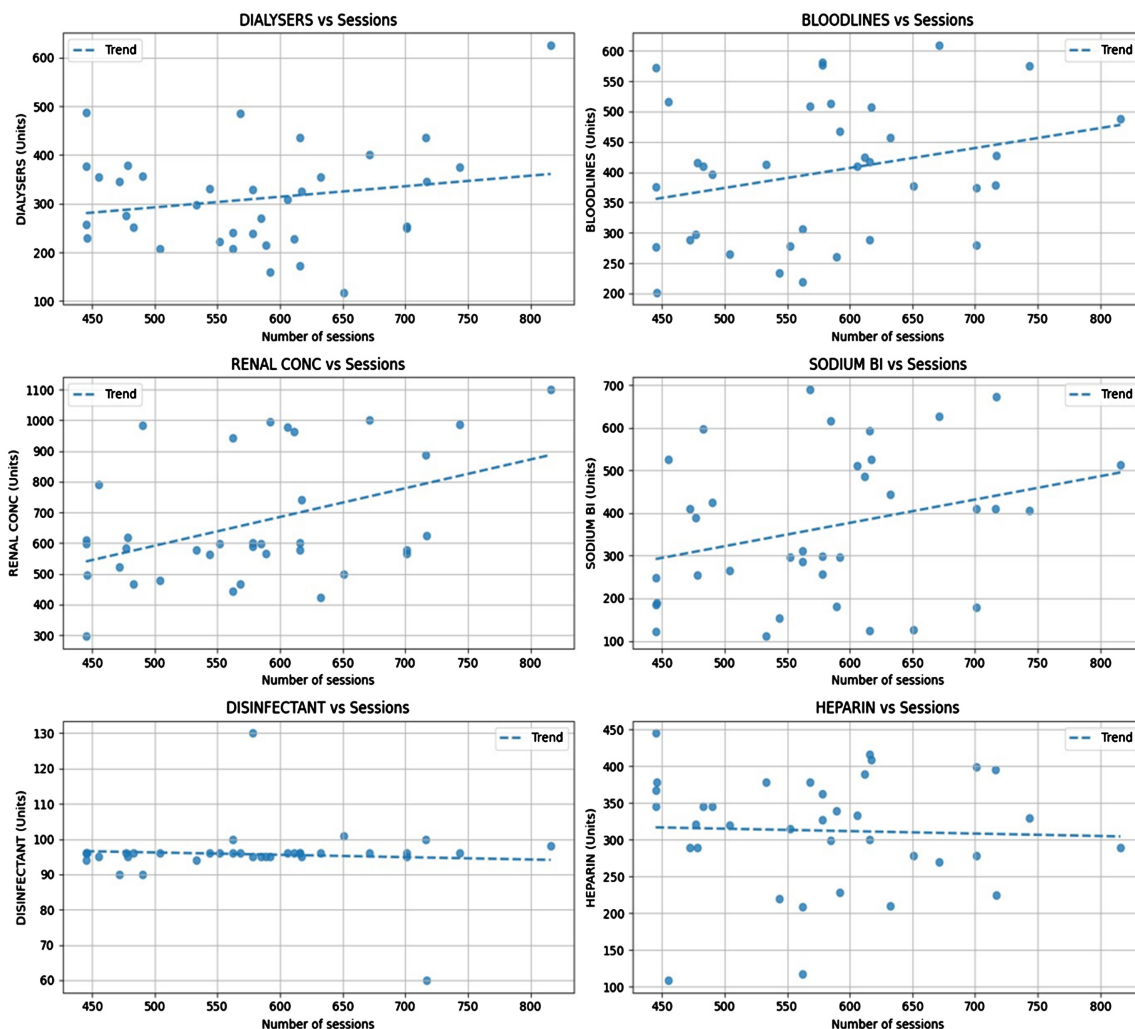


Figure 3. Faceted scatter plots showing the relationship between monthly consumable usage and the number of dialysis sessions, with fitted linear trend lines.

3.5. Assessing Irregularity in the Consumption of Renal Consumables at UTH from 2023-2024

Python was used across all consumables to assess whether there was an observable trend during the monthly profiles for 2023 and 2024 (Figure 4). Consumables did not exhibit consistent or repeating peaks and troughs in the same calendar months, indicating that consumption patterns of renal consumables at UTH showed no predictable seasonal or cyclical fluctuations within the year.

Seasonality Check: Monthly Consumption Patterns (Training Period)

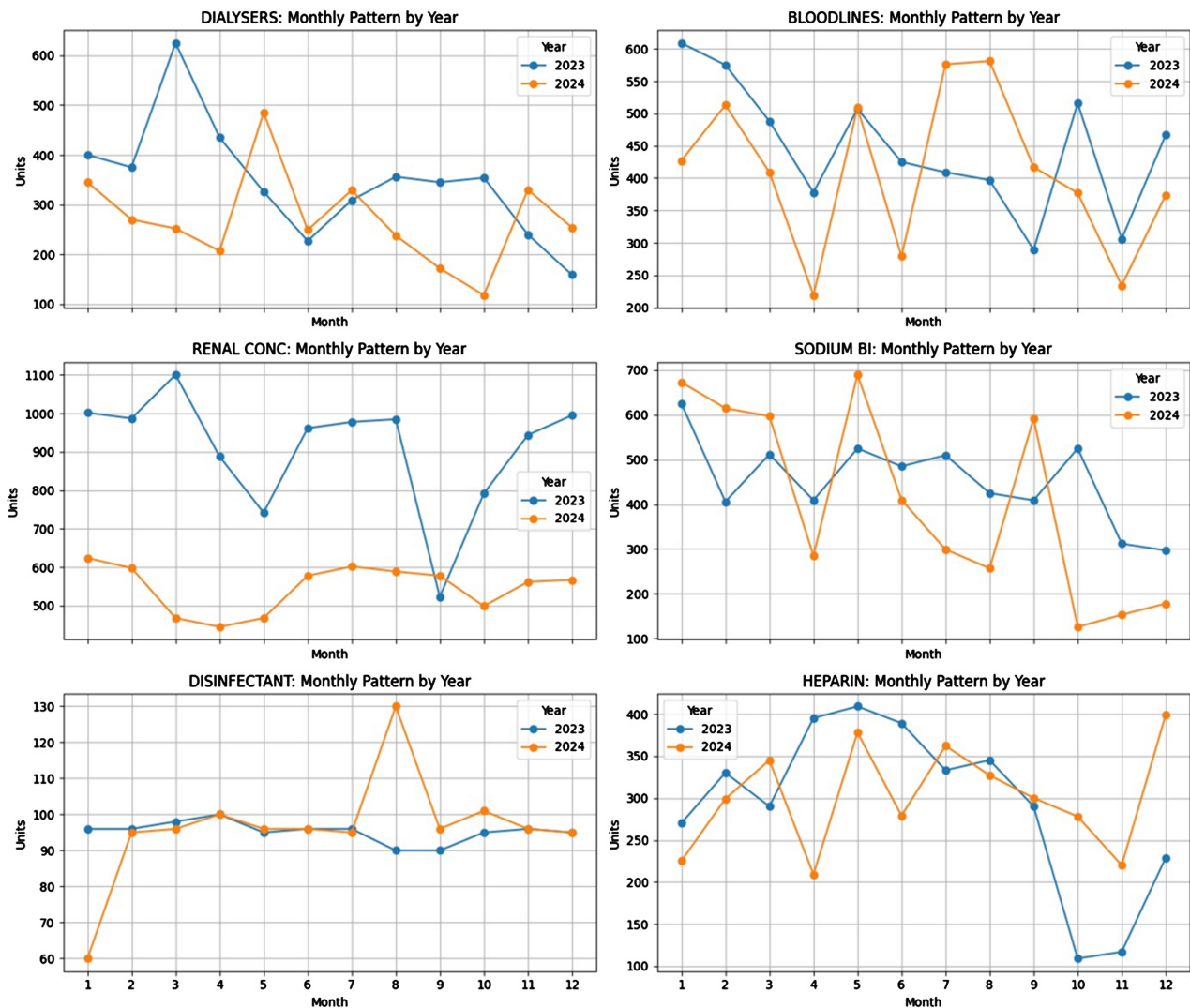


Figure 4. Faceted monthly consumption patterns by year (2023-2024) for renal consumables, indicating the absence of consistent effects.

For all consumables, the autocorrelation coefficients at a 12-month gap detected yearly irregular patterns in monthly data. At 95% confidence limits no statistical significance was observed (see Figure 5). This indicates an absence of consistent annual seasonal patterns in the demand.

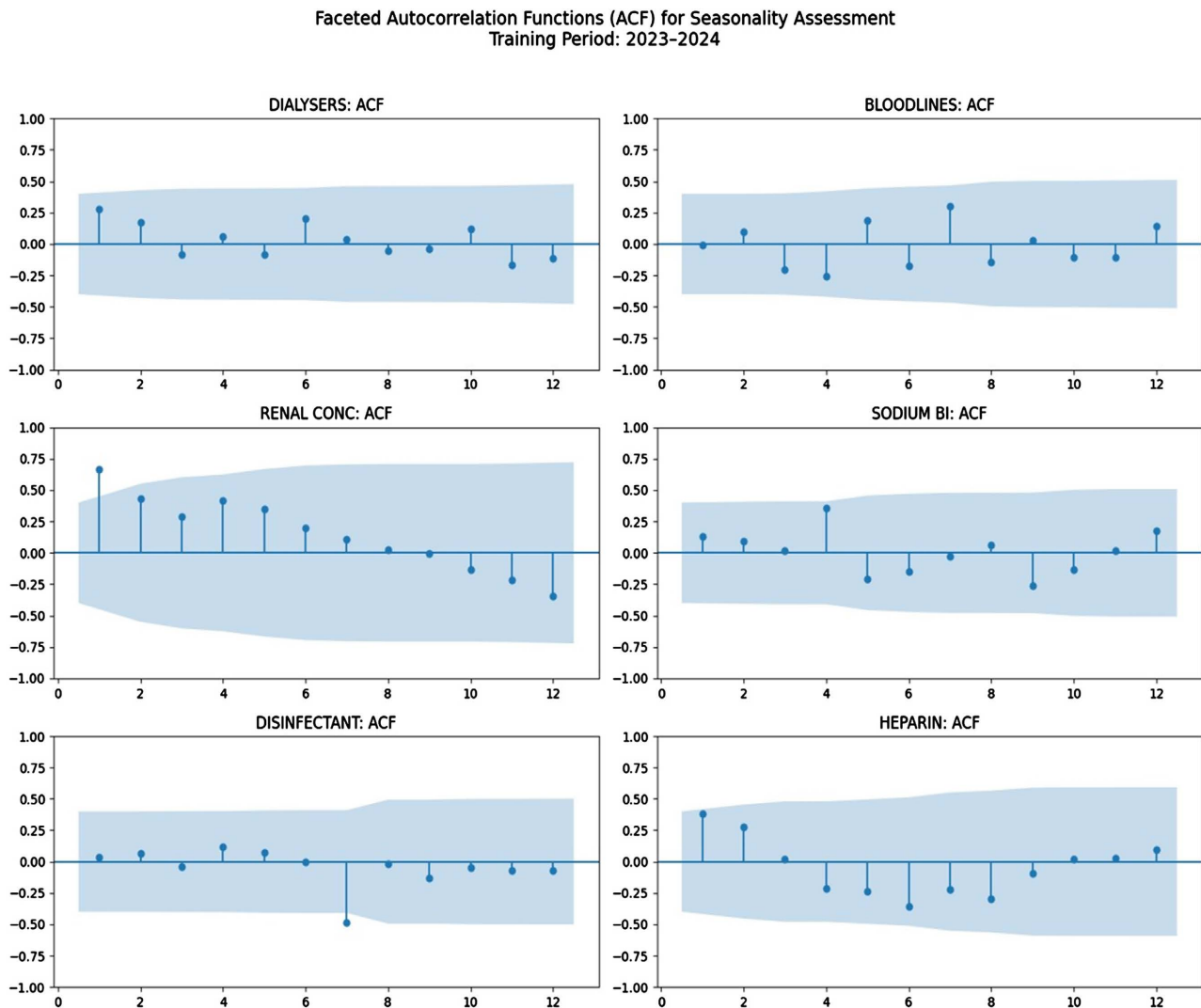


Figure 5. Faceted autocorrelation function (ACF) plots for monthly renal consumable usage during the training period (2023-2024), showing no evidence of seasonal autocorrelation at lag 12.

Renal concentrate had stronger connections with itself at short time. This showed slow changes over time but these connections became weaker at longer gaps and did not follow an irregular demand pattern. Sodium bicarbonate exhibited irregular autocorrelation patterns with alternating signs, indicating high fluctuations rather than structured irregularity. Renal disinfectant showed very little connection with itself over time because demand was very steady and was based on a set routine. Heparin exhibited modest autocorrelation at short time intervals but did not show significant correlations at longer time intervals.

3.6. Forecasting Accuracy and Performance of Different Time-Series Models (SMA, WMA, ETS, SARIMA, Dynamic Regression) for Renal Consumables at UTH-Adult Hospital in 2025

Model performance differed noticeably depending on the type of consumable.

This differed performance reflected the variability of the demand at UTH. To evaluate how well each model performed, two standard error metrics were used, the mean absolute error (MAE) and mean absolute percentage error (MAPE). These metrics compare forecasted values with actual consumption for the length of the study period.

Mean Absolute Error (MAE) measures the average size of the errors without considering their direction (Wang & Lu, 2018). It is calculated as:

$$\text{MAE} = (1/n) \times \sum |\text{Actual}_t - \text{Forecast}_t|$$

where n is the number of observations and $|\text{Actual}_t - \text{Forecast}_t|$ is the absolute difference at time t . MAE is easy to interpret and gives a good sense of typical error in the same units as the data.

The mean absolute percentage error (MAPE) expresses errors as a percentage of the actual values, making it easier to compare across consumables with significantly different scales (Khoshvaght et al., 2025).

$$\text{MAPE} = (1/n) \times \sum |(\text{Actual}_t - \text{Forecast}_t) / \text{Actual}_t| \times 100.$$

The MAPE is intuitive for communicating performance to non-technical stakeholders, although it can become very large or undefined when the actual consumption is zero. This occurred occasionally for some items, such as sodium bicarbonate (Kim & Kim, 2016).

All data processing, statistical analysis, and visualisation were performed in Python (version 3.x) within a Jupyter Notebook environment for reproducibility. Key libraries included,

- 1) **Pandas**—for data cleaning, descriptive statistics, rolling calculations, and data frame manipulation
- 2) **NumPy**—for numerical operations and array-based computations
- 3) **SciPy. Stats**—for correlation tests and paired t-tests
- 4) **Matplotlib**—for line plots and scatter plots
- 5) **Stats models**—for Exponential Smoothing, SARIMA, and ACF diagnostics
- 6) **Custom functions**—for SMA, WMA, MAPE and MAE

Table 2 shows the formulas used to acquire the results that are displayed in **Table 3**.

Table 2. Formulas used in this study.

Method	Description	Formula
Simple moving average (SMA)	Averages the most recent past values in the data	Simple Moving Average = $X_1 + X_2 + X_3/n$ Where: X_1, X_2, X_3 = past monthly demand n = number of periods
Weighted moving average (WMA)	Assigns predetermined weights to each price point, typically assigning higher weights to more recent data.	$\tilde{\sigma}_{t+1}^2 = \frac{\sum_{j=0}^{m-1} w_j \hat{\sigma}_{t-j}^2}{\sum_{j=0}^{m-1} w_j}$ where w_j are the weights

Continued

Exponential smoothing (ETS)	Gives more weight to recent observations and decreases the weights of older ones exponentially	$\hat{\sigma}_{t+1}^2 = (1-\beta)\hat{\sigma}_t^2 + \beta\hat{\sigma}_t^2$
SARIMA	Seasonal autoregressive integrated moving average model for time series data with components	$\Phi(B^s)\phi(B)(1-B)^d(1-B^s)^D Y_t = \Theta(B^s)\theta(B)\epsilon_t$
Dynamic Regression	Regression model that incorporates lagged values of both the dependent and independent variables to predict future values. It relies on external factors like patient load or number of dialysis sessions per month which were factored in.	$Y_t = \beta_0 + \beta_1 X_t + \dots + \gamma_1 Y_{t-1} + \dots + \epsilon_t$

Table 3. Comparison of forecasting model performance for monthly consumable usage.

Consumable	Model	MAE	MAPE (%)
Bloodlines	Exponential Smoothing (SciPy)	86.68	25.80
	Simple Moving Average	104.11	36.54
Dialysers	Weighted moving average (SciPy)	85.12	23.22
	Simple Moving Average	77.63	22.88
Disinfectant	SARIMA (SciPy)	0.57	0.60
	Simple Moving Average	0.83	0.88
Heparin	Exponential Smoothing (SciPy)	45.40	14.80
	Simple Moving Average	59.25	17.10
Renal concentrate	Weighted Moving Average (SciPy)	70.67	16.59
	Simple Moving Average	72.28	16.73
Sodium bicarbonate	Weighted Moving Average (SciPy)	81.83	35.94
	Simple Moving Average	178.04	108.78

In **Table 3**, for bloodlines, exponential smoothing had the lowest MAPE (25.80%) and dialysers were best forecasted by SMA (22.88). Disinfectant was the easiest to forecast, with nearly every model performing well, but SARIMA yielded the smallest errors (MAPE = 0.60%). This fits very stable usage. Heparin forecasts were strongest with exponential smoothing (MAPE = 14.80%), whereas renal concentrate came out best using weighted moving average (MAPE = 16.59%). Sodium bicarbonate had the highest item error levels across the board, although weighted moving average still yielded the least bad result (MAPE = 35.94%).

Formula for Error Reduction

Error Reduction % = $\frac{\text{Baseline Error (SMA)} - \text{Time Series Model Error}}{\text{Baseline Error (SMA)}} \times 100$

The results in **Table 4** show the error improvement reduction baseline that was achieved by the time-series models.

Table 4. Shows the summary of time-series model error improvement reduction of baseline.

Category	Optimal Model	MAPE (%)	Improvement Over Baseline
Bloodlines	Exponential smoothing	25.80	↓29% Error Reduction
Disinfectants	Seasonal Autoregressive Integrated Moving Average	0.60	↓32% Error Reduction
Heparin	Exponential smoothing	14.80	↓13% Error Reduction
Sodium bicarbonate	Weighted Moving Average	35.94	↓67% Error Reduction
Dialysers	Simple Moving Average	22.88	↓1.5% Error Reduction
Renal concentrate	Weighted Moving Average	16.59	↓0.8% Error Reduction

3.7. The Observed vs Forecasted Renal Consumables at UTH in 2025-Comparison Using SMA, WMA, ETS, SARIMA, and Dynamic Regression Models

Figure 6 compares actual 2025 consumption with model forecasts for each consumable at the UTH. SMA, WMA, exponential smoothing produced flat forecasts that captured the yearly average level well but missed sharp monthly fluctuations for dialysers, bloodlines, renal concentrate, sodium bicarbonate and heparin. SARIMA exhibited weak trends and did not align well with peaks and troughs reflecting no seasonality. Dynamic regression showed session-linked patterns but deviated when the relationship was weak. Disinfectant showed stable demand. Therefore, all models tracked actual values closely.

3.8. Paired t-Test Results (MAPE Comparison)

Table 5 compared the forecasting accuracy of SMA with the best forecasting model for each consumable using MAPE. The error between months was calculated from January to December, and a paired t-test was calculated in Python (SciPy) at every time step. Difference in error was calculated by subtracting SMA MAPE from advanced model MAPE. Sodium bicarbonate error difference was 72.84%, showing significant improvement. Bloodlines error difference was 10.74%, disinfectant reduced difference was 0.28%, heparin error difference was 2.3%, renal concentrate error difference was 0.14% and dialysers error difference was 0.34%. Heparin, renal concentrate and dialyser error difference was not significant. Advanced models significantly improved the forecasting for sodium bicarbonate, bloodlines and disinfectant. Heparin improvement was marginal, no meaningful improvement for renal concentrate and dialysers were observed.

Forecast vs Observed Monthly Consumption (2025)

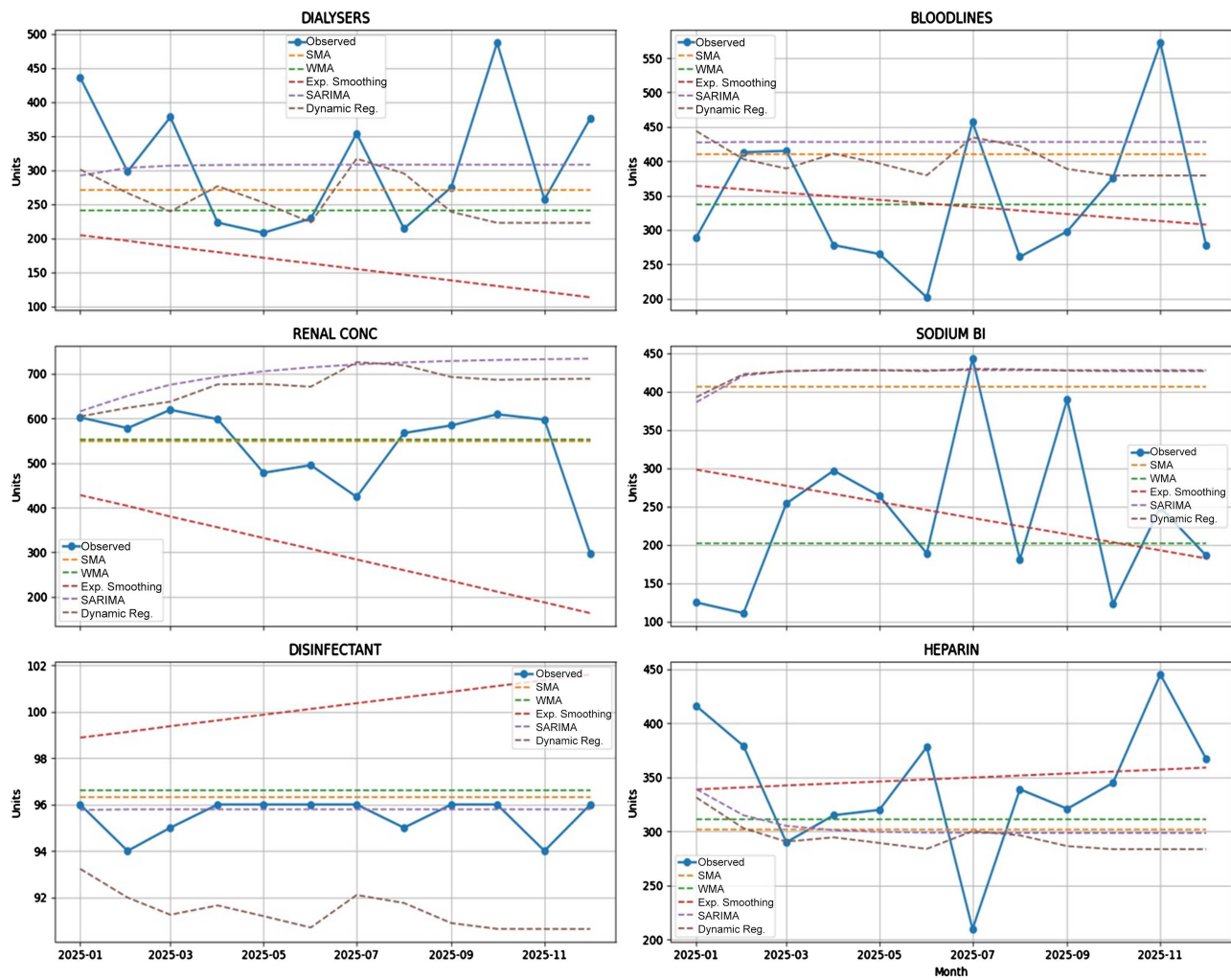


Figure 6. Observed versus forecasted monthly consumption for renal consumables in 2025, comparing Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Smoothing, SARIMA, and Dynamic Regression models across consumable type.

Table 5. Comparison of best-fit models with SMA for each consumable using MAPE.

Consumable	SMA MAPE	Best Advanced Model	Advanced model MAPE	Difference in Error	T-Statistic	p-Value	Significantly better
Sodium bicarbonate	108.78%	WMA	35.94%	72.84%	9.126	<0.0001	Yes
Bloodlines	36.54%	Exponential smoothing	25.80%	10.74%	4.418	0.0010	Yes
Disinfectant	0.88%	SARIMA	0.60%	0.28%	4.760	0.0006	Yes
Heparin	17.10%	Exponential smoothing	14.80%	2.3%	2.0716	0.0626	No (Marginal)
Renal concentrate	16.73%	WMA (4 months)	16.59%	0.14%	0.1293	0.8994	No
Dialyzers	22.88%	WMA	23.22%	0.34%	0.229	0.8229	No

3.9. Paired t-Test Results (MAE Comparison)

In **Table 6**, the error between months was calculated from January to December, and a paired t-test was calculated in Python (SciPy) at every time step. Difference in error was calculated by subtracting SMA MAE from advanced model MAE. Sodium bicarbonate error difference was 96.21, showing significant improvement. Disinfectant reduced difference was 0.26, heparin error difference was 13.85, bloodlines error difference was 17.71, renal concentrate error difference was 1.61 and dialysers error difference was 1.97. The difference in renal concentrate and dialyser error was not significant. Advanced models significantly improved the forecasting for sodium bicarbonate, disinfectant, heparin and bloodlines. No meaningful improvement for renal concentrate and dialysers was observed.

Table 6. Comparison of best-fit models with SMA for each consumable using MAE.

Consumable	SMA MAE	Best Advanced Model	Advanced Model MAE	Difference in Error	T-Statistic	p-Value	Significantly Better?
Sodium bicarbonate	178.04	WMA (SciPy)	81.83	96.21	7.6628	<0.0001	Yes
Disinfectant	0.83	SARIMA	0.57	0.26	4.6912	0.0007	Yes
Heparin	59.25	Exp smoothing	45.40	13.85	3.5530	0.0045	Yes
Bloodlines	104.11	WMA	86.40	17.71	2.6098	0.0243	Yes
Renal concentrate	72.28	WMA	70.67	1.61	0.3444	0.7370	No
Dialysers	77.63	SARIMA	79.60	1.97	0.3912	0.7031	No

4. Discussion

Efficient supply chain management for critical renal consumables in resource-constrained public health settings, relies heavily on accurate demand forecasting to minimise stock-outs and sustain uninterrupted dialysis services (Subramanian, 2021). As demonstrated by the findings of this study, no single forecasting method consistently outperformed others across all renal consumables. Instead, model performance was strongly determined by the specific demand characteristics of each SKU. That is, demand stability, presence of trend and degree of variability a pattern widely observed by Stacey (Stacey et al., 2024), who emphasised context-specific forecasting model selection in healthcare supply chains over the universal application of complex techniques.

The SMA is commonly used in Zambia's public sector inventory systems because of its computational simplicity. Though outperformed by the majority of advanced time-series models, SMA performed well for consumables with a stable supply. As observed with renal concentrate MAPE $\approx$ 16.73%, SMA produced results comparable to or slightly better than more advanced models. This reflected its effectiveness in smoothing short-term noise when demand exhibited little underlying structure beyond recent averages. However, as reported by Nguyen (Nguyen et al., 2021), SMA's lagging response and failure to explicitly capture

trends or temporal dependencies results in substantially higher errors for items showing greater variability such as sodium bicarbonate (MAPE 108.78%) and bloodlines (MAPE 36.54%). This limitation frequently led to systematic under- or over-forecasting at UTH during periods of change, a weakness consistently documented in healthcare forecasting literature (Sarvestani et al., 2022).

In contrast, time series models delivered meaningful error reductions over baseline SMA for the majority of renal consumables at UTH. As evidenced by statistically significant improvements, exponential smoothing reduced error over baseline by 67% while SARIMA achieved 32% error reduction improvement over baseline for disinfectants. As reported by Stacey and colleagues, ETS reduced errors by over 20% compared with SMA in healthcare forecasting by weighting recent observations more heavily a mechanism that explained its better forecast performance for bloodlines and heparin (Stacey et al., 2024). Bloodlines and heparin showed mild demand trends. This is consistent with Beshay (Beshay et al., 2022). SARIMA and similar models outperformed SMA by capturing short-lag autocorrelation, even without strong seasonal demand. As observed by Nguyen (Nguyen et al., 2021), SMA forecasts lagged during changing dialysis utilisation, leading to high errors on variable consumables with high demand variability such as sodium bicarbonate. WMA mathematically corrected this bias effectively.

Dynamic regression underperformed when dialysis session volume was reduced. For example, heparin and sodium bicarbonate, aligning with a previous study which reported that exogenous variables only improve accuracy with stable and strong variable relationships (Perone, 2022). These results support the view, as highlighted by Yin and colleagues who reported that moderately advanced classical forecasting models offer practical advantages in data-constrained LMIC settings (Yin et al., 2023). These findings reinforce this study's use of SKU-tailored time series models application in improving accuracy over SMA for different demands. Tailored time-series would enhance inventory reliability amid Zambia's rising CKD burden (Bosomprah et al., 2023).

As observed with the SMA in stable supply systems, heavy smoothing reduced variance effectively but introduced lag bias when the demand began trending. Conversely, structured models, such as ETS, WMA, and SARIMA, reduced systematic bias by explicitly modelling dependence and progression. However, as noted in more complex demand scenarios excessive structural assumptions increased variance and harmed generalisation when the data did not support structural assumptions (Perone, 2022).

Descriptive statistics in this study showed differences in the use of renal consumables at the University Teaching Hospital. Analysis of the consumption data revealed a marked coefficient of variation in the consumables under investigation. Coefficient of variation range from 9.0% to 47.4%. This indicated the presence of both stable and highly variable demands. Disinfectants showed the lowest values, suggesting consistent use over time, while sodium bicarbonate showed the highest fluctuation, reflecting significant demand variability. Dialysers, bloodlines, and

heparin demonstrated moderate fluctuations, indicating a relatively stable consumption pattern. From an operational perspective, high variability means that the UTH needs to maintain higher safety stock levels to avoid stockouts. Consumables with stable demands can be managed with more consistent supply. The observed patterns are consistent with study done by Sarvestani and colleagues who indicated that consumables that directly link to patient load tend to show moderate fluctuation while protocol-based consumable like disinfectant remain stable (Sarvestani et al., 2022). According to a study by Bosomprah and colleagues (Bosomprah et al., 2023), Zambia's growing prevalence of ESKD and CKD will lead to a greater reliance on high-volume consumables like bloodlines and renal concentrate. This is because of the rising cases of diabetes and hypertension.

Blood products demand forecasting showed considerable variability (CV often >40% for some groups), as reported in a study elsewhere (Sarvestani et al., 2022). The study concluded that variability, was caused by erratic clinical needs and supply factors mirroring the irregularity seen in this study for non-volume-stable renal consumables. Similarly, Hamad (Hamad et al., 2023) described growing haemodialysis population trends in a resource-limited setting, where descriptive analyses of patient load projected increasing variability in consumable requirements. The difference in variability showed how well different forecasting models perform. This supports the research findings that different types of consumables require different forecasting approaches rather than relying on a single forecasting method for all critical renal consumables (Stacey et al., 2024).

Consumption trends over 2023-2024 showed positive associations between dialysis session volumes and the usage of key consumables. Python-based correlation analyses and scatter plots confirmed strong positive linear relationships for volume-driven consumables. This positive linear relationship indicated that consumption was predominantly driven by service delivery intensity. These trends indicate that demand was largely service-driven rather than driven by isolated seasonal or random factors. As reported by Bosomprah (Bosomprah et al., 2023), the growing incidence of ESKD in Zambia intensified pressure on consumable stocks through increased session volumes reinforcing the need to incorporate variables, such as dialysis session counts, in predictive models to improve forecast responsiveness. This service-demand linkage mirrored patterns observed by Sarvestani (Sarvestani et al., 2022) in blood product forecasting, where volumes emerged as a primary driver of consumption variability and upward trends, highlighting the value of covariate integration for high correlation items in resource limited settings.

Autocorrelation function (ACF) plots and monthly consumption profiles revealed no statistically significant seasonality. With lag-12 coefficients consistently falling within 95% confidence intervals. Fluctuations appeared predominantly irregular or trend-related. The absence of strong seasonality, as observed by Stacey (Stacey et al., 2024), noted that many healthcare supply time series in low-resource settings exhibited limited or absent seasonal patterns but were often dominated

instead by trends and irregularities due to inconsistent service delivery and supply chain factors. This finding further supported the study's methodological choices and highlighted that renal consumable demand at UTH was more responsive to service volume and episodic variability than to calendar-based dialysis session cycles.

Time series forecasting models showed an improvement in forecasting accuracy compared to the simple moving average forecasting method. Similar findings have been reported in the literature, where time series models such as exponential smoothing and ARIMA outperformed SMA in healthcare forecasting (Sarvestani et al., 2022). The Advanced time series models outperformed SMA across most consumables, with statistically significant improvements in Mean Absolute Error and Mean Absolute Percentage Error. These results demonstrate that SMA's equal weighting of historical observations failed to accommodate emerging trends, short-term autocorrelation, resulting in higher errors during periods of demand change (Lima et al., 2023).

In contrast, the advanced models captured SKU-specific dynamics more effectively. The superior performance of advanced models is consistent with the established principle that no single forecasting method is universally optimal. Different demand characteristics require tailored approaches. As seen in the study by Makridakis (Makridakis et al., 2018), statistical and hybrid methods frequently outperform simpler baselines when consumption data display complexity or irregularity. This confirms the value of model comparison on a per-SKU basis in this study.

The findings further support the broader evidence that time series techniques reduce forecast error relative to SMA in healthcare supply chain applications. As seen in the study by Nguyen (Nguyen et al., 2021), refined forecasting methods improve accuracy for unstable or variable supplies, whereas Beshay (Beshay et al., 2022) emphasised the benefits of improved monitoring and prediction in renal care settings. However, the results also showed that SMA performed well for stable demand consumables, such as renal concentrates, because SMA works best when demand is stable. This was supported by Nguyen (Nguyen et al., 2021) who found that simple methods can perform well in adequate stable demand environments but tend to perform poorly when demand is irregular or changing.

These findings align closely with existing healthcare supply chain literature in low-and middle-income countries. As seen in the study by Sarvestani (Sarvestani et al., 2022), ARIMA and exponential smoothing models outperformed SMA in blood demand forecasting by more effectively capturing temporal dependencies and variability, with similar relative error reductions in high-variability items. Similarly, Stacey (Stacey et al., 2024) reported that ETS and SARIMA reduced errors by substantial margins compared with SMA in hospital consumable prediction tasks, particularly when trends or covariates were present. The SKU-specific performance extends insights from Perone (Perone, 2022), who demonstrated the context-dependent good performance of classical time series models and rein-

forced the value of tailored approaches in resource-limited settings. Alternative explanations for the observed superiority include potential data quality limitations that may have exaggerated irregularity and favoured noise-robust models, such as WMA and ETS. The short data horizon could also have masked longer-term cycles, structural breaks, or subtle multi-year trends, potentially overstating SMA's long-term inadequacy.

Reliable inventory systems ensure continuous availability of critical renal consumables, thereby preventing stockouts that could compromise patient care. An analysis of demand patterns revealed constraints in inventory management. This was evidenced by declining trends, which suggested supply shortages and rationing of renal consumables, indicating poor inventory optimisation and possible disruption in dialysis services. Therefore, understanding consumption trends and applying accurate forecasting supports better planning, timely ordering, and uninterrupted dialysis services (Nguyen et al., 2021).

The importance of accurate demand forecasting ensures inventory reliability and directly influences stock levels, procurement cycles, and overall supply chain efficiency. Demand forecasting models for renal consumables play an important role in supporting inventory management. Nguyen (Nguyen et al., 2021) stated that SMA systematically underestimates demand during periods of increasing utilisation and overestimates demand during declining phases, leading to either stockouts or excess stock, both of which undermine inventory reliability. Similarly, in dialysis services, where consumable demand is closely linked to scheduled treatments, inaccuracies in demand prediction can disrupt service delivery.

Advanced time series forecasting models improve predictions by clearly representing patterns, including trends and seasonal changes. Beshay (Beshay et al., 2022) stated that ARIMA-based forecasts outperformed SMA in hospital settings, improving inventory reliability by providing more accurate demand estimates. These models reduce the frequency of stockouts and overstocking, supporting better stock management and reducing waste.

A study by Wu and colleagues provided evidence that improved forecasting accuracy through advanced models enhances procurement planning and reduces emergency procurement costs (Wu et al., 2025). In resource-limited settings, where procurement delays and stockouts are common, using time-series models can significantly improve inventory reliability. Waheed and colleagues further emphasised that reliance on weak forecasting practices results in inefficient inventory levels, increased costs, and service interruptions (Waheed et al., 2022). Accurate forecasts not only optimise stock levels but also support the timely replenishment of consumables. In dialysis, where treatment schedules are strict and interruptions can have serious consequences, maintaining optimal stock levels is especially critical.

The findings of this study support the technology acceptance model (TAM) in forecasting, particularly the concept of perceived usefulness. TAM explains how users come to accept and use a new technology. TAM can be used in forecasting

to assess whether users are willing to adopt and use forecasting systems based on how useful and easy to use the system is (Schorr, 2023). The forecasting models demonstrated improved accuracy, indicating their usefulness in supporting decision-making in hospital supply chains. Additionally, Python-based models reflect perceived ease of use, as these tools can be implemented with minimal complexity once users are trained (Davis, 1989; Venkatesh et al., 2003). Recent studies further confirm that TAM remains a widely applicable framework for understanding technology adoption across different contexts (Kim & Kim, 2016; Schorr, 2023; Galimova et al., 2024).

The findings advanced the study's general objective by providing empirical evidence that time series models outperformed SMA for the majority of renal consumables, offering a feasible pathway to strengthen dialysis service continuity amid Zambia's escalating CKD and ESKD burden. As seen in the study by Bosomprah and colleagues, fewer than 10% of adults with ESKD accessed chronic dialysis services, therefore, a reliable, uninterrupted supply of consumables became essential to prevent missed sessions, acute complications, and excess morbidity or mortality (Bosomprah et al., 2023).

Theoretically, the interpretability and relative simplicity of models such as ETS and SARIMA align with the technology acceptance model (TAM). By potentially increasing perceived usefulness and ease of use among supply chain personnel, pharmacists, and clinicians, TAM would facilitate adoption in routine operations. These implications reinforce the broader value of moving beyond basic SMA methods, as highlighted by Stacey (Stacey et al., 2024) and Perone (Perone, 2022) in analogous healthcare forecasting applications.

4.1. Study Limitations

The study was conducted solely at the UTH-Adult Hospital. Therefore, the findings may not fully represent consumption patterns or forecasting performance in other provincial or district facilities. The analysis relied entirely on historical consumption records and did not incorporate external factors, such as supply chain disruptions, budget constraints, procurement delays, or policy changes. These factors influence actual demand and model performance. Potential data quality issues, including manual recording errors, incomplete stock cards, and missing entries, may have affected the results despite efforts to clean and impute data. Finally, the short historical series limited the detection of longer-term trends or structural shifts.

4.2. Policy Recommendations and Implications

The findings of this study highlight critical policy implications for strengthening forecasting and supply chain management of renal consumables in Zambia (Table 7). Evidence demonstrates that reliance on a single, basic forecasting method such as the simple moving average is insufficient, particularly for commodities with variable demand. Instead, adopting SKU-specific, data-driven time-series models,

such as exponential smoothing, SARIMA, and weighted moving averages, can significantly improve forecasting accuracy and reduce stockouts. These improvements are essential for ensuring uninterrupted dialysis services and better patient outcomes.

Table 7. Policy recommendations and implications for strengthening renal consumables forecasting and supply chain management in Zambia.

Policy Area	Key Recommendation	Rationale (Based on Findings)	Expected Impact	Implementation Considerations
Forecasting Systems	Adopt SKU-specific forecasting models (e.g., ETS, SARIMA, WMA) instead of a single-method approach	Study shows no single model performs best across all consumables; advanced models significantly reduce forecasting error compared to SMA	Improved forecasting accuracy; reduced stockouts and overstocking	Develop national guidelines for model selection; integrate into existing forecasting tools
National Supply Chain Policy	Transition from basic SMA-based forecasting to data-driven time-series models at national level	SMA showed poor performance for variable demand items (e.g., sodium bicarbonate with high error rates)	Enhanced procurement planning and supply reliability	Policy revision by Ministry of Health and ZAMMSA; phased implementation
Inventory Management	Implement differentiated inventory strategies based on demand variability (stable vs variable items)	High variability (CV up to 47.4%) requires tailored stock management approaches	Optimised stock levels; reduced wastage and emergency procurement	Introduce safety stock policies linked to demand variability
Digital Health & Data Systems	Strengthen digital data capture systems for real-time consumption and dialysis session tracking	Data quality and availability directly influence forecasting accuracy	Improved data-driven decision-making and responsiveness	Invest in electronic logistics management information systems (eLMIS)
Capacity Building	Provide training in time-series forecasting and data interpretation for pharmacists and supply chain personnel	Adoption of advanced models depends on user understanding (aligned with Technology Acceptance Model)	Increased uptake and sustainability of forecasting tools	Incorporate into CPD programs and national training curricula
Service Delivery Integration	Integrate service utilisation data (e.g., dialysis sessions) into forecasting models	Strong association between consumable use and dialysis sessions improves prediction accuracy	More responsive and demand-driven supply planning	Strengthen coordination between clinical and supply chain units
Procurement Planning	Institutionalise routine model comparison before procurement decisions	Model performance varies by SKU; evidence-based selection improves accuracy	Reduced procurement errors and cost inefficiencies	Develop standard operating procedures (SOPs) for forecasting validation
Health Systems Strengthening	Expand forecasting approaches to other chronic disease commodities (e.g., diabetes, hypertension)	Similar variability patterns expected in chronic disease supply chains	System-wide improvement in supply chain efficiency	Pilot and scale across disease programs

Continued

Research & Innovation	Promote integration of advanced analytics (e.g., machine learning) alongside classical models	Study highlights benefits of advanced modelling; future gains possible with hybrid approaches	Continuous improvement in forecasting performance	Support research collaborations and innovation funding
Policy & Governance	Embed data-driven forecasting into national AMR and NCD strategies	Reliable supply chains are essential for uninterrupted treatment and improved outcomes	Strengthened health system resilience and patient care continuity	Align with national health strategies and policy frameworks

At the systems level, there is a need to transition toward integrated, digital forecasting platforms that incorporate real-time consumption data and service utilisation indicators, such as dialysis session volumes. Strengthening electronic logistics management systems and improving data quality will enhance decision-making and responsiveness. Capacity building for pharmacists and supply chain personnel is equally important to support the adoption and sustainability of advanced forecasting tools.

Furthermore, policy reforms should institutionalise routine model comparison and evidence-based procurement planning, while promoting differentiated inventory strategies based on demand variability. Scaling these approaches beyond renal care to other chronic disease commodities will strengthen overall health system resilience. Collectively, these measures provide a practical pathway toward more efficient, data-driven supply chains in Zambia.

4.3. Future Research Directions

Future studies should extend the analysis to multiple provinces and facilities to improve generalisability. Comparative assessments between urban and rural dialysis units would provide valuable insights into regional variations. The incorporation of machine learning approaches alongside classical time series models could be explored where data volume permits. Similar forecasting methods should also be applied to other chronic disease commodities, such as antihypertensive drugs, antidiabetic agents, and oncology drugs. This would broaden the evidence base for data-driven supply chain management in Zambia.

Based on these findings, it is recommended that health facilities adopt SKU-specific forecasting models rather than relying on a single method for all consumables, and routinely compare model performance before finalising procurement quantities to ensure optimal accuracy. Renal consumables should be integrated into the national forecasting system to strengthen coordinated planning and supply chain efficiency. In addition, there is a need to build capacity among pharmacists, supply chain personnel, and dialysis unit staff through structured training in basic time-series forecasting and interpretation of model outputs. Finally, improving data quality through routine digital capture of dialysis session volumes and consumable utilisation at the facility level will enhance the accuracy, timeliness, and reliability of forecasting, ultimately supporting uninterrupted dialysis

services and better patient outcomes.

5. Conclusion

This study tested time series models to predict demand for renal supplies at UTH in Lusaka, Zambia and compared time-series models with the SMA. The analysis of historical monthly consumption records from 2023 to 2024 revealed different demand profiles. SMA forecasts performed well for stable demand consumables like renal concentrates. However, but for supplies with more demand variation, advanced time-series models such as weighted moving average, exponential smoothing, and SARIMA gave better and more accurate forecasts.

SMA therefore would be inadequate in the forecasting high value, life critical consumables. Reliance on SMA would likely contribute to inaccuracies leading to intermittent stockouts and service disruption. The study showed that no single time series forecast outperformed across all the SKUs. Model choice should match varying demand patterns. Empirical evidence from this study also shows predictive models can reduce MAPE for products with high demand variability over baseline SMA.

No significant irregularities were detected in the consumption patterns. Using advanced models can improve inventory management, reduce stock-outs, and ensure continuous dialysis services, especially in Zambia where demand is rising and access is limited. Relying only on SMA is not enough for variable or trend-driven supplies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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