Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Child Immunization Vaccine Demand Forecasting using Holt-Winters Exponential Smoothing Model

Marilou Benoza-Lansangan[1], Thelma Palaoag[2]

[1]*College Dean, Information Technology Department, Infotech Development Systems Colleges, Inc./ Ligao City, Philippines*
[2]*Associate Professor, College of Information Technology and Computer Science, University of the Cordilleras/ Baguio City, Philippines*
Email: mvjc88@yahoo.com

Recognizing the critical significance of vaccination in reducing vaccine-preventable diseases, as well as the limitations of obtaining appropriate vaccine stock levels in the Bicol Region, this study use the Holt-Winters Exponential Smoothing model to accurately forecast future vaccine demand. The study uses data from the Family Health and Safety Information System (FHSIS) from 1999 to 2022 to systematically process vaccination data for BCG, Hepatitis B, DPT or Pentavalent 1, OPV1, PCV1, and MCV1 vaccinations. The Holt-Winters Exponential Smoothing model is used in this research to identify and predict demand patterns with novel reliability. Key discoveries include the identification of suitable smoothing parameters for each vaccination, revealing the different features of vaccine demand: BCG and MCV1 vaccines had a more stable demand, which was reflected in lower smoothing factors, but the Pentavalent vaccination had less seasonal variability, indicating a steady demand pattern. The study displays Mean Absolute Percentage Error (MAPE) values for each vaccine, which range from 5.85% to 15.40%, demonstrating varied degrees of predicting precision, with lower MAPE values suggesting closer alignment with actual vaccination rates. Furthermore, the study systematically assesses forecast accuracy using the Shapiro-Wilk and Ljung-Box tests, which validate the normality of residuals and the absence of substantial autocorrelation where p value is greater than 0.05. These statistical tests demonstrate that the Holt-Winters model is reliable and effective in capturing the complicated dynamics of vaccine demand. This study makes a significant contribution to vaccination program optimization by offering a comprehensive analysis of vaccine demand forecasts and its implications for public health policy, potentially improving vaccine accessibility and coverage in Region 5 and beyond.

Keywords: Child immunization, Holt-Winter, exponential smoothing, parameters, vaccine, demand forecasting, Nelder-Mead, optimization, algorithm, Shapiro-Wilk Test, Ljungbox Test.

1. Introduction

Routine child immunization is a crucial element of global public health initiatives aiming to mitigate morbidity and mortality among children and prevent the transmission of vaccine-preventable illnesses. [1]. Immunization, or vaccination, is the process of administering vaccines to protect people, especially children against infectious diseases. Vaccines have been viewed the single most life-saving advancement in healthcare history. [2] [3] It is a significant public health matter since it is a low-cost approach for preventing diseases that might otherwise necessitate costly treatments and hospitalizations. [4] [5]. Vaccines have contributed to reduce the incidence of infectious diseases such as tetanus, measles, and polio, measles. Furthermore, the World Health Organization (WHO) estimates that immunization prevents 2-3 million deaths every year. [4] However, it can be challenging to ensure that children receive the required immunizations at the proper time and place, especially in low-resource locations where resources are restricted. [1]

A fully immunized child (FIC) is a newborn who has received one dose of BCG, two doses of Measles Containing Vaccine by 12 months of age, and three doses of DPT or Pentavalent, Hepatitis B, and OPV vaccines. [6] The BCG vaccine is commonly used for tuberculosis, HepaB for hepatitis B, MCV1 for the first dose of measles containing vaccine, PENTA1 for the first dose of a combination vaccine such as diphtheria, tetanus, pertussis, hepatitis B, and Haemophilus influenzae type b, OPV1 for first dose of oral polio vaccine, and PCV1 for pneumococcal conjugate vaccine.[43]

In the Philippines, like any other countries, increasing immunization coverage is a serious goal. However, to achieve this goal, it is necessary to make precise projections regarding the utilization of vaccines to guarantee optimal stock levels and effective distribution. Accurate forecasting of vaccine utilization is one of the challenges that different countries are facing and need to overcome to move closer to this goal. The accurate forecasting of vaccine demand for routine immunization is a critical undertaking, particularly when considering worldwide health. A potential consequence of underestimating vaccine demand results in reduced coverage and stock-outs of vaccines. [7] Conversely, an overestimation could lead to an increase in vaccine wastage. By integrating a demand forecasting system into the supply chain of a low-income nation, it is possible to prevent both oversupply and deficiency of vaccines, thereby guaranteeing their distribution to individuals who are really in need of vaccines. Accurate predictions reduce waste by ensuring that vaccines are administered before its expiration dates. This is critical for cost efficiency and sustainability. It also allows health officials to assess safety and efficacy more effectively. Knowing which vaccines are likely to succeed allows for efficient distribution of funding, personnel, and infrastructure. Governments and organizations can prepare for vaccine deployment, prioritize vulnerable populations, and allocate doses strategically. Health facilities can plan for timely deliveries, storage, and transportation based on expected demand. By forecasting demand and effectiveness, we can address disparities and reach underserved communities. Accurate predictions prevent missed vaccination opportunities, protect vulnerable populations, and contribute to disease control. Accurate predictions guide policies on mask-wearing, social distancing, and other preventive measures. Transparent communication about vaccine development builds confidence and encourages vaccination. [8] [9] Currently, there are a lot of vaccine utilization forecasting methods but updating the forecast requires re-estimation and complex to update. Also, a real-time data update is less flexible. Some approaches for addressing missing data are sensitive and model dependent.

Time series forecasting is an analytical approach which utilizes historical and current data to estimate future values. Forecasting is a technique of computing future values by evaluating the behavior of current and previous values in a time series. Forecasting model may be univariate or multivariate. Predictions in the univariate model are dependent upon the current and historical values of the independent time series under consideration while multivariate models are influenced by the values of one or more explanatory variables. [10] A method for predicting univariate time series data is exponential smoothing. This approach creates predictions in the form of weighted averages of previous observations, with the weights assigned to historical data decreasing exponentially. Exponential smoothing techniques enable the modeling of data that includes seasonal and trend components. It has proven to be an efficient method for producing precise predictions across various domains, with a particular emphasis on industry. In signal processing, it is also employed to filter out high-frequency noise and normalize signals. [11] Moreover, it is a powerful tool for denoising time series, forecasting future demand and reducing inventory costs. [12]

Bicol Region or Region 5, a geographically diverse area, experiences unique challenges and opportunities in vaccine demand forecasting. According to NIP Unit Head for Region V, they faced challenges in predicting demand for vaccines and ensuring that sufficient antigen is available in the region. They added that this sometimes leads to vaccine shortages in some areas and vaccine wastage in others as vaccines expire before they can be used. The study aimed to propose an interpretable predictive model using novel data for routine immunization in Region 5. By analyzing data from a variety of sources, such as vaccine administration data, this can accordingly help forecast the demand for vaccines and allocate resources, reducing the risk of vaccine wastage and ensuring that vaccines are available where it is most needed. Moreover, by proper demand forecasting, DOH can begin planning the resources required for expanding vaccination initiatives, as well as the potential economic and population-health benefits. This study also aimed to contribute to existing knowledge of applying the Holt-Winters Exponential Smoothing model in forecasting vaccine demand.

2. Methodology

The study obtained the necessary data from the Family Health and Safety Information System (FHSIS) Annual Report from the year 1999-2022 of the Department of Health (DOH) in the form of a pdf file. The researcher extracted the vaccine administered of BCG, Hepatitis B, DPT or Pentavalent, OPV, PCV and MCV in Region 5 from the pdf file and converted it into an Excel format for further analysis and processing. For data processing, the researcher cleaned the extracted data by removing any irrelevant and incomplete records, addressing missing values and correcting errors to ensure accuracy and consistency. The study used Holt-Winters exponential smoothing model for vaccine demand forecasting given the presence of both trend and seasonality in the data.

The study utilized Phyton programming language and Jupyter notebook v6.5.4 to implement the selected exponential smoothing model. Libraries and packages such as pandas, Numpy, and statsmodels were imported for time series analysis and exponential smoothing. Seasonal decomposition and Nelder-Mead optimization algorithm were used in choosing and optimizing best model parameters. The researcher used scikit-learn library for machine learning and model performance evaluation. Mean Absolute Percentage Error (MAPE) evaluation metrics, Shapiro Wilk Test and Ljungbox Test were utilized to assess the performance and accuracy of the implemented exponential smoothing models.

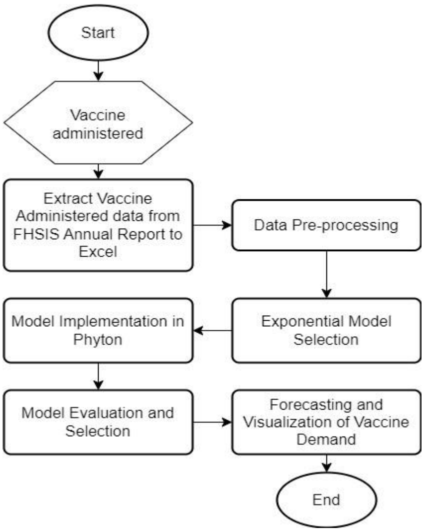

Figure 1 Flowchart of the research process

In forecasting and visualization, the study applied the selected exponential smoothing model to forecast future vaccine demand based on the available historical data. The Matplotlib library was used in generating time series plots to present the historical vaccine demand, actual values, and forecasted values, allowing for an intuitive understanding of the forecasting performance. Fig. 1 shows that flowchart of the research process.

3. Results and Discussion

A. Vaccine Administered Over Time

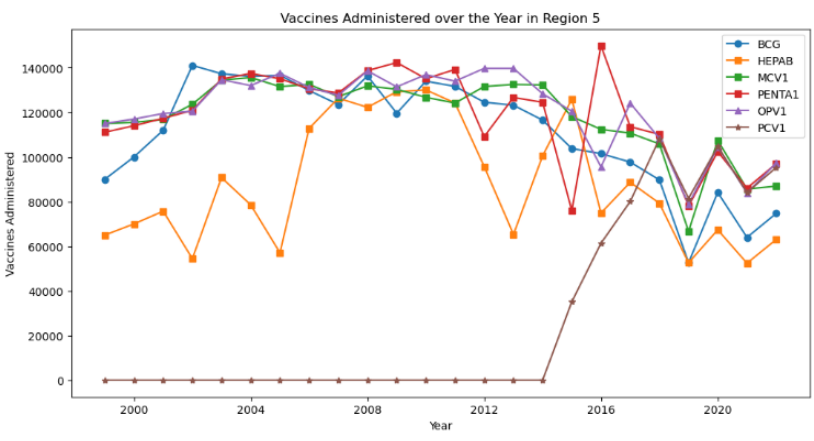

Figure 2 Vaccine Administered Over Time

Fig. 2 shows the total number of various vaccines administered from year 1999 to 2022 in Region 5. The overall trend seems to increase initially, peaks around 2008-2012, and then displays a downward trend towards 2019. On BCG vaccines shows an increasing trend until 2008, with some fluctuations, and then it remains relatively stable with slight declines towards 2019. HepaB has significant volatility. There is a sharp decline around 2008, but it generally follows the same pattern as BCG, peaking around 2008 and then declining.

MCV1 also has an upward trend until around 2008, followed by a relatively stable period with minor fluctuations, and then a decline towards 2019. For Pentavalent1 (Penta1) vaccine shows a sudden increase to align with the other vaccines, suggesting rapid adoption or rollout. Moreover, it has a noticeable drop around 2016 and 2019. OPV1 follows the general trend of peaking around 2008-2012 and then decreasing. It has some of the most pronounced slopes, particularly around 2019. PCV1 vaccine's administration starts around 2015 [13], grows significantly, and then falls sharply towards 2019. in 2013 signifies a broadening of preventive measures to include pneumonia, a leading cause of infant mortality by introducing the pneumococcal conjugate vaccine (PCV) into the national immunization program. This expansion, alongside existing vaccines, represents a significant step towards reducing child mortality rates and achieving health-related Millennium Development Goals.[14]

The peak in BCG in 2002 indicated that the roll out of the vaccination was successful getting 96% of the eligible population [15] for that particular year. In contrast to the HepaB, this due to unavailability of the vaccine that resulted to decline. The national EPI of the Philippines, which procures its own vaccines and is not supported by donors, experienced monovalent hepatitis B vaccine shortages in 2012 from January to April and June to December. [16] For measles, the trend and fluctuation were because of the efforts and challenges of eliminating measles in the Philippines by 2012 as part of the WHO Western Pacific Region's goal set in 2005. In 2011, the "Iligtas sa Tigdas ang Pinas" campaign was launched to vaccinate 18 million children aged 9 months to below 8 years, addressing vaccine gaps since 2004. Supported by local governments and WHO, this campaign stressed the cost-effectiveness and urgency of vaccination amidst rising measles cases and provided door-to-door vaccinations and Vitamin A supplements. [17] However, despite implementing strategies like high vaccination coverage and surveillance, the country faced increased measles cases and outbreaks between 2013-2014 and 2018-2019 in Bicol region along with vaccine hesitancy because of the Dengvaxia vaccine controversy [18] [19] Scoring the need for sustained health system investments and strategy adjustments to meet elimination targets. [20] The Dengvaxia issue cause panic to the community and led to increased vaccine hesitancy not only for the dengue vaccine but also for other routine immunizations, such as measles and polio and even BCG and HepaB vaccines that resulted decline of vaccine administration in 2019. [21] [22] The Bicol Region pressed on with measles-rubella and oral polio vaccine supplemental immunization following typhoon damage in 2020, indicating resilience in public health efforts amidst natural disasters. However, certain areas faced delays due to severe impacts or quarantine measures, highlighting the influence of environmental factors and infrastructure on health initiatives. The decline in the trend also was due to external factors, such as the COVID-19 pandemic, which have disrupted healthcare services and vaccination campaigns. [23] A contributing factor also to the trend could be the region's insufficient data management practices, impacting the comprehensive documentation of vaccine administration. The National Immunization

Program (NIP) Unit in Region 5 highlighted that their data submissions to the DOH Central Office were not always complete, due to gaps in the data collection at the local level, occasionally leading to instances of vaccine wastage. Reliable and timely data for effective vaccine supply chain management and development of strategies to improve vaccine access globally. [24]

Historical records, trends and seasonality are used to identify patterns, directions and fluctuations and establish a baseline for future predictions. These three factors are essential for creating an accurate and reliable demand forecast, leading to cost optimization and waste reduction. Many researchers are striving to propose refined models for examining current situations and predicting future scenarios. [25]

B. Exponential Smoothing Model Application

In the quest to forecast vaccine demand accurately, the researchers employed the Exponential Smoothing (ES) model, leveraging its capability to accommodate data with complex patterns. The ES model was chosen for its simplicity, flexibility, and efficacy in handling time-series data with both trend and seasonal components. The exponential smoothing methods are simple, but the best approach and popular methods used for forecasting. They are widely used for forecasting demand for inventories. [26] [27]

To robustly predict the demand for various vaccines, the researchers applied the Holt-Winters Exponential Smoothing model, recognizing its adeptness at capturing seasonality and trends in time series data. The strength of this model lies in its incorporation of three smoothing parameters (level, trend, and seasonal) that are fine-tuned to echo the observed data patterns. The Holt-Winters method See (1), often referred to as triple exponential smoothing, is a very common time series forecasting procedure capable of including both trend and seasonality. Winter's exponential smoothing is the expansion of Holt's exponential smoothing that enables seasonality to be integrated in the method. [28]

$$\text{Level: } \mathrm{L_t} = \alpha(\mathrm{y_t} - \mathrm{S_t}^{-}{}_{\mathrm{s}}) + (1-\alpha)(\mathrm{L_t}^{-1} + \mathrm{T_t}^{-1})$$

$$\text{Trend: } \mathrm{T_t} = \beta(\mathrm{L_t} - \mathrm{L_t}^{-1}) + (1-\beta)\mathrm{T_t}^{-1}$$

$$\text{Seasonal: } \mathrm{S_t} = \gamma(\mathrm{y_t} - \mathrm{L_t}) + (1-\gamma)\mathrm{S_t}^{-}{}_{\mathrm{s}}$$

$$\text{Forecast: } \hat{\mathrm{y}}_{\mathrm{t+m}} = \mathrm{L_t} + \mathrm{mT_t} + \mathrm{S_{t-s+1}}(\mathrm{m} - 1)\mathrm{mods}$$

Where:

yt is the actual value at time *t*,
Lt is the level at time *t*,
Tt is the trend at time *t*,
St is the seasonal component at time *t*,
is the length of the seasonal cycle,
α, *β*, and *γ* are the smoothing parameters for the level, trend, and seasonal components, respectively, and
m is the number of periods ahead for the forecast.

Triple exponential interpolation can account for additive or multiplicative seasonality. There is a pattern to multiplicative seasonality in which the magnitude increases as the amount of data increases. Additive seasonality refers to a seasonal pattern whose magnitude remains constant despite variations in the observations. [11] These two components serve different purposes and are used to analyze time series data.

1) Model Component Identification: A preliminary analysis was conducted to determine the suitability of additive or multiplicative components for each vaccine's time-series data. Holt-

Winters models offer two variations: additive for data with stable seasonal variations and multiplicative for data with seasonal variations that change proportionally to the level of the time series.

The researchers utilized Seasonal Decomposition to identify the trend and seasonal components, either additive or multiplicative. Seasonal decomposition is a method used in time series analysis to represent a time series as a sum (or, sometimes, a product) of three components – the linear trend, the periodic (seasonal) component, and random residuals. It is useful in analysis of time series affected by factors that change in time in a cyclic (periodical) manner. [29] For each vaccine series, decomposition revealed the optimal model type, aligning with the underlying data characteristics—whether showing consistent seasonal fluctuations or those amplified during peak periods. In Table I shows the model component suitable for each vaccine from the decomposition.

BCG, HepaB, MCV1, Pentavalent1, OPV1 and PCV1 vaccine specifies the nature of the trend and seasonal components of the model as 'additive', suggesting that seasonal variations and trends are linearly related to the level of the series.

VACCINES	MODEL COMPONENTS	
	Trend	Seasonal
BCG	additive	additive
HEPAB	additive	additive
MCV1	additive	additive
PENTA1	additive	additive
OPV1	additive	additive
PCV1	additive	additive

Table 1. Model components for each vaccine

This means that the number of vaccines administered over time presented in Fig. 1 does not significantly increase or decrease in the amplitude, and there is no clear seasonality that changes over time, and the fluctuations appear relatively consistent. Despite various challenges, including vaccine hesitancy and environmental factors, the relatively stable vaccination rates over time, without significant peaks or troughs, justify the additive approach. This model captures the linear relationship between time series components, effectively representing the data despite external disruptions, highlighting the importance of sustained health system efforts and accurate data management for future planning and response strategies.

2) Best Parameters Identification: Having determined the appropriate model framework for each vaccine, the researchers then turned to the Nelder-Mead simplex algorithm to optimize our smoothing parameters. The Nelder-Mead method is particularly advantageous when the derivative information is not available, and its application ensured the determination of the most suitable alpha (level), beta (trend), and gamma (seasonal) parameters. This method is a direct search method of optimization that works moderately well for stochastic problems. It is based on evaluating a function at the vertices of a simplex, then iteratively shrinking the simplex as better points are found until some desired bound is obtained. [30] Finding the best combination of parameters is crucial for model accuracy. This optimization aimed to achieve the best possible balance between the model's sensitivity to recent observations and its

generalization performance, and to minimize the one-step ahead forecast errors on the validation set, ensuring a model that is both sensitive to recent trends and stable enough to avoid overfitting. Table II shows the model fit the best parameters suitable for each vaccine. These parameters represent the optimized hyperparameters for a set of Holt-Winters Exponential Smoothing models for various vaccines, using the Nelder-Mead optimization algorithm. These parameters suggest about the vaccination data and their trends.

For BCG, a relatively high smoothing level (0.7) and seasonal smoothing (1.0) with a lower trend smoothing (0.2) suggest that the level and seasonal effects are considered to have a strong impact on the forecast, while trend changes are less influential. HEPAB, with a smoothing level of 0.6, trend smoothing of 0.3, and seasonal smoothing of 0.6, implies a balanced weighting across all components, indicating moderate confidence in the influence of the observed series, trend, and seasonal factors. MCV1 and OPV1 have a high smoothing level and seasonal parameter (both 0.7 and 1.0, respectively), but no smoothing for the trend (0.0), indicating a strong emphasis on the level and seasonality without trend adjustment, suggesting a stable trend over time. PENTA1 has a lower smoothing level and trend parameter (both 0.3), and no seasonal smoothing (0.0), suggesting less variability in seasonality and more stability in the observed data. Finally, PCV1 with high smoothing level, trend, and seasonal parameters (0.7, 1.0, and 1.0, respectively) places substantial weight on recent observations, trend changes, and seasonal variations, implying that all components are highly influential and dynamic. These parameters were likely chosen based on their performance in fitting the historical data, with each set aiming to best capture the underlying patterns and structures in the vaccine data over the given time period.

VACCINES	MODEL FIT BEST PARAMETERS		
	Smoothing Level	Smoothing Trend	Smoothing Seasonal
BCG	0.7	0.2	1.0
HEPAB	0.6	0.3	0.6
MCV1	0.7	0.0	1.0
PENTA1	0.3	0.3	0.0
OPV1	0.7	0.0	1.0
PCV1	0.7	1.0	1.0

Table 2. Model fit best parameters for each vaccine

The chosen smoothing parameters suggest differences in the underlying data patterns, and behavior for each vaccine, reflecting how the level, trend, and seasonality are believed to affect the forecasts. The smoothing parameters applied in the forecasting models reveal that for BCG, level and seasonal effects are considered more impactful than the trend, suggesting that these two factors should be the focus of future planning efforts. The high smoothing level and seasonal parameter indicates that the administration of BCG vaccine is strongly influenced by consistent factors each year and may peak at certain times, possibly related to specific health campaigns and birth of newborn babies annually. A study suggested that being a newborn, particularly in areas with high TB prevalence or in settings where non-specific benefits of BCG vaccination have been observed, can indeed be a predictor for the administration of the BCG vaccine. This practice aligns with the World Health Organization's recommendations for BCG vaccination at birth in countries with a high burden of TB, aiming to leverage the vaccine's protective effects as early as possible in life. [31] In 2020, the leading illness by number of cases in the Bicol region is tuberculosis. [32] The low trend parameter suggests that year-on-year changes are not as significant, indicating that the overall demand for BCG is stable and does not show a clear upward or downward trajectory. In contrast, the balanced weighting of all components for HepaB points to the need for a more nuanced approach that accounts for moderate fluctuations in trends and seasonality. This suggests that vaccine uptake is affected by a combination of steady demand, yearly changes, and seasonal factors, which might be influenced by supply issues or public health challenges specific to Hepatitis B. Vaccine shortages are another significant issue and establishing a contingency plan for vaccine supply is recommended. [16] The high level and seasonal smoothing parameters for MCV1 and OPV1, with no trend adjustment, implies that while the demand is stable, there should be proactive measures in place for seasonal outbreaks. Measles has been the most outbreak-prone in the last 23 years in Bicol Region. In 2013, 140 suspected cases were confirmed. In 2014, the Bicol region experienced a surge in measles cases, prompting the Department of Health (DOH) to declare an outbreak, and in 2019, the DOH raised a red alert due to a surge in cases. Measures include mandatory immunization, fast lanes in hospitals, and community and school vaccination drives. [33] [34] [35] Regular vaccination programs are crucial to manage and minimize the risk of widespread outbreaks. The lower parameters for PENTA1 suggest a stable demand having less seasonal variability, and the high parameters for PCV1 emphasize the influence of recent observations and the need to remain responsive to rapidly changing trends.

C. Predictive Analysis

After establishing the parameters, the researchers fitted Holt-Winters model to the historical vaccine data. Predictions were then extrapolated to measure the model’s forecasting prowess. Each vaccine’s demand forecast was accurately crafted, considering the unique patterns and seasonalities that had been previously identified.

Fig. 3 shows the projected annual administration figures for the BCG, HepaB, MCV1, Penta1, OPV1, and PCV1 vaccine from 2023 to 2027. For each year, the figure displays the lower and upper bounds of the 95% confidence interval ('lower_CI' and 'upper_CI', respectively) and the projected number of vaccine doses to be administered ('prediction'). These intervals frame the likely range of the actual administration figures, given the historical data and identified patterns.

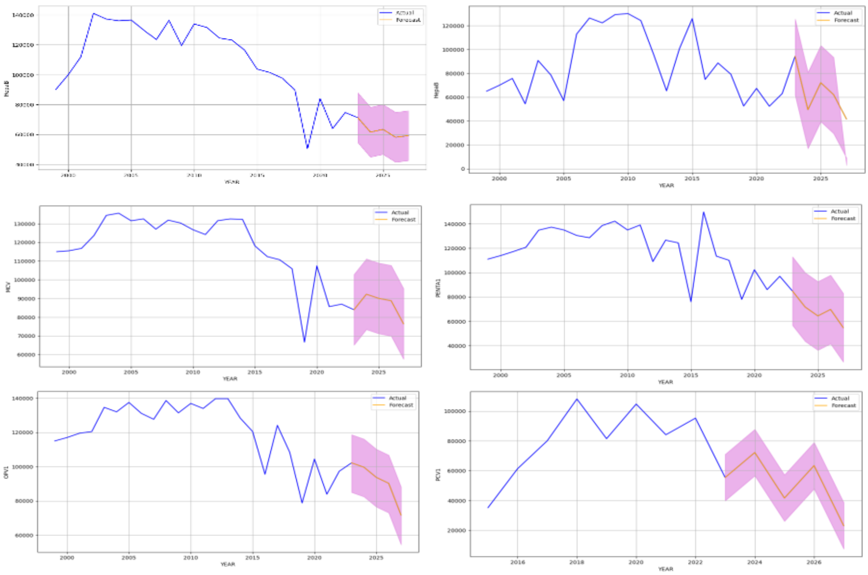

Figure 3 Actual and Forecasted Annual Vaccine Administration

1) BCG Vaccine: Table III shows that it is apparent that the model anticipates a decreasing trend in the administration of the BCG vaccine over the given period. Starting with a prediction of approximately 71,253 for 2023, there is a noticeable drop each subsequent year, with the forecast dipping to around 59,246 by 2027. The confidence intervals suggest there is a degree of uncertainty associated with these predictions, particularly noticeable by their expansion over time. For instance, the lower confidence limit in 2023 is around 54,565, which broadens to approximately 42,557 by 2027, while the upper limit stretches from around 87,942 to 75,935 across the same timeframe.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	54565	71254	87943	BCG
2024-01-01	44909	61598	78286	BCG
2025-01-01	46746	63434	80123	BCG
2026-01-01	41463	58152	74841	BCG
2027-01-01	42558	59246	75935	BCG

Table 3. BCG vaccine administration prediction

2) HepaB Vaccine: Table IV reveals that the annual forecasts for the HEPAB vaccine demand or coverage show variability over time.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	65748	97391	127742	HEPAB
2024-01-01	15471	47114	77465	HEPAB
2025-01-01	40594	72237	102588	HEPAB
2026-01-01	31703	63345	93696	HEPAB
2027-01-01	9236	40879	71230	HEPAB

Table 4. HepaB vaccine administration prediction

The 2023 forecast predicts a demand of approximately 97,391 units, with a confidence interval ranging from about 65,748 to 127,741, suggesting a high degree of uncertainty or variability in the forecast. As time progresses, the forecasted demand seems to fluctuate, dropping significantly in 2024 to around 47,113 units, then rebounding to about 72,237 units in 2025, and adjusting again to approximately 63,345 units in 2026. The confidence intervals for these years also reflect substantial uncertainty, although the range tightens somewhat as we progress through the years. By 2027, the forecasted demand reduces further to roughly 40,878 units, with the narrowest confidence interval in the observed period, indicating increased confidence in the forecast or reduced expected variability.

3) MCV1: Table 5 displays the number of predicted MCV1 vaccine administrations are generally increasing each year from 2023 to 2027. The forecast starts with about 83,959 administrations in 2023 and grows to roughly 88,777 by 2026, with a slight decrease projected for 2027 to approximately 76,399. While there is a year-to-year variance, the overarching trend suggests an initial increase followed by a dip as we reach 2027.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	65067	83959	102852	MCV1
2024-01-01	73365	92257	111150	MCV1
2025-01-01	71147	90039	108932	MCV1
2026-01-01	69885	88777	107670	MCV1
2027-01-01	57507	76399	95292	MCV1

Table 5. MCV1 vaccine administration prediction

4) Pentavalent1: Table 6 model forecast begins with a demand prediction of approximately 84,813 units in 2023, paired with a relatively wide confidence interval, signaling considerable uncertainty. In the following year, there is a notable decrease in the central prediction to about 71,684 units. Moving through to 2025 and 2026, demand is expected to experience a slight rebound, hovering in the mid-60,000s, before a dip to roughly 54,728 units in 2027.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	56599	84813	113028	Penta1
2024-01-01	43470	71684	99899	Penta1
2025-01-01	36195	64410	92625	Penta1
2026-01-01	41518	69733	97947	Penta1
2027-01-01	26514	54728	82943	Penta1

Table 6 Penta1 Vaccine Administration Prediction

5) OPV1. Table V7 presents the annual forecast data for the OPV1 vaccine covering the years 2023 through 2027. The model offers the expected number of vaccine administrations for each year. The forecast begins at approximately 102,187 doses for the year 2023 and shows a general declining trend, reaching about 71,614 doses by 2027. Every prediction is accompanied by a lower and upper confidence interval, which establishes a statistically significant range for the anticipated number of vaccine administrations. A progressive decrease in the forecasted administration of the OPV1 vaccine over the five-year span. The initial forecast for 2023 is the highest, with subsequent years showing a steady decrease in predicted numbers.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	84941	102187	118666	OPV1
2024-01-01	82398	99644	116123	OPV1
2025-01-01	76460	93706	110185	OPV1
2026-01-01	73006	90252	106731	OPV1

2027-01-01	54369	71615	88094	OPV1

Table 7. Opv1 vaccine administration prediction

6) PCV: Table 8 show a declining trend in forecasted demand for the PCV1 vaccine. The model predicts a starting demand of approximately 55,380 units in 2023, with the confidence interval ranging from about 39,788 to 70,971 units, indicating a reasonable level of uncertainty around this initial forecast. As the years progress, there is a notable decrease in both the predicted demand and the width of the confidence intervals, which is indicative of an increasing level of certainty in the predictions. By 2024, the forecasted demand decreases to around 72,158 units, and this downward trend continues steadily, reaching a predicted demand of around 41,584 units in 2025, further declining to approximately 63,386 units in 2026, and then sharply dropping to about 22,985 units in 2027.

Date	lower_Cl	prediction	upper_Cl	Vaccine_Name
2023-01-01	39789	55380	70971	PCV1
2024-01-01	56567	72158	87749	PCV1
2025-01-01	25993	41585	57176	PCV1
2026-01-01	47795	63386	78977	PCV1
2027-01-01	7394	22986	38577	PCV1

Table 8. PCV1 vaccine administration prediction

The predicted data on the vaccine administration, particularly for BCG, HepaB, MCV, Penta1, OPV1, and PCV1 vaccines, indicate varying trends and levels of uncertainty in demand forecasts, which could influence public health strategies. The described variability and the shifting confidence intervals imply that the forecast model is considering complex factors that cause both the expected demand and the uncertainty around it to vary from year to year. There is a general trend of initial demand uncertainty expanding over time, suggesting the need for adaptable vaccination strategies and supply chain adjustments. The advantage of a large-scale vaccination campaign and improvements in immunization supply chains is that it rapidly reduces the phenomenon and achieving higher and more equitable immunization coverage, ultimately ensuring that vaccines reach all populations effectively. [36] [37] For MCV, predictions suggest a stable demand, while the decline in OPV and PCV may call for a review of current health policies and an investigation into the reasons behind the changing vaccination needs. Understanding the impact of specific public health policy interventions will help to establish causality in terms of the effects on health inequalities. [38] Overall, these insights are crucial for planning and ensuring that public health objectives align with evolving healthcare needs and demographic changes.

D. Model Performance Evaluation

1) MAPE: The MAPE, or Mean Absolute Percentage Error, is a common measure used to

Where:

n is the number of fitted points,
At is the actual value,
Ft is the forecast value.
Σ is summation notation (the absolute value is summed for every forecasted point in time).

(2)

assess the accuracy of forecast models. It represents the average absolute percent difference between the observed actual outcomes and predicted values. See (2) Percentage errors are calculated in terms of absolute errors, without regards to sign. This avoids the problem of positive and negative errors canceling each other out. [39] [40] [41] Lower MAPE values indicate a better fit of the model to the historical data, suggesting more accurate predictions. [42] MAPE is particularly useful because it provides a quick and intuitive percentage-based metric that can be easily understood and compared across different forecasting models or various datasets.

$$M = (1/n) * \Sigma_{\mathrm{t=1}}{}^{\mathrm{n}} \left|(A_{\mathrm{t}} - F_{\mathrm{t}}) / A_{\mathrm{t}}\right|$$

In Table 9 shows Mean Absolute Percentage Error (MAPE) for each vaccine, indicating the average percentage deviation between forecasted and actual values. The MAPE results in Table IX for each vaccine administered indicates varying levels of forecast accuracy. BCG vaccine forecasts show a MAPE of 7.12%, indicating predictions that are generally close to the actual values with an average error of around 7%. The HepaB vaccine, with a MAPE of 15.40%, pointing to moderate forecast accuracy. Forecasts for the Measles vaccine show higher accuracy, with a MAPE of 6.38%, suggesting a strong fit between the predicted and actual values. Penta1 and PCV1 vaccine predictions also presented a high accurate forecast, as reflected by a MAPE of 9.52% and 9.46%. The OPV vaccine model's performance is reasonably accurate, with a MAPE of 5.85

Vaccines	Test MAPE %
BCG	7.12%
HepaB	15.60%
MCV1	6.38%
PENTA1	9.52%
OPV1	5.85%
PCV1	9.46%

Table 9. Mape result for each vaccine

The MAPE results show the accuracy of vaccine demand forecasts, with lower percentages indicating closer predictions to actual values. [42] BCG and MCV1 vaccines demonstrate higher accuracy, suggesting reliable demand forecasting, which is critical for effective vaccine stock management and distribution planning. The higher MAPE for HepaB indicates moderate accuracy, highlighting potential areas for model improvement or to consider alternative models to Holt-Winters Exponential Smoothing. Without affecting the model's efficacy for other vaccines, the fluctuating nature of HepaB administration data might be better captured by a model that can account for such variability and potentially irregular events influencing these patterns. Exploring models adept at handling non-linear trends could improve forecast precision for HepaB without compromising results for other vaccines where Holt-Winters has proved suitable.

2) Shapiro Wilk-Test and Ljung Box Test: In Table 10 displays that all vaccines show Shapiro Wilk test statistics near one and p-values greater than 0.05. BCG has a statistic of 0.965 with a p-value of 0.540, HepaB is at 0.980 with 0.880, MCV1 at 0.956 with 0.904, PENTA1 at 0.952 with 0.293, OPV1 at 0.977 with 0.864, and PCV1 at 0.894 with 0.257.

Vaccines	Shapiro-Wilk Test statistics	Shapiro-Wilk Test p-value	Ljung-Box Test lb_statistics	Ljung-Box Test lb_p-value
BCG	0.97	0.54	8.03	0.63
HepaB	0.98	0.88	15.57	0.11
MCV1	0.96	0.90	5.58	0.85
PENTA1	0.95	0.29	9.81	0.46
OPV1	0.98	0.86	8.75	0.56
PCV1	0.89	0.26	0.09	0.70

Table 10. Shapiro-wilk and Ljung-Box test result

Moreover, the p-values in Ljung-Box test are above 0.05 for all vaccines, which suggests there is no significant autocorrelation in the residuals at different lags. BCG shows a p-value of 0.626, HepaB is slightly lower but still above the usual threshold for significance at 0.113, MCV1 has a p-value of 0.849, PENTA1 at 0.457, OPV1 at 0.556, and PCV1 has a high p-value of 0.700. This means that for all vaccines, there's no indication of leftover patterns in the residuals after the Holt-Winters forecast, indicating that the model captures the data patterns well.

These results suggest that the residuals for each vaccine's demand forecast are consistent with a normal distribution, which implies that the prediction errors are random and not biased, an indication of a good fit for the Holt-Winters model. The data means that diagnostic tests for the residuals from the Holt-Winters Exponential Smoothing forecasts do not show any significant problems. There is evidence of normality and no significant autocorrelation across all vaccines, pointing to a generally well-performing forecasting model. This performance suggests the Holt-Winters model successfully captures the true vaccine demand patterns, making it a valuable tool for planning and managing vaccine supplies across these various immunization programs.

4. Conclusion

The comprehensive analysis conducted in this study has revealed significant insights into the trends and seasonality of vaccine administration in Region 5, employing the Holt-Winters Exponential Smoothing model for accurate forecasting. The investigation systematically identified an increasing trend in vaccine administration up to 2008-2012, followed by a decline, highlighting the influence of various factors such as vaccine availability, public health campaigns, and external events like the Dengvaxia controversy and the COVID-19 pandemic on vaccine uptake. The use of the Holt-Winters Exponential Smoothing model, chosen for its simplicity, flexibility, and efficacy in handling time-series data, demonstrated its capability to handle complex data patterns, including both trend and seasonal components. The predictive research demonstrated the model's efficacy, providing future demand predictions for vaccines from 2023 to 2027 while considering known patterns and seasonality.

Model evaluation metrics, specifically the Mean Absolute Percentage Error (MAPE), indicated varying levels of forecast accuracy across different vaccines, suggesting the model's effectiveness in capturing the underlying patterns of vaccine demand. Additionally, diagnostic tests such as the Shapiro-Wilk and Ljung-Box tests confirmed the model's suitability, showing no significant problems in the residuals, which implies that the predictions are unbiased, and the model accurately captures the data patterns.

Finally, this study accomplished its goals by determining the pattern and seasonality of vaccine delivery in Region 5 and how these parameters might help foresee vaccination demand. By determining an interpretable predictive model that captures these parameters, research provides a valuable tool for healthcare planners and policymakers. This predictive model enables the formulation of informed strategies for vaccine distribution and inventory management, aiming to optimize vaccine utilization, reduce waste, and ultimately improve public health outcomes in Region 5. The findings of this research emphasize the importance of utilizing modern forecasting models for effective vaccine management. It highlights the need for continuous monitoring of vaccine administration trends, adjusting immunization programs accordingly to address the identified challenges and the need for enhanced data management systems to ensure accurate tracking and utilization of vaccines. The study's methodology and findings contribute significantly to the existing body of knowledge, offering a guide for future research and practical applications in vaccine demand forecasting and public health planning.

The research evaluated the vaccine used for routine immunization, and only one dose was used; researchers recommend future research to determine the pattern for the other doses. Also, investigate other aspects such as data management, which may have an impact on the study, particularly if the research requires historical data.

ACKNOWLEDGMENT

Above all, the authors express gratitude and appreciation to Almighty God for making everything possible. Sincere gratitude to DOH Region 5 NIP Unit Dr. Desiree Bricenio and Kendall Louise Luna, Dr. Florivel D. Villacorta, Kennedy Cuya, Mary Joy Canon, Jocelle Monreal, and Ramona Mic Magtangob for their humble ideas and support. The expert panel provides insightful input and valuable time to help enhance the study. Finally, appreciation to the authors' colleagues and family, particularly Luna and Lance, for their motivation and inspiration.

References

1. Immunization Coverage. (2018). Retrieved from World Health Organization: https://www.who.int/news-room/fact-sheets/detail/immunization-coverage
2. Vaccines and Immunization. (2021). Retrieved from Centers for Disease Control and Prevention: https://www.cdc.gov/vaccines/index.html
3. W. A. Orenstein, & R. Ahmed (n.d.). Simply put: vaccination saves lives. Proc. Natl. Acad. Sci. U.S.A., 144(16), 4031-4033. doi:10.1073/pnas.1704507114
4. Why is immunizat ion important? (2021). Retrieved from GAVI, the Vaccine Alliance: https://www.gavi.org/vaccineswork/why-immunisation-important
5. Why is immunization important? (2021). Retrieved from GAVI, the Vaccine Alliance: https://www.gavi.org/vaccineswork/why-immunisation-important
6. (2021). FHSIS Annual Report 2021. Retrieved November 2023
7. L. E. Mueller, L. A. Haidari, A. R. Wateska, R. J. Phillips, M. M. Schmitz, D. L. Connor, et al. (2016). The impact of implementing a demand forecasting system into a low-income country's supply chain. Vaccine 34 (32), 3663–3669. doi: 10.1016/j.vaccine.2016.05.027

8. R. Hariharan, S. Johnna, G. Giacomo, A. Schimdt, A. Drew, & B. Fels, (2020). An Interpretable Predictive Model of Vaccine Utilization for Tanzania. Frontiers in Artificial Intelligence, 3. doi:10.3389/frai.2020.559617
9. Vaccine efficacy, effectiveness and protection. (2021, July 14). Retrieved February 2024, from Who Health Organization: https://www.who.int/news-room/feature-stories/detail/vaccine-efficacy-effectiveness-and-protection
10. Das, P. (2019). Time Series. Econometrics in Theory and Practice.
11. J. Frost, (2021). Exponential Smoothing for Time Series Forecasting. Retrieved March 9, 2024, from statisticsbyjim.com:https://statisticsbyjim.com/time-series/exponential-smoothing-time-series-forecasting/
12. L. F. Tratar, B. Mojškerc, & A. Toman, (2016). Demand Forecasting with Four-Parameter Exponential Smoothing. International Journal of Production Economics(181), 162-173.
13. J. Perdrizet, H. E.-P.-L. (2021, Dec). Cost-Effectiveness of the 13 Valent Pneumococcal Conjugate Vaccine (PCV13) Versus Lower-Valent Alternatives in Filipino Infants. Infect Dis Ther. , 10(4):, 2625-2642. doi:doi: 10.1007/s40121-021-00538-z
14. (2013, July 17). DOH: Vaccine vs. pneumonia in children now part of government immunization program. Department of Health. Official Gazette. Retrieved from https://www.officialgazette.gov.ph/2013/07/17/doh-vaccine-vs-pneumonia-in-children-now-part-of-government-immunization-program/
15. Field Health Service Information System Annual 2002. (2002). Legazpi City, Albay, Philippines.
16. M K, Patel, C. R. (2014, Sep 3). Findings from a hepatitis B birth dose assessment in health facilities in the Philippines: opportunities to engage the private sector. Vaccine, 32((39):5140-4.), doi: 10.1016/j.vaccine.2013.11.097. Epub 2013 Dec 19. PMID: 24361121; PMCID: PMC4663669.
17. DOH. (2011, April 4). DOH launches nationwide Iligtas sa Tigdas ang Pinas campaign. Retrieved from www.officialgazette.gov.ph: https://www.officialgazette.gov.ph/2011/04/04/doh-launches-nationwide-iligtas-sa-tigdas-ang-pinas-campaign/
18. DOH Bicol to Conduct Measles Immunization for 6 month to 5 year old. (2018, May 16). Retrieved from region5.healthresearch.ph: https://region5.healthresearch.ph/index.php/local-health-news/121-doh-bicol-to-conduct-measles-immunization-for-6-month-to-5-year-old
19. E. Mascariñas, & M. Arguelles, (2019, June 27). Measles remains health concern in Bicol, Caraga. Retrieved from https://newsinfo.inquirer.net/: https://newsinfo.inquirer.net/1134532/measles-remains-health-concern-in-bicol-caraga
20. Y. Takashima, S. W.,(2015 , Apr 10). Progress toward measles elimination—Philippines, 1998-2014. MMWR Morb Mortal Wkly Rep, 64(13), 357-62.
21. K. Fatima, S. N. (2018, Dec). Dengvaxia Controversy: Impact on Vaccine Hesitancy. J Glob Health, 8((2):010312). doi: doi: 10.7189/jogh.08.020312
22. H. Larson, J.-G. (2019). Vaccine confidence plummets in the Philippines following dengue vaccine scare: why it matters to pandemic preparedness. Human Vaccines & Immunotherapeutics, 15(3), 625-627. doi:DOI: 10.1080/21645515.2018.1522468
23. Z. Lassi, R. Naseem, R. Salam, F. Siddiqui, & J. Das, (2021). The impact of the COVID-19 pandemic on immunization campaigns and programs: a systematic review. Int J Environ Res Public HealAth, 18(3), 988.
24. H. Lee, et al. (2017). Improving Global Vaccine Access: A Framework for Designing and Optimizing Vaccine Supply Chains. Vaccine.
25. I. Djakaria, & S. Saleh, (n.d.). Covid-19 forecast using Holt-Winters Exponential Smoothing. Journal of Physics Conference Series 1882(1):012033. doi:DOI:10.1088/1742-6596/1882/1/012033

26. E. S. Gardner, (1985). Exponential Smoothing: The state of the art. Journal of Forecasting, vol. 4, pp. 1-28.
27. Y. Feng, (2011). Demand Forecast Based on Exponential Smoothing. Logistics Engineering and Management.
28. A. Lleyton, (2021, February 23). A Thorough Introduction to Holt-Winters Forecasting. Retrieved March 10, 2024, from medium.com: https://medium.com/analytics-vidhya/a-thorough-introduction-to-holt-winters-forecasting-c21810b8c0e6
29. Seasonal Decomposition. (n.d.). Retrieved March 19, 2024, from www.statistics.com: https://www.statistics.com/glossary/seasonal-decomposition/
30. J. A. Nelder, & R. Mead, (1965). A Simplex Method for Function Minimization. Comput. J., 7, 308-313.
31. BCG Vaccine Fact Sheet. (2012, May 4). Retrieved from cdc.gov: https://www.cdc.gov/tb/publications/factsheets/prevention/bcg.htm
32. Leading illnesses in the Bicol region of the Philippines in 2020, by number of cases. (2024, Feb 20). (S. R. Department, Producer) Retrieved from www.statista.com:
33. E. Mascariñas, & M. Arguelles, (2019, June 27). Measles remains health concern in Bicol, Caraga. Retrieved from https://newsinfo.inquirer.net/: https://newsinfo.inquirer.net/1134532/measles-remains-health-concern-in-bicol-caraga
34. Deaths due to measles reach 15 in Bicol region. (2019, August 28). Retrieved from https://www.gmanetwork.com/: https://www.gmanetwork.com/news/topstories/regions/706084/deaths-due-to-measles-reach-15-in-bicol-region/story/
35. C. Calipay, (2018, October 2). DOH-Bicol monitors 300% rise in measles cases. Retrieved from www.pna.gov.ph: https://www.pna.gov.ph/articles/1049770
36. G. Tradigo, J. Das, P. Vizza, S. Roy, P. Guzzi, & P. Veltri, (2023). Strategies and Trends in COVID-19 Vaccination Delivery: What We Learn and What We May Use for the Future. Vaccines, 11, 1496. . doi:https://doi.org/10.3390/vaccines11091496
37. R. S. Rao, (2017). Immunization supply chains: Why they matter and how they are changing. Vaccines(35(2017)), 2103–2104. doi:https://doi.org/10.1016/j.vaccine.2017.02.062
38. K. Thomson, H.-B. (2018). The effects of public health policies on health inequalities in high-income countries: an umbrella review. BMC Public Health, 18, 869. doi:https://doi.org/10.1186/s12889-018-5677-1
39. Mean Absolute Percentage Error (MAPE). (n.d.). Retrieved March 20, 2024, from www.statisticshowto.com: https://www.statisticshowto.com/mean-absolute-percentage-error-mape/
40. Zach. (2021, May 10). How to Interpret MAPE Values. Retrieved March 20, 2024, from www.statology.org: https://www.statology.org/how-to-interpret-mape/
41. N. Azaria, (n.d.). A Comprehensive Guide to Mean Absolute Percentage Error (MAPE). Retrieved March 20, 2024, from www.aporia.com: https://www.aporia.com/learn/a-comprehensive-guide-to-mean-absolute-percentage-error-mape/
42. Zach. (2020, December 24). What is Considered a Good Value for MAPE? Retrieved from www.statology.org: https://www.statology.org/what-is-a-good-mape/
43. ATP, Silva, L. E.-F. (2018). Compliance with the vaccination schedules in children hospitalized with pneumonia and associated factors. Rev Saude Publica, 52:38.