Improving Public Health Supply Chains: Time Series Techniques for Medication Demand Forecasting.

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Abstract. The National Pharmaceutical Assistance Policy (PNAF) in Brazil aims to ensure universal access to essential medications through primary care. To achieve this goal and reduce healthcare access inequalities, efficient health system supply chains are crucial. This study evaluates time series forecasting methods, specifically exponential smoothing (ETS) and autoregressive integrated moving average (ARIMA) models, to predict the demand for captopril, a widely used antihypertensive drug, in São Paulo's Basic Health Units. Data on medicine consumption and demand from January 2018 to March 2023 were collected and analyzed to address current inefficiencies in demand prediction, compared through the Mean Absolute Percentage Error (MAPE). Results indicate that the ETS model achieved the best performance in captopril demand forecasting, with a MAPE of 2.26%, significantly improving on the 77.97% MAPE of the existing methodology. Holt-Winters seasonal models and ARIMA also demonstrated robust predictive capabilities, with MAPEs of 3.81% and 3.47%, respectively. This research highlights the potential of data-driven forecasting techniques, such as the ETS model, to optimize resource allocation, ensure medication availability, and improve service quality, providing a framework for future applications in similar contexts.

Keywords: demand forecasting, ARIMA, public health supply chains, exponential smoothing, efficiency improvement.
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1. Introduction

The National Pharmaceutical Assistance Policy (PNAF), established in 1998 in Brazil, fulfills Article 6 of Law 8,080/90, which mandates comprehensive therapeutic care, including pharmaceutical assistance, within the Unified Health System (SUS) (Brazil, 1990). This policy aligns with the provisions of the World Health Organization, which, has long emphasized that the right to health requires equitable access to essential medicines (WHO, 1978). In this context, the PNAF supports the constitutional principles of universality, comprehensiveness, and equity in health (Brazil, 1988), ensuring essential medicines availability in primary care through municipal supply chains (Oliveira et al., 2010). Lack of access to medicines at this level compromises care delivery (Álvares et al., 2017; Yadav, 2015), therefore, ensuring their efficient distribution is essential to reducing inequalities (Dickman et al., 2017).

However, demand uncertainty poses significant challenges in supply chain management in general (Storey et al., 2006) and is a major issue in healthcare (Subramanian, 2021). Factors like epidemiology and supply shortages are a significant operational barrier for governments managing healthcare supply chains (Dixit et al., 2022). While many causes of medicine shortages are beyond managerial control (Reis & Perini, 2008), better forecasting improves planning and resource use (Subramanian, 2021). Addressing demand distortions is critical, as their effects amplify upstream in the supply chain in a phenomenon known as the bullwhip effect, leading to inefficiency (Lee et al., 1997).

Improving forecasting boosts supply chain efficiency by reducing costs and waste (Al-Zaidi et al., 2018), and

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enhancing healthcare delivery. In this regard, Saha and Rathore (2024) highlight that innovation and digital tools can support sustainable healthcare supply chain performance. Though underexplored, evidence suggests efficiency gains from adopting demand-oriented healthcare supply chains (Bvuchete et al., 2020). Time series analysis, which consists of analyzing a set of observations ordered over time (Morettin & Toloi, 2004), is one such effective method for forecasting demand (Shah et al., 2023). Its application relies on the premise of serial dependence among data, meaning that future observations are influenced by past behaviors (Villani et al., 2017). Thus, it employs a univariate modeling approach, based solely on time as the input variable (Ackermann & Sellitto, 2022). While no single approach applies universally, healthcare demand forecasting relies on time series patterns—trend, seasonality, cycles, and randomness—for accurate estimates (Soyiri & Reidpath, 2013).

Given this context, this study evaluates the use of time series techniques for forecast captopril demand in São Paulo's basic health units, comparing these forecasts with current models to assess potential efficiency gains in service delivery. It aims to address the scarcity of data-driven tools based on real consumption data in public health systems (Tetteh et al., 2025). Given the role of primary care in reducing health disparities (Starfield, 2001), improving forecasting at the local level—as in São Paulo's municipal system—can inform more accurate planning under real-world constraints.

2. Research Methods

According to Gil (2017), this research is quantitative in data nature, applied in purpose, and exploratory in objectives, having its design carried out through literature review and data collection to better understand the problem presented. The methodology used was adapted from the Cross Industry Standard Process for Data Mining (CRISP-DM) framework (Chapman et al., 2000), applying its first five stages—business understanding, data understanding, data preparation, modeling, and evaluation—while omitting the final stage, deployment, which Schroer et al. (2021) observed is often not included in most studies adopting this process.

Data were requested from the São Paulo Municipal Health Department (SMS-SP), in CSV format, covering monthly consumption and demand of the twenty most dispensed medicines. The selection included medicines purchased directly by SMS-SP and identified as the most dispensed based on the average of the first quarter of 2023. The dataset spanned from January 2018 to March 2023 and included information on month, year, health region, health supervision territory, medicine code, name, demand, and average consumption. This selection aimed to ensure at least one viable time series for the study.

To identify the behavioral patterns of the selected series components, a decomposition method based on moving average filters was applied (Barros et al., 2017). This procedure allows isolating trend, seasonality, and random effects components for graphical visualization. The series were then split into training (January 2018–September 2022) and test (October 2022–March 2023) sets, with predictions evaluated on the last six observations.

According to Choudhary et al. (2022), although machine learning models are increasingly popular for forecasting purposes, classical univariate time series methods, such as exponential smoothing and autoregressive integrated moving average (ARIMA), the two most widely used approaches in time series forecasting (Hyndman & Athanasopoulos, 2021), generally present good results. The use of both model classes was chosen because, although exponential smoothing models perform well for short-term forecasts and for series that do not show severe changes in their behavior, their performance worsens considerably for long-term forecasts, making it interesting to resort to alternatives, such as Box-Jenkins models (Thomaz et al., 2018).

The analysis began with simple exponential smoothing (SES), suitable for stationary series, followed by the Holt-Winters model with linear trend. Additive (HWAS) and multiplicative (HWMS) seasonal Holt-Winters models were then applied to capture both trend and seasonality (Barros et al., 2017). The Error-Trend-Seasonality (ETS) model was also tested using an R function that automatically selects the most appropriate model based on the combination of error (additive or multiplicative), trend (none, additive or multiplicative, with or without damping), and seasonality (none, additive, or multiplicative) (Hyndman et al., 2008; Hyndman & Khandakar, 2008). Finally, the Box-Jenkins methodology was applied using ARIMA models (Ingle et al., 2021), which combine three components: autoregressive (based on past values), integrated (reflecting accumulated effects over time), and moving average (accounting for past forecast errors) (Fattah et al., 2018).

To develop Box-Jenkins models, it is first necessary to assess seasonality and stationarity, applying differencing if required, then identify and estimate the appropriate ARIMA model and evaluate its fit (Wang, 2011). In this study, these steps were performed automatically to identify the optimal ARIMA model based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Hyndman et al., 2008), which balance model fit and complexity. The lower these values, the better the combination of parameters p, d, and q, corresponding respectively to the order of the autoregressive component, the order of differentiation, and the order of the moving average component (Choudhary et al., 2022).

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After generating the models, accuracy was assessed using the Mean Absolute Percentage Error (MAPE), which is used to measure the accuracy of forecasting models, through the average of absolute percentage differences between forecasts and actual values (Hyndman & Koehler, 2005). It is calculated as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100$$

where: Yt is the actual value at time t; Ŷt is the forecasted value at time t; Yt - Ŷt is the forecast error, $\sum_{t=1}^{n}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right|$ represents the sum of absolute errors for each observation divided by the actual values, transforming them into a proportion relative to the actual values which, multiplied by 100, is converted into a percentage error relative to the actual values and $\frac{1}{n}$ indicates the division by the total number of observations n, providing a measure of the mean error in percentage terms.

As all time series values were positive and well above zero, the MAPE was preferred for its simplicity. The model with the lowest MAPE was selected as the most accurate for the case under study.

3. Results

The results will be presented following the CRISP-DM methodology stages.

3.1 Business Understanding

Medicines purchased directly by SMS-SP are distributed from a central warehouse to primary health care units, based on monthly demand values recorded in the inventory system—referred to in this study as *informed consumption*. Although a manual defines this value as the average of consumption over a set number of months (Prodam-SP, 2008), this method is not consistently applied in practice, and the actual calculation remains unclear. Nonetheless, this value is used for supply planning under the current SMS-SP methodology.

Dispensation to patients is also recorded in the system, and the monthly output is referred to here as *actual consumption*. Based on these definitions, the study aims to assess the accuracy of SMS-SP's current demand forecasting approach and compare it with time series forecasting methods using the same data. Considering the scale of São Paulo's operation—over 450 health units across 27, health supervision territories in 6 health regions—the requested data were structured at the health supervision territory level to enable better tracking of discrepancies and support the study's objectives.

3.2 Data Understanding and Preparation

The data request was submitted to SMS-SP on May 4, 2023, and they were provided on June 24, 2023. The file contained consumption and demand data for 20 medicines (January 2018 to March 2023) from 472 primary health care units, organized by territories. These were aggregated by health supervision territory, resulting in a dataset imported into RStudio with information from 27 territories. During data exploration, medicines with fewer than 1,701 observations—due to missing data across 27 territories and 63 months—were excluded to avoid distortions. For the remaining 10 medicines, boxplots (Figure 1) were used to detect outliers and assess pandemic-related impacts on their time series.

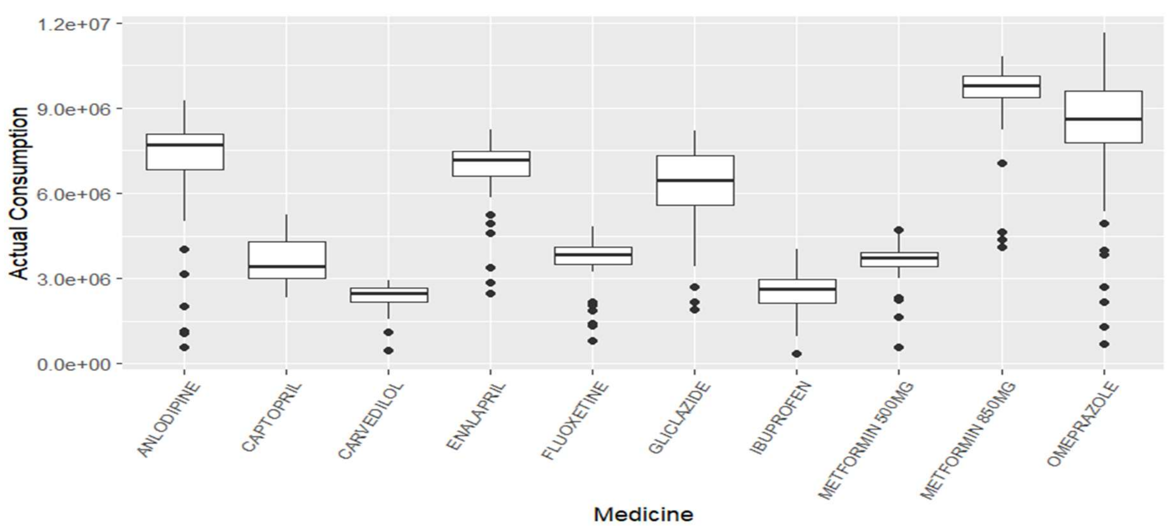

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Fig. 1 - Boxplot of actual medication consumption from January 2018 to March 2023. Source: Original research results.

Since captopril was the only medication without outliers and showed no significant pandemic-related changes, it was selected for modeling and prediction. The dataset was then limited to this medication. Figure 2 shows the time series of its actual consumption (dispensed quantity) and informed consumption (reported demand).

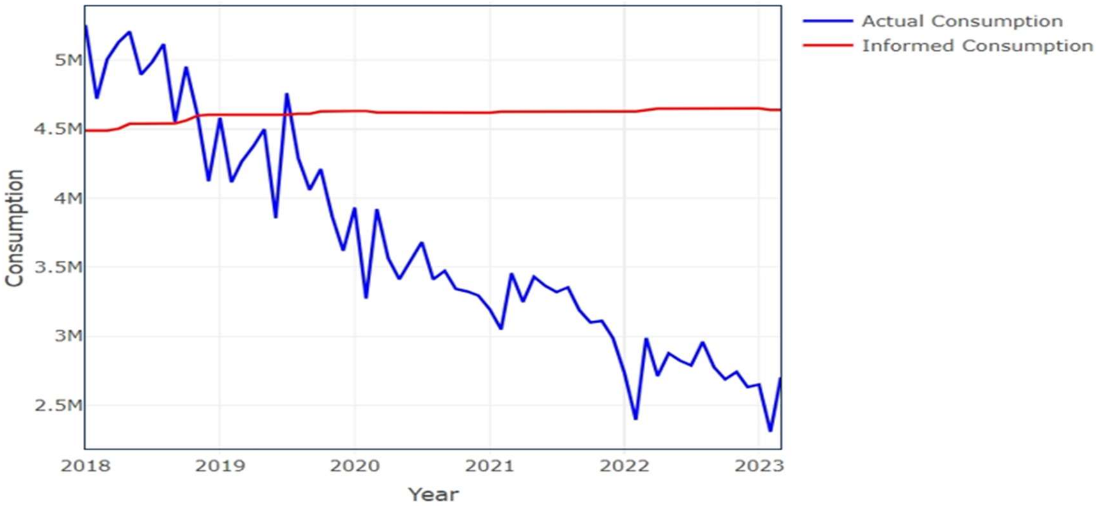

Fig. 2 - Actual Consumption and Informed Consumption of Captopril from January 2018 to March 2023. Source: Original research results

Actual consumption shows a strong downward trend, while informed consumption (forecasted demand) remains more stable. To analyze the components of the time series under study, an additive decomposition method was applied (Hyndman & Athanasopoulos, 2021). Seasonality and a decreasing linear trend can be seen in Figure 3 below.

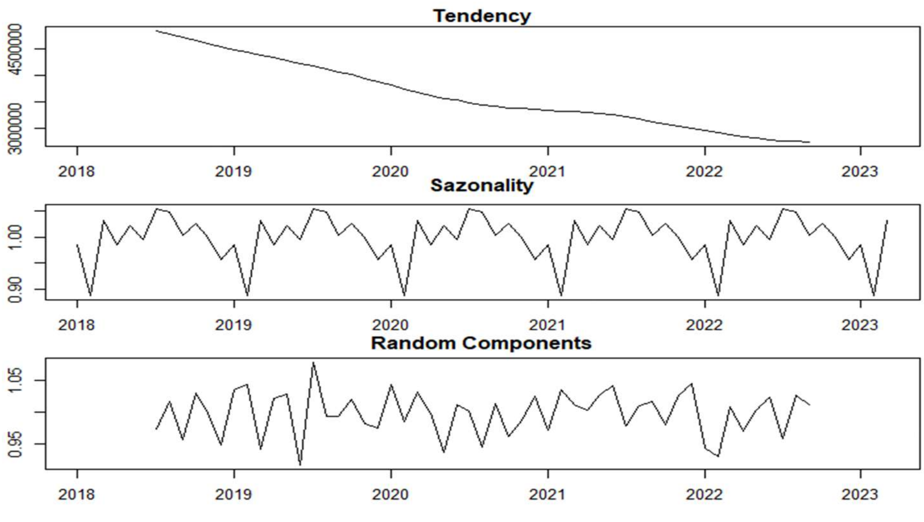

Fig. 3 - Additive Decomposition of the Captopril Actual Consumption Series. Source: Original research results

3.3 Modeling

Modeling started by splitting the data into training (January 2018–September 2022) and test sets (last 6 points: October 2022–March 2023), as shown in Figure 4.

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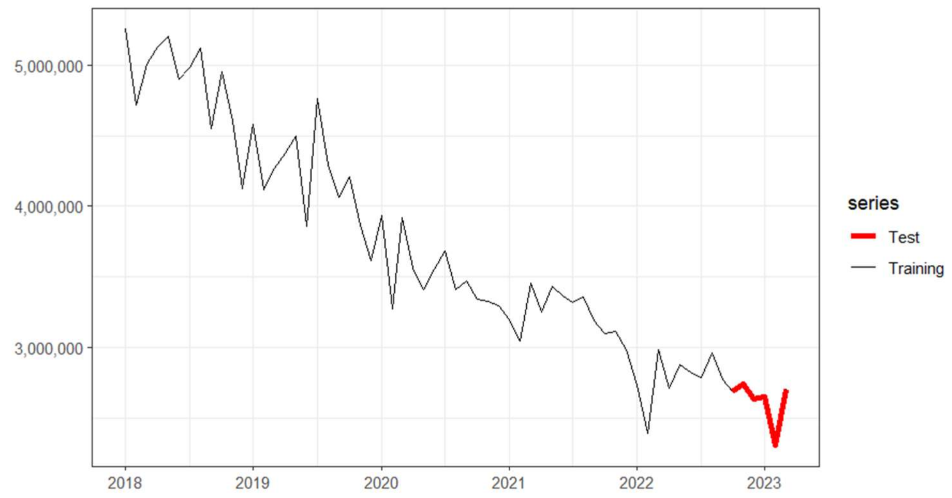

Fig. 4 - Separation of the Captopril Actual Consumption Time Series into Training and Test Data. Source: Original research results.

The MAPE for the original forecast (informed consumption) over the last 6 points was 77.97%, indicating a high average error compared to actual consumption.

The predictions made using exponential smoothing techniques are shown in Figures 5 to 9 below. Figure 5 shows the simple exponential smoothing model; Figure 6, the Holt-Winters trend model; Figure 7, the additive seasonal Holt-Winters model; Figure 8, the multiplicative seasonal Holt-Winters model; and Figure 9, the ETS model.

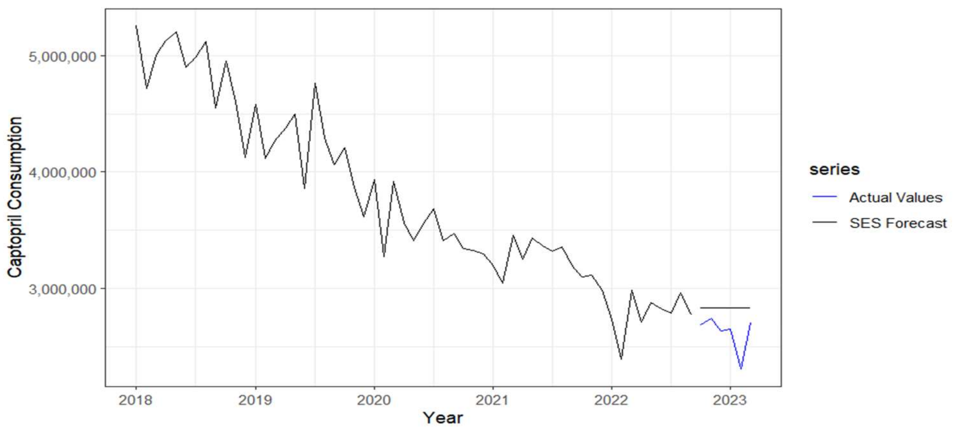

Fig. 5 - Comparison of forecast using the exponential smoothing method with actual values. Source: Original research results.

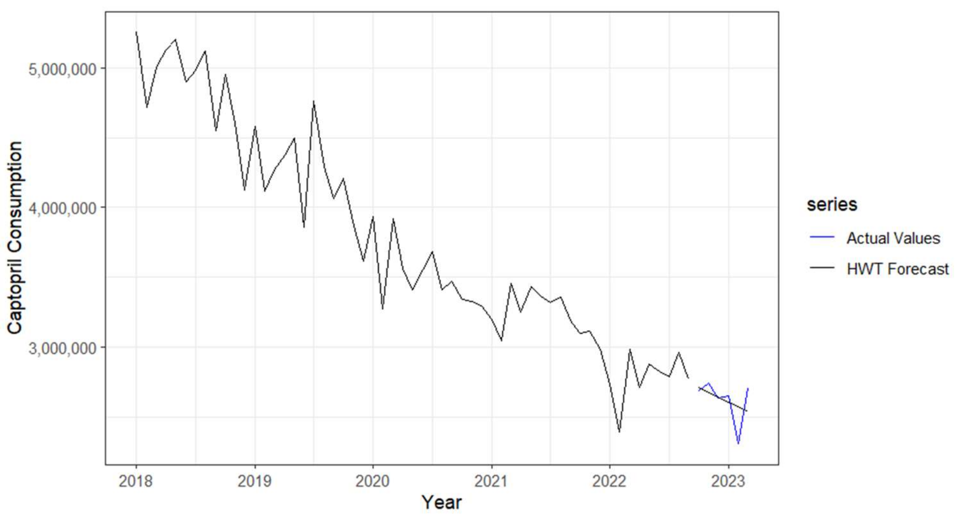

Fig. 6 - Comparison of forecast using the Holt-Winters method with trend and actual values. Source: Original

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research results.

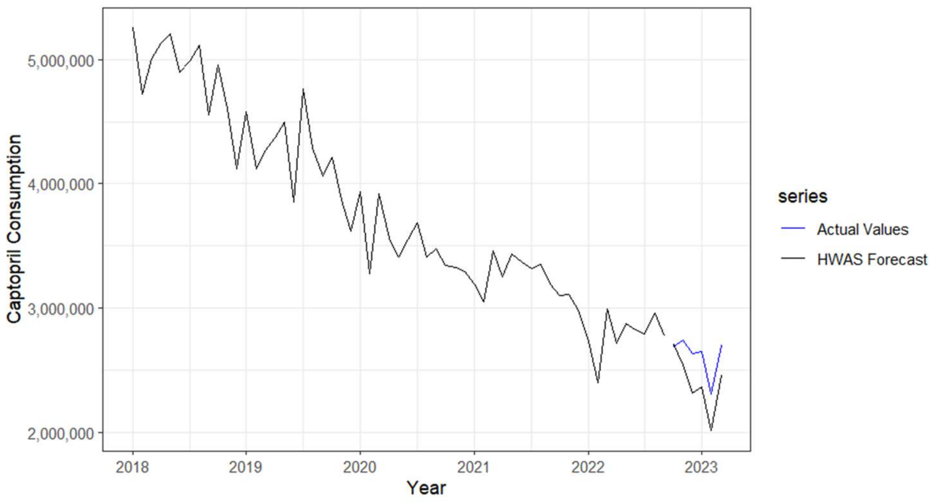

Fig. 7 - Comparison of forecast using the Holt-Winters additive seasonal method with actual values. Source: Original research results.

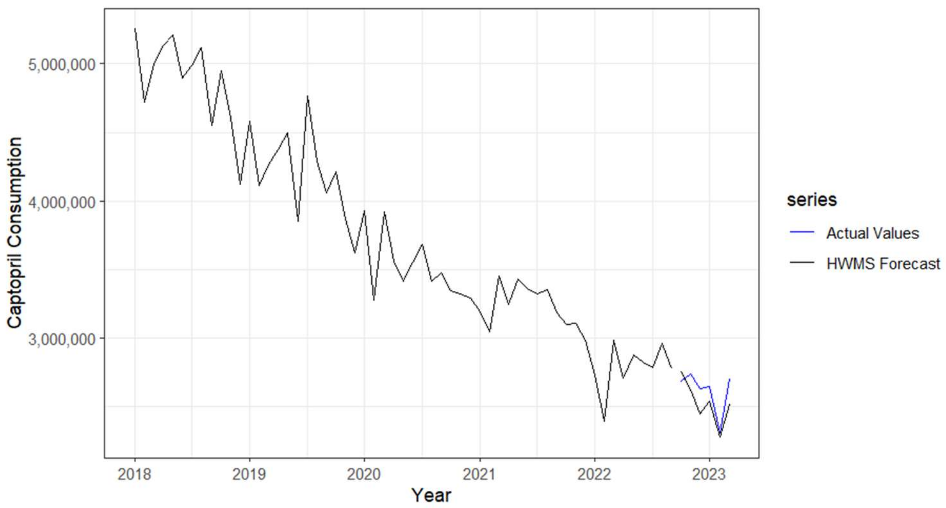

Fig. 8 - Comparison of forecast using the Holt-Winters multiplicative seasonal method with actual values. Source: Original research results.

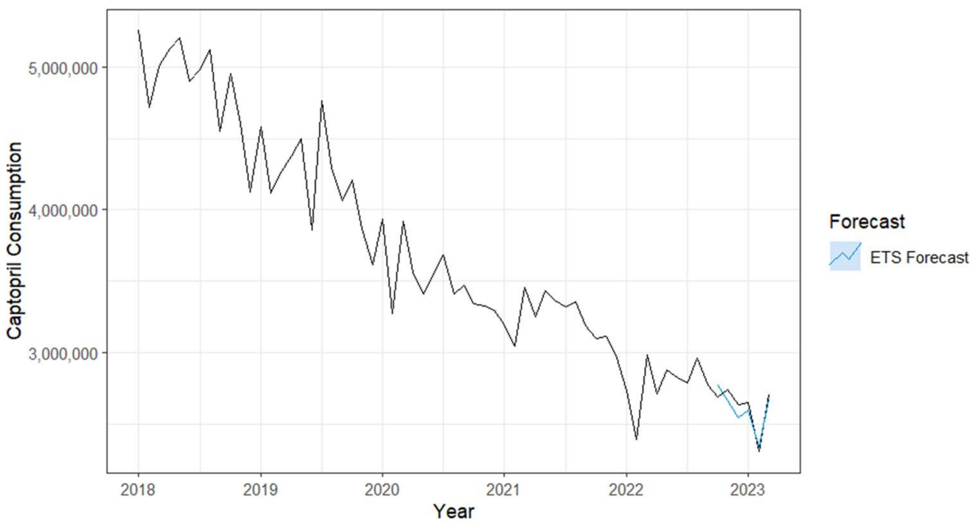

Fig. 9 - Forecast using the ETS model compared to actual consumption data. Source: Original research results.

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The last class of models applied was ARIMA. Among these, the most accurate was ARIMA(2,1,0)(1,0,0)(12) with drift, selected based on the AIC criterion, where the lowest value indicates the model with the best balance between fit and complexity (Choudhary et al., 2022). This model includes two autoregressive terms, one differencing, no moving average terms, and a seasonal autoregressive component of order one with a 12-month period. The "drift" term indicates the presence of a linear trend.

Forecasts for the next six months using this model are shown in Figure 10.

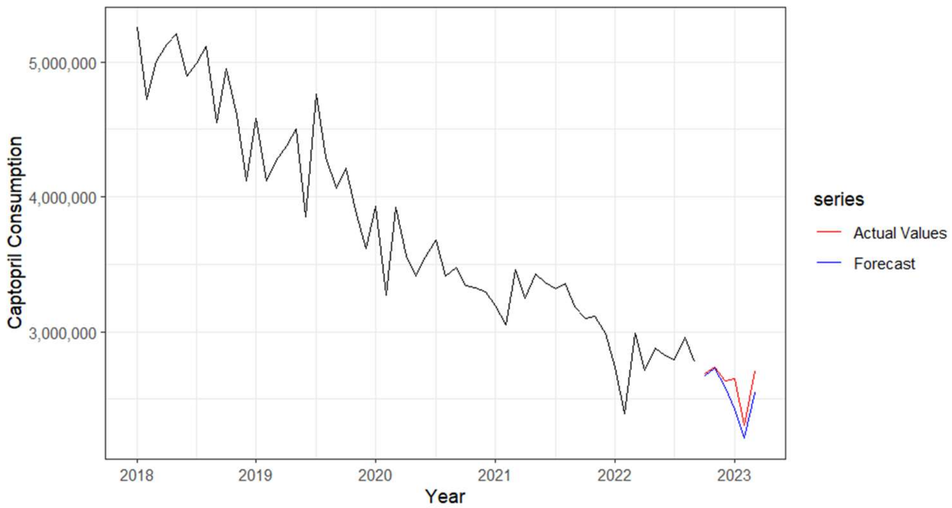

Fig. 10 - ARIMA Model Forecast Compared to Actual Consumption Data. Source: Original research results.

3.4 Evaluation

After applying all models, MAPE was used to identify the best performer. MAPE's simplicity allows direct interpretation without further comparison (Chen et al., 2017). Table 1 shows that the model with the highest predictive capacity for the time series under study was the ETS.

Tab. 1 - MAPEs of Models.

Modelos	MAPE
Previsão atual	77,97
Holt-Winters aditivo sazonal	8,84
Suavização exponencial simples	8,36
Holt-Winters multiplicativo sazonal	4,33
Holt-Winters com tendência	3,81
ARIMA	3,47
ETS	2,26

Source: Original research results

After identifying ETS as the best model, its residuals' autocorrelation was tested using the Ljung-Box test, indicating whether the autocorrelations found are more significant than expected in a random series (Hyndman & Athanasopoulos, 2021). Table 2 shows a p-value of 0.1381, indicating no significant autocorrelation at the 0.05 level. Thus, the residuals are independent, confirming a good model fit. This result indicates the ETS model fits well and outperforms the current model based on MAPE.

Tab. 2 - Ljung-Box Test Result.

Elementos	Valor
X-squared	21.995
df	1
p-value	0,1381

Source: Original research results.

4. Discussion

The results show that time series methods can effectively improve forecast accuracy for captopril consumption in São Paulo's health units, though dataset and modeling limitations should be considered. While this study focused on a stable, complete series, predictive methods can also be applied to series with irregularities, requiring contextual analysis to address anomalies caused by supply shortages or reporting errors—common in public

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sector supply chains.

This issue is critical in the public sector, where inconsistent operations and stockouts lead to suppressed demand not reflected in the actual consumption data, thereby potentially distorting the time series. Infante and Santos (2007) found that automatic replenishment based on historical consumption is biased by frequent stockouts, while replenishment driven by subjective requests introduces significant errors—findings that align with this study and highlight structural challenges in public supply chains.

Structural constraints—such as limited personnel, bureaucracy, and low local autonomy—continue to hinder public supply chain management. Although Supply Chain Risk Management (SCRM) is essential to mitigate disruptions, its application in Brazil remains limited. Senna et al. (2022) noted that centralized, risk-insensitive decision-making often leads to reactive and fragmented actions, a pattern reflected in this study. This highlights the importance of integrating predictive models with broader institutional strategies to build resilience and coordination.

While univariate models used here improved forecast accuracy, they overlook key drivers of demand such as demographics, disease patterns, policy shifts, and supply issues. Given the growing pressures on Brazil's SUS from epidemiological and technological changes (Elias, 2013), future studies would benefit from adopting multivariate models that incorporate these factors to strengthen planning and responsiveness.

Bhat et al. (2024) highlight the potential of integrating stochastic, causal, and projective forecasting—combined with machine learning and inventory optimization—to improve access, reduce stockouts, and optimize resources in public primary care. These hybrid approaches are promising for decentralized systems, especially when adapted to institutional constraints.

This study reinforces that applying forecasting techniques and digital tools can improve demand prediction, public spending, service efficiency, and equity in access to essential medicines. Beyond practical contributions, the findings add to the theoretical understanding of forecasting in decentralized public supply chains with limited autonomy. While structural barriers are well documented (Yadav, 2015; Dixit et al., 2022), this study offers empirical evidence that even simple models can enhance decision-making in resource-constrained settings.

5. Conclusions

Beyond its practical contributions, this study also provides important theoretical implications for public administration and health policy. It reinforces the relevance of evidence-based decision-making frameworks in public logistics and the need to strengthen institutional capacity to operationalize predictive analytics in decentralized health systems. Moreover, the findings support the view that supply chain transparency and forecasting accuracy are not only technical challenges but also governance issues, requiring alignment between data infrastructure, managerial autonomy, and policy objectives.

From a theoretical standpoint, the study reinforces the role of local-level data analytics as a governance instrument in health policy. It suggests that forecasting is not merely a technical function, but also a strategic capability that shapes how public administrations manage uncertainty and allocate resources. In this context, the results point to the need for public policies that improve access to medications dispensed at the primary care level within the SUS, as shortages can lead to treatment discontinuity and, consequently, an increase in the number of hospitalizations. Failing to address this issue may further burden the health system with avoidable inpatient care resulting from gaps in outpatient treatment (Oliveira et al., 2021).

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- **Data/Software Access Statement:** Data were obtained from the São Paulo Municipal Health Department via formal request and are not publicly available due to institutional restrictions. Analyses and forecasts were performed using RStudio (v2023.12.1+402) with R (v4.3.3) and relevant packages.
- **Contributor Statement:**
  - **Ilka De Meo:** Conceptualization, Methodology, Data Curation, Formal Analysis, Software, Visualization, Writing – Original Draft, Writing – Review and Editing.
  - **João Gonçalves:** Supervision, Validation, Writing – Review.
- **Use of AI:** The authors used ChatGPT (OpenAI) to support R code development for time series modeling and to enhance the clarity and academic tone of the text. All content was critically reviewed, edited, and validated by the authors, who take full responsibility for the final version.
- **Conflict of Interest:** There is no conflict of interest.

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