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Free Healthcare Policy and Childhood Pneumonia: A Time Series Impact Evaluation of a State Government Intervention

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Abstract
Pneumonia continues to be the foremost infectious contributor to global mortality across all age groups, with a particularly heavy burden of deaths occurring among children younger than five years worldwide. Beyond its direct health consequences, the disease imposes profound social and economic burdens on affected individuals, families, communities, and the broader society. In response to this public health challenge, the State government has committed considerable financial resources to the health sector through the Ministry of Health. These efforts are particularly focused on the provision of free healthcare services for vulnerable populations, including children, older adults, and pregnant women, with the overarching goal of preventing avoidable deaths from preventable diseases. This study aims to evaluate the impact of government interventions on the prevalence of childhood pneumonia by employing an appropriate time-series analytical approach. The findings indicate that before the implementation of the intervention, 2,609 cases of pneumonia were recorded among children, whereas 596 cases were documented during the post-intervention period. The study identified 3,243 pneumonia cases among children aged 0 to 14 years. A value of 19.5285 for the impact parameter shows that the intervention failed because the number of admissions increased after the intervention. The postintervention admissions fluctuated between a minimum of 10 and a maximum of 34, which is wider than the fluctuation recorded before the intervention. The estimated onset effect of the intervention, valued at 20, is equivalent to its long-term impact. This equivalence further substantiates that the intervention produced an instantaneous and abrupt effect.

Keywords: Paediatric Pneumonia, Impact analysis, Government's intervention
AMS Classification: 62M10, 62P10.

1. Introduction

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Pneumonia is recognized as a severe subtype of acute lower respiratory infection (ALRI), chiefly affecting the lungs and contributing markedly to the global burden of ALRI related disease (UNICEF, 2023). Anatomically, the lungs consist of branching airways known as bronchi, which subdivide into smaller bronchioles and ultimately end in microscopic air sacs called alveoli. These alveoli are surrounded by capillaries where gas exchange occurs, allowing oxygen to enter the bloodstream and carbon dioxide to be removed. During pneumonia, alveolar inflammation leads to the filling of air spaces with fluid or pus, compromising oxygen absorption and causing respiratory symptoms. The possible causes of the disease include bacterial infection, viral infection, and fungal infection. Among children, Streptococcus pneumoniae is the leading cause of disease in bacterial infection, while Haemophilus influenzae type b (Hib) is the second-leading cause. Respiratory syncytial virus predominates among viral causes, whereas Pneumocystis jiroveci is a principal pathogen in HIV exposed infants, contributing to approximately one quarter of pneumonia related deaths in this subgroup.

Transmission occurs through multiple pathways, including inhalation of pathogens present in the upper respiratory tract, exposure to airborne droplets released during coughing or sneezing, and hematogenous spread, particularly during or shortly after childbirth. Clinically, pneumonia is commonly characterized by respiratory symptoms such as persistent coughing and rapid or laboured breathing associated with chest complications (IEA, IRENA, UNSD, World Bank and WHO, 2022; UNICEF, 2012, 2015, 2016a, 2016b, 2023; WHO and UNICEF, 2023; WHO, 2013, 2022, 2023).

Pneumonia remains the leading infectious cause of mortality among children worldwide, resulting in the deaths of more than 700,000 children under the age of 5 annually, equivalent to approximately 2,000 deaths per day, including an estimated 190,000 neonatal fatalities. The vast majority of these deaths are considered preventable. On a global scale, pneumonia incidence exceeds 1,400 cases per 100,000 children each year, corresponding to roughly one episode per 71 children, with the highest burden observed in South Asia and West and Central Africa, where incidence rates reach approximately 2,500 and 1,620 cases per 100,000 children, respectively (UNICEF, 2023). Mortality from childhood pneumonia is strongly linked to socioeconomic and environmental determinants, such as limited access to quality healthcare, exposure to indoor and ambient air pollution, malnutrition, and inadequate sanitation and safe water infrastructure. Air pollution alone is estimated to contribute to nearly half of paediatric pneumonia related deaths, with indoor air pollution accounting for a greater proportion of mortality than outdoor exposure. Concurrently, nearly 2 billion children aged 0 to 17 live in areas where ambient air pollution levels exceed internationally recommended standards (UNICEF, 2023; WHO and UNICEF, 2023).

A growing body of literature has examined the modelling and forecasting of pneumonia incidence using time series methodologies. For instance, Fagerli *et al*. (2023) performed a time series analysis to evaluate temporal changes in pneumonia related hospitalizations across four district hospitals in Mongolia. Their findings indicated that individuals aged sixty-five years and above experienced the highest mean annual hospitalization rate for all cause pneumonia: 63 per 10,000 population, with incidence declining progressively in younger age groups. After adjusting for the effects of the ‘COVID 19’ pandemic, the authors observed that pneumonia hospitalization rates remained

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relatively stable over time, with no evidence of a reduction across any age category. Both restricted and sensitivity analyses corroborated the primary findings, demonstrating no measurable decrease in the overall pneumonia burden.

Similarly, Kalule (2022) applied an ARIMA framework to model pneumonia cases in Uganda over the period 2014 to 2021, identifying ARIMA(2,1,0) as the most suitable model for the series. In another study, Coma *et al*. (2021) employed time series techniques to investigate pneumonia trends during two waves of the 'COVID 19' pandemic spanning January 2014 – December 2020. Their analysis revealed an excess of 11,704 pneumonia cases between March 4 and May 5, 2020, alongside a previously reported 20 percent increase among individuals older than 15 years between January and March 2020. Additionally, an excess of 1,377 cases was documented between October 22 and November 15. Conversely, reductions were observed during other periods, with 131 fewer days and 3,534 fewer pneumonia cases recorded between March and July, and 54 fewer days with 1,960 fewer cases between October and December.

Wangdi *et al*. (2021) examined the 'spatio temporal' distribution of childhood pneumonia in Bhutan using a Bayesian analytical framework. Over a surveillance period of 108 months, the authors reported overall pneumonia incidence rates of 144 per 1,000 children under 5 years of age and 10 per 1,000 children aged 5 to 14 years. The burden of pneumonia was higher among male children younger than 5 years compared with their female counterparts. The findings reveal that a 1-degree centigrade change in maximum temperature would cause an increase of 1.3 percent, while a 10 percent change in relative humidity would result in a decrease of 1.2 percent in the cases of pneumonia. In addition, a modest monthly decline of 0.3 percent in pneumonia incidence was observed. These findings suggest that environmental factors, particularly temperature and humidity, play an important role in shaping the seasonal patterns and spatial variability of childhood pneumonia observed in the study area.

Shen (2019) evaluated the impact of vaccination programs on the incidence of pneumonia and gastrointestinal diseases in Brazil using a time series analytical framework. The findings indicated that, relative to cases estimated through a synthetic control approach, the implementation of pneumococcal vaccination across five Brazilian locations was associated with a substantial increase in the number of cases averted and a corresponding reduction in observed pneumonia cases. Conversely, the vaccine targeting gastrointestinal disorders demonstrated limited effectiveness in certain regions of Brazil across both age groups. In a related study, Ruchiraset and Tantrakarnapa (2018) applied time series modelling to examine pneumonia hospital admissions and their relationship with polluted air and climatic factors in the Chiang Mai Province of Thailand. Over 12 years, from 2003 to 2014, a total of 67,583 pneumonia cases were reported in the province. Seasonal analysis revealed that monthly pneumonia incidence increased between February and September, corresponding to the winter and rainy seasons, and declined between April and July, spanning the summer to early rainy periods. They identified a SARIMA$(1,0,2)(2,0,0)_{12}$ with PM_{10} (ARMODEL 5) as the most suitable specification for the data.

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Beninca *et al*. (2017) conducted a 'spatio temporal' examination of pneumonia-related hospital admissions in the Netherlands. Their analysis employed wavelet based clustering techniques on regional time series data from 5 major areas, alongside the identification of spatial clusters at both annual and seasonal scales. The findings demonstrated pronounced temporal and geographic aggregation of pneumonia admissions layered over a consistent yearly pattern, with peak incidence occurring during winter and the lowest levels observed in summer. Cluster analysis revealed considerable spatial heterogeneity, with the most prominent clusters located in the highly urbanized western regions and the intensively agricultural eastern areas of the country. Quantitatively, age standardized incidence within these dominant clusters exhibited relative risks ranging from 1.2 to 2.2. The authors further discussed potential underlying drivers of these observed patterns, including fluctuations in air pollution levels.
Ayieko *et al*. (2012) examined differences in mortality among children hospitalized with pneumonia across Kenyan healthcare facilities. Their study reported that 195 children, representing 5.9 percent of pneumonia admissions across nine hospitals between March 2007 and March 2008, died during hospitalization. Mortality was found to be strongly associated with both age and disease severity, even after adjusting for sex, comorbid conditions, and hospital level effects. The analysis also provided evidence of substantial variation in mortality rates between hospitals. Notably, the introduction of the Haemophilus influenzae type b (Hib) vaccine did not coincide with a measurable change in pneumonia related mortality, as death rates remained stable both before and after its implementation.

The concept of intervention modelling was first suggested by Box and Tiao (1975). This technique is used to understand the impacts of various external shocks or changes in policy on time-series analysis. This methodology has been widely adopted across diverse empirical contexts. For example, Inyang *et al*. (2024b) applied an intervention framework incorporating exponential smoothing (ETS) and ARIMA models to examine fluctuations in the conversion rate between the BDT and the NGN following the 2016 economic downturn. Their findings indicated that the intervention resulted in a 68.49 percent depreciation of the Naira relative to the Taka, with an estimated decay rate of 0.6. Similarly, Inyang *et al*. (2023) employed the Box and Tiao (1975) approach based on exponential smoothing and Box and Jenkins (1976) techniques to analyse day-to-day conversion rate movements between the PKR and the NGN.
On another note, according to Inyang *et al*. (2022), Nigerian crude oil prices influenced by the global-oil-politics have been examined through the application of Box and Tiao's intervention analysis method. They discovered that the intervention undertaken by OPEC in December 2016 had an instantaneous effect, responsible for 33.72% increase in price level. The impact of the government's clemency initiative in the crude oil–producing region in Nigeria was examined by Moffat and Inyang (2022), whereas Etuk *et al*. (2022) focused on the effects of the declaration of cooperation on national oil output. In a related contribution, Shittu and Inyang (2019) utilized the Box and Tiao framework to analyse monthly crude oil prices in Nigeria and compared its performance with an alternative intervention model incorporating lag operators. Beyond the energy and financial sectors, Mrinmoy *et al*. (2014) evaluated the influence of Bacillus thuringiensis variety on Gossypium yields, treating the 2002 adoption of Bacillus thuringiensis as

a step intervention. Additionally, Yang (2014) applied ARIMA intervention models to assess the revenue effects associated with new product launches.

Using the Box-Tiao framework, Darkwah *et al*. (2012) analysed both the impact and key attributes of community policing implementation across communities in Ghana. Meanwhile, Jarrett and Kyper (2011) explored how the global economic instability affected stock prices within the Chinese market. Lam *et al*. (2009) employed an intervention time series analysis in assessing the effect and lasting effects associated with business process reengineering, where activity model analysis was the main foundation of the study. Using Box-Tiao procedure, Min (2008) examined the extent to which the earth tremors and SARS epidemic of 1999 and 2003, respectively, generated either temporary or persistent impacts on tourism inflows from Japan.

Similarly, Lai and Lu (2005) examined the effects of the September 11, 2001 terrorist attacks on air passenger demand in the United States using an intervention modelling approach. Girard (2000) applied an ARIMA intervention model to analyse the epidemiological trends of whooping cough in England and Wales between 1940 and 1990. Nelson (2000) applied the Box-Tiao method to evaluate the impact of the debt resolution law. Similarly, Sharma and Khare (1999) employed the technique due to Box-Tiao to examine impact-regulatory policies enforced by the authorities to curb road transport pollutants in India. Earlier, Deutsch and Alt (1977) investigated the effects of Massachusetts' gun control legislation on firearm related crimes in Boston. More recent applications of the Box and Tiao intervention methodology can be found in Inyang *et al*. (2026), Inyang (2024), and Inyang *et al*. (2024a, 2024d), among others.
This study investigates how government interventions in the state health sector have influenced childhood pneumonia outcomes. In particular, it highlights the Ministry of Health's financial commitments to ensuring free access to medical care for children, pregnant women, and the elderly. Against the backdrop of this objective, this study seeks to answer the following question: What is the impact of the State Government's free healthcare intervention on the prevalence and hospital admission rates of pneumonia among children aged 0-14 years, and did the intervention reduce the case burden over the study period?

2. Methodology

2.1 *Data Description*

This study examines the effects of the government's childhood pneumonia intervention. The dataset comprises monthly records of paediatric pneumonia cases collected from January 1997 to December 2011 across five hospitals selected from the three senatorial districts of Akwa Ibom State. Data were segmented into pre–intervention (Jan. 1997–Feb. 2009) and post–intervention (Mar. 2009–Dec. 2011) periods, and all analyses were executed using R software (R Core Team, 2022).

2.2 *ARIMA(p,d,q)-Intervention Model*

The approach due to Box-Jenkins has been widely recognized as a leading approach for time series modelling and forecasting (Box and Jenkins, 1970, 1976; Box et al., 1994). However, the effectiveness of ARIMA modelling might be affected in situations where there are other events that affect the time series. To address this limitation, (Box and Tiao, 1975) proposed the

ARIMA(p,d,q)-intervention analysis, which accounts for the effects of external interventions, expressed as follows:

$$\mathcal{Q}_t = \Re(\mathbb{B}) + \mathfrak{F}_t \tag{1}$$

Where:
$\Re(\mathbb{B})$ = transfer function
$\mathfrak{F}_t$ = noise

The $ARIMA(p,d,q)$ framework incorporating effects can be represented as follows:

$$\mathcal{Q}_t = \frac{\ni(\mathbb{B})}{\oint(\mathbb{B})}\rho_{t-\varrho} + \frac{\nu(\mathbb{B})}{\pi(\mathbb{B})}z_t \tag{2}$$

Where:

$$\Re(\mathbb{B}) = \frac{\ni(\mathbb{B})}{\oint(\mathbb{B})}\rho_{t-\varrho};\ \mathfrak{F}_t = \frac{\nu(\mathbb{B})}{\pi(\mathbb{B})}z_t \tag{3}$$

$$\pi(\mathbb{B}) = 1 - \pi_1\mathbb{B} - \pi_2\mathbb{B}^2 - \cdots - \pi_p\mathbb{B}^p \tag{4}$$

$$\nu(\mathbb{B}) = 1 + \nu_1\mathbb{B} + \nu_2\mathbb{B}^2 + \cdots + \nu_q\mathbb{B}^q \tag{5}$$

$$\oint(\mathbb{B}) = 1 - \oint_1\mathbb{B} - \cdots - \oint_r\mathbb{B}^r \tag{6}$$

$$\ni(\mathbb{B}) = \ni_0 - \ni_1\mathbb{B} - \cdots - \ni_s\mathbb{B}^s \tag{7}$$

$\mathcal{Q}_t$=childhood Pneumonia at time t; $\ni$ =impact parameter; $\oint$ =growth rate; ϱ=delay parameter; π = autoregressive parameter; ν = moving average parameter; z_t = white noise (WN).
The term $\mathfrak{F}_t$ refers to the $ARIMA(p,d,q)$ model used to characterize the monthly childhood pneumonia series before the intervention.
The variable ρ_t serves as an indicator and is defined mathematically by:

$$\rho^T{}_t = \begin{cases}1, & t = T\\ 0, & t \neq T\end{cases}, \text{ (the pulse function)} \tag{8}$$

2.3 *Unit Root Test*
A fundamental step in time series modelling involves diagnosing the statistical characteristics of the series under investigation. Thus, the technique introduced by Dickey and Fuller (1979) relies on the regression framework specified below.

$$\mathcal{Q}_t = \pi\mathcal{Q}_{t-1} + \sum_{j=1}^{p-1}\mathcal{Q}_j\Delta\mathcal{Q}_{t-j} + \epsilon_t \tag{9}$$

Where $\mathcal{Q}_t$ = the tested series; p = lagged differenced terms
Hypothesis:

$$H_{null}: \pi = 0 \text{ vs } H_{Alternative}: \pi \neq 0$$

$$T = \frac{\hat{\pi}-1}{S.E(\hat{\pi})} \sim t_{\propto}(n-1) \tag{10}$$

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Note: When H_0 is rejected, it implies that the series is free from a unit root.

2.4 *Model Validation (Diagnostics)*

In time series analysis, diagnostic checking plays a vital role in validating model performance by assessing several diagnostic indicators to ensure that the chosen model is well specified and capable of generating reliable forecasts. Accordingly, below are the model diagnostics evaluated:

2.4.1 *Plot of the residual ACF & PACF*

The goodness of fit of an estimated ARIMA model is evaluated by analysing the correlogram of its residuals. If most of the estimated autocorrelation coefficients lie within the interval $\pm\frac{2}{\sqrt{T}}$, with T representing the sample size, the residuals are considered uncorrelated, thereby indicating an acceptable model fit (Inyang et al., 2024c, 2025).

2.4.2 *Akaike Information Criterion (AIC)*

According to (Akaike, 1974), the AIC can be written in the following form:

$$AIC = M_T\left[1 + \frac{2P}{T-P}\right] \tag{11}$$

Where:
$M_T =$ residual sum of squares (index related to production error); $T =$ Number of data points;
$p =$ Number of parameters in the model,

2.4.3 *Bayesian Information Criterion (BIC)*

The technique, as discussed by (Clement, 2014) and (Schwarz, 1978), serves as a tool for selecting the best model among various models. Among competing specifications, the model that has the smallest BIC value is preferable.

$$BIC = n.\, ln\hat{\sigma}_e^2 + kln.(n) \tag{12}$$

$$\hat{\sigma}._e^2 = \frac{1}{T}\sum_i^T(\mathcal{Q}_i - \bar{\mathcal{Q}})^2 \tag{13}$$

Where:
$\mathcal{Q} =$ Observed data as earlier defined
$T =$Length of series
$k =$ Parameter involved

2.4.4 *Ljung Box Test*

Developed by Ljung and Box (1978), this technique provides a formal procedure for assessing the null hypothesis of no serial correlation in the series.
The test involves calculating the statistic, $\mho$, for an observed series $\mathcal{Q}_t$ with sample size ς, given by:

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$$\mho(m) = \varsigma(\varsigma + 2)\sum_{j=1}^{\aleph} \frac{r_j^2}{\varsigma - j} \tag{14}$$

Where: r_j = sample autocorrelations (accumulated), $\aleph$ = time lag.

Hypothesis:

H_{Null}: (no autocorrelation) vs $H_{Alternative}$: (not true)

3. Results and Discussion

Table 1 presents the basic descriptive statistics of the dataset analysed in this study, providing insight into the behaviour of the series over time. The data comprise 180 monthly observations covering January 1997 to December 2011. The minimum number of reported paediatric pneumonia cases, equal to three, was observed in May 1999 and April 2003, whereas the maximum count of 38 cases occurred between October 2007 and March 2009. Prior to the intervention, 2,609 cases of childhood pneumonia were recorded, compared with 596 cases during the post-intervention period. Overall, 3,243 youngsters between the ages of zero and fourteen years were affected over the study horizon, with a mean prevalence of 18 cases and an estimated variance of 61, indicating overdispersion in the distribution.

Table 1: Summary Statistics of Childhood Pneumonia Prevalence

Full Series							Pre-Series		Post-Series	
Nobs	Min	Max	Sum	Mean	Var	Stdev	Nobs	Sum	Nobs	Sum
180	3	38	3243	18	61	8	146	2609	34	596

The temporal evolution of monthly pneumonia prevalence between January 1997 and December 2011 is illustrated in Figure 1. The series exhibits irregular fluctuations without a clear long-term trend, with the most pronounced peak observed between October 2007 and March 2009, suggesting the presence of an intervention effect. In line with the indicator function framework, the assumed timing of the intervention is given by:

$$\rho^{T}{}_{t} = \begin{cases} 1, & t = March\ 2009 \\ 0, & t \neq March\ 2009 \end{cases} \tag{15}$$

Where T = March 2009 and $\rho^{T}{}_{t}$ = Pulse function.

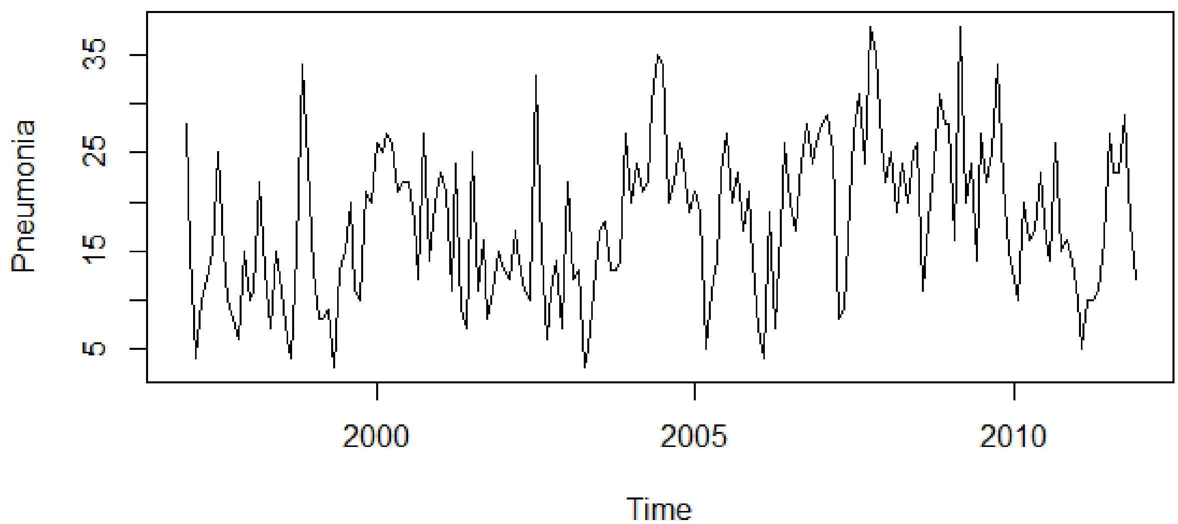

Figure 1: Childhood Pneumonia (Time Plot)

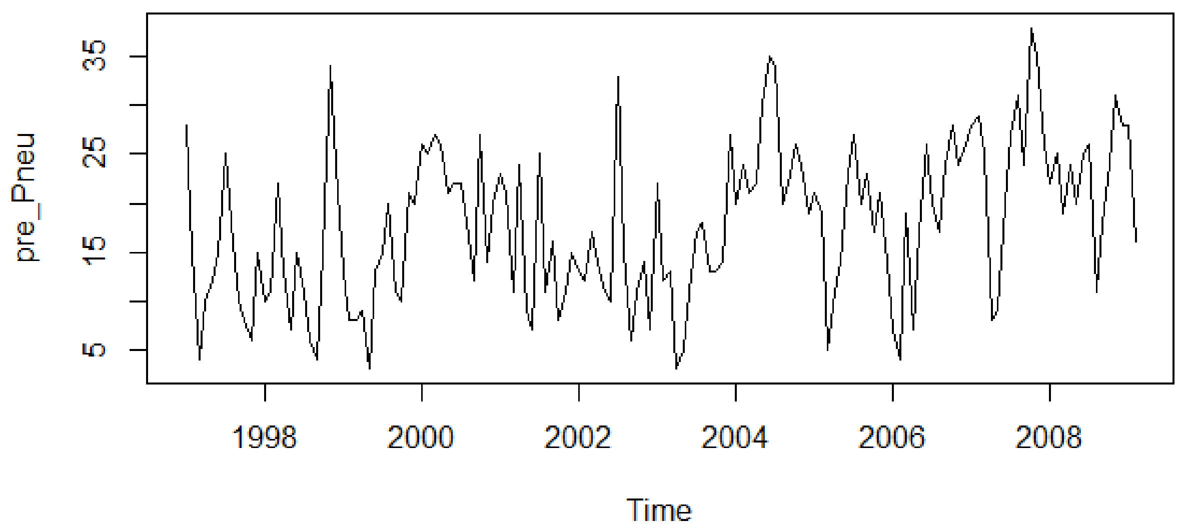

Figure 2: Pre-Series Childhood Pneumonia (Time Plot)

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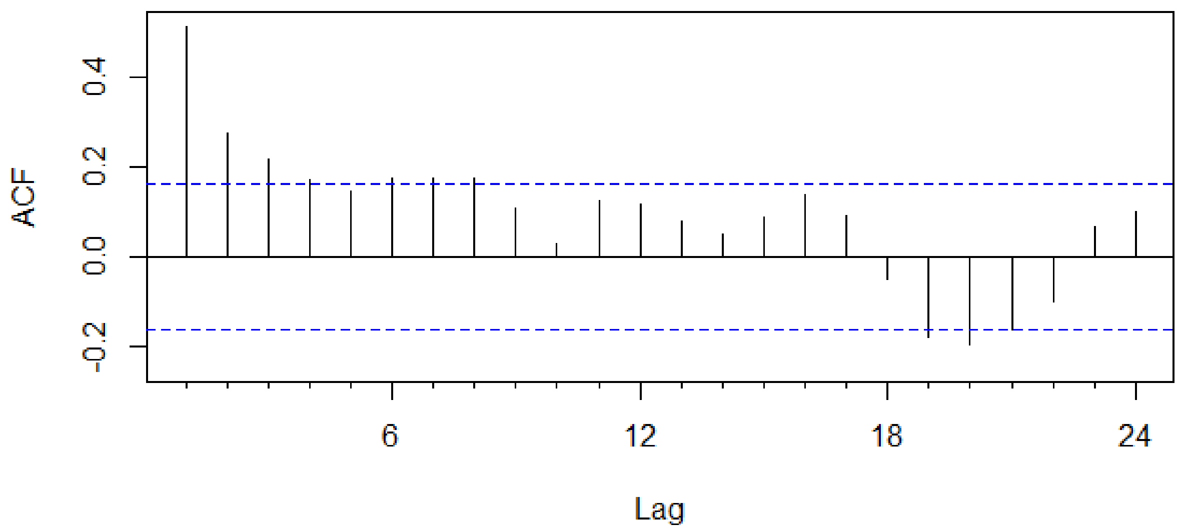

Figure 3: Pre-Series (ACF Plot)

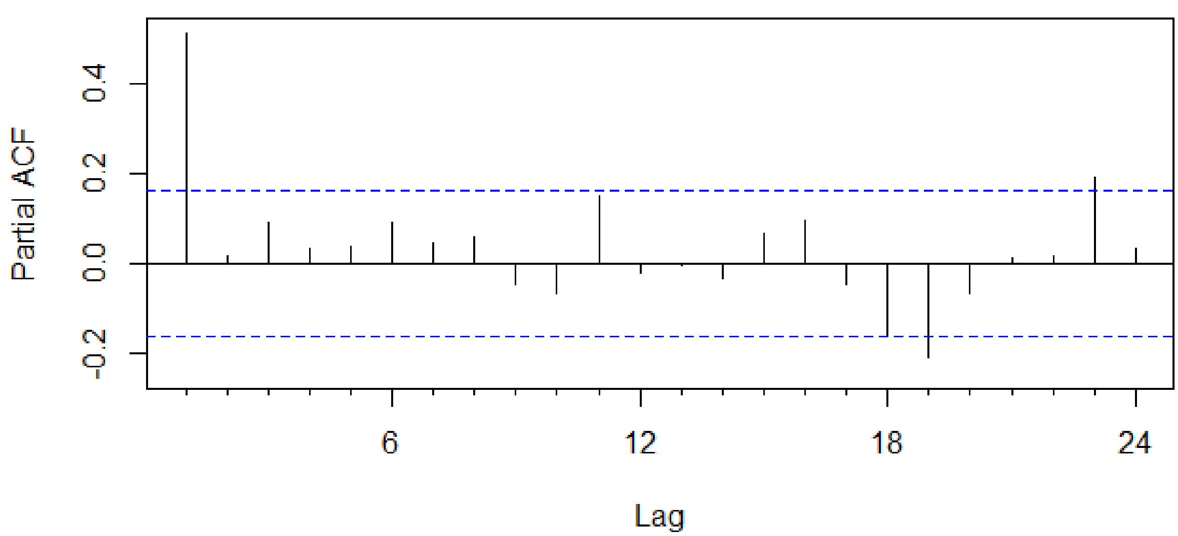

Figure 4: Pre-Series (PACF Plot)

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The observations are classified into pre-intervention and post–intervention segments. Data collected between January 1997 and February 2009 represent the pre–intervention period shown in Figure 2, while observations from March 2009 to December 2011 comprise the post–intervention period. The ARIMA specification for the error term in equation (2) is estimated using the pre-intervention series, whereas the transfer function describing the intervention effect is obtained from post–intervention observations. Despite visual evidence of stationarity in Figures 2, 3, and 4, the slow decay of the autocorrelation function at higher lags suggests non–stationarity, prompting the application of differencing to remove any underlying trend. First differencing is therefore applied to remove any remaining trend. The transformed series demonstrates stationarity, as illustrated in Figures 5, 6, and 7, a finding that is corroborated by the Augmented Dickey and Fuller test results reported in Table 2, where the p–value of 0.01 is less than the 0.05 threshold.

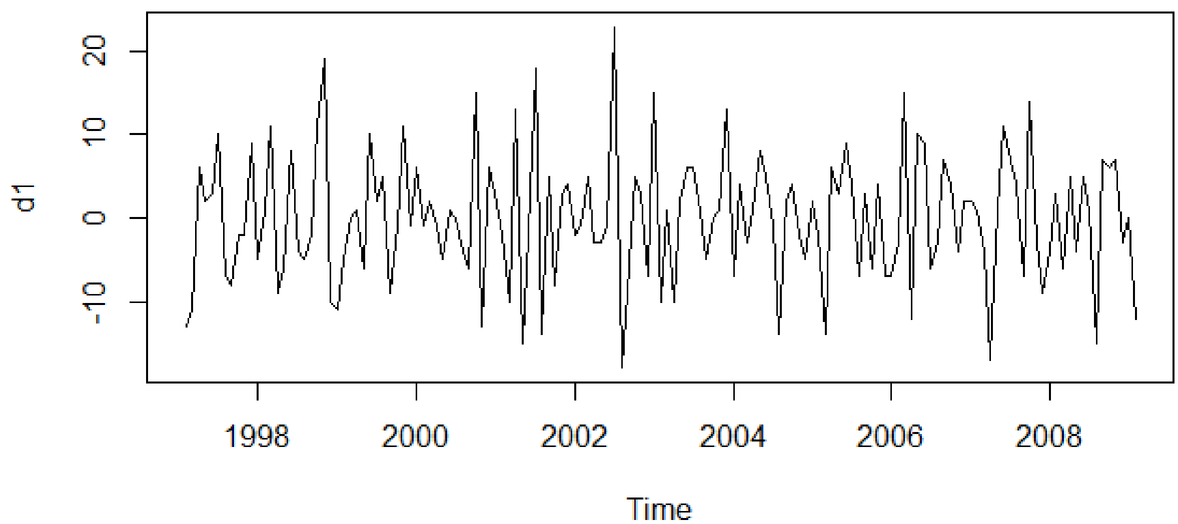

Figure 5: First Difference (Pre-series)

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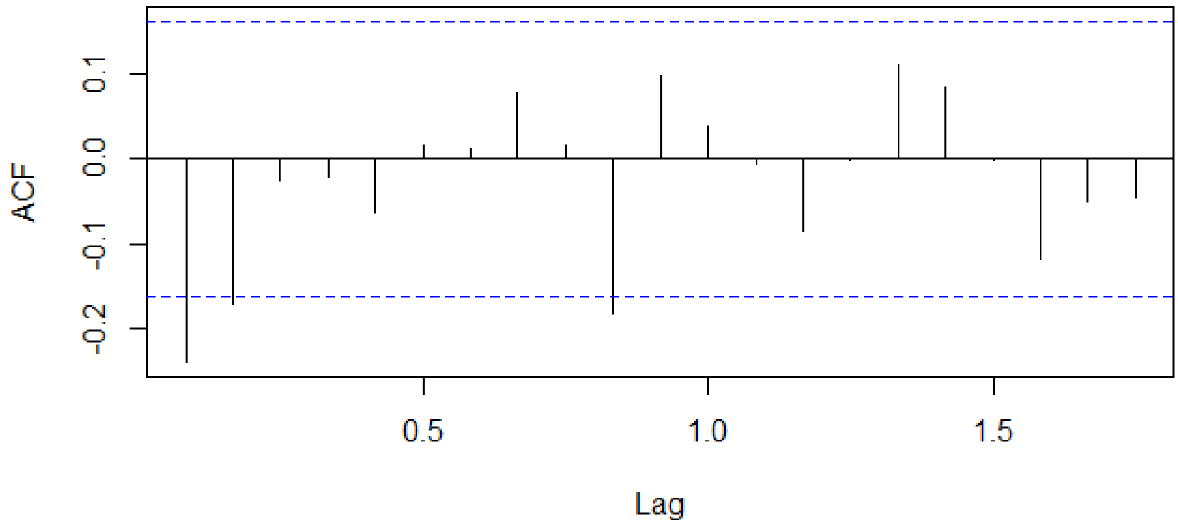

Figure 6: First Difference ACF (Pre-series)

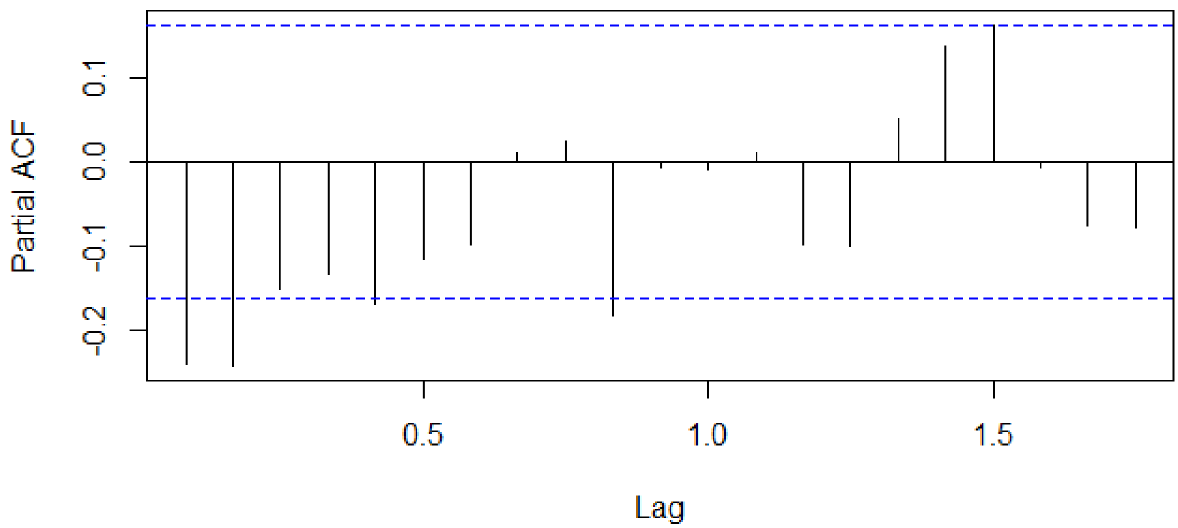

Figure 7: First Difference PACF (Pre-series)

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Table 2: Unit Root Test (ADF)

Test	ADF
Variable	Childhood Pneumonia
Statistic	-7.4821
Lag order	5
Prob. value	0.01
$H_{Alternative}$	No unit root

Inspection of the correlograms presented in Figures 6 and 7 informed the tentative selection of three models in the family of $ARIMA(p, d, q)$ framework from the list of numerous integrated and non-integrated models. However, as guided by the Box–Jenkins ARIMA modelling approach, only models exhibiting stationarity after first-order differencing ($d = 1$) were considered for further analysis, while models that did not satisfy the integration requirement were excluded. Thus, the three tentative models are the $ARIMA(1,1,0)$, $ARIMA(0,1,1)$, $ARIMA(1,1,1)$, with their associated parameter estimates reported in Table 3. The $ARIMA(1,1,1)$ model outperforms other tentative models during the model diagnostics test. The model appears adequate, as nearly all residual autocorrelations are within the $(-0.1655, 0.1655)$ significance limits depicted in Figure 8, indicating non-significance. Furthermore, the model yields the minimum BIC (981.6072) and AIC (972.677), Table 4. The Ljung and Box test, with a p–value of 0.2001 (see Table 5), provides additional evidence of the model's appropriateness, confirming its suitability for forecasting the given dataset.

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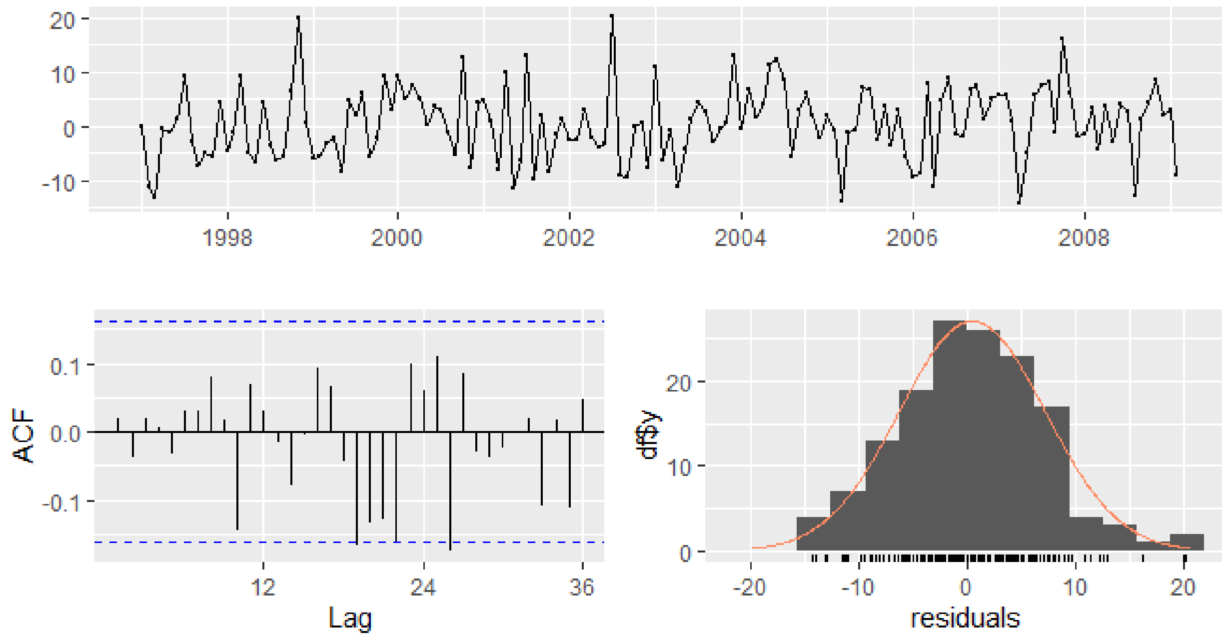

Figure 8: ARIMA(1,1,1) Model (Residuals)

Table 3: Model Estimation

Parameter		Estimate	Std. Error	Z-value	Prob. Value
(1,1,0)	π_1	-0.246712	0.081717	-3.0191	0.002535 **
(0,1,1)	ν_1	-0.66102	0.11866	-5.5709	2.535e-08 ***
(1,1,1)	π_1	0.448160	0.085410	5.2472	1.544e-07 ***
	ν_1	-0.956655	0.029213	-32.7477	< 2.2e-16 ***

Table 4: Model Evaluation

Model	BIC	AIC
ARIMA(1,1,0)	1006.224	1000.271
ARIMA(0,1,1)	993.3986	987.4452
ARIMA(1,1,1)	981.6072	972.677

Table 5: Ljung-Box Test

Q* =27.299
Degrees of freedom: 22
No. of Lags: 24

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Prob. Value: 0.2001 Model degrees of freedom: 2

Table 6: Forecasts from fitted Pre-series Model

Period	Year	True value	Prediction	Residuals
147	Mar 2009	38	19	19
148	Apr 2009	20	21	1
149	May 2009	24	21	3

The parameters of the intervention component's transfer function were estimated by first forecasting several post-intervention observations using the fitted ARIMA model to determine the delay parameter. As indicated in Table 3 and Figure 9, the effect of the intervention was observed immediately at the point of implementation, with $\varrho = 0$. The impact parameter was estimated at 19.528485, with a statistically significant p–value of 0.0009205. The positive and significant value of the impact parameter suggests that the intervention did not fully achieve its intended effect. This is confirmed as hospital admissions in the post–intervention period continued to rise, ranging from 10 to 34 cases compared to the pre–intervention period.
The resulting intervention model is expressed mathematically as follows:

$$\mathcal{Q}_t = 19.5285\, \rho^{T}{}_{t-0} - \frac{0.965794B}{(1-0.4693B)} z_t \tag{16}$$

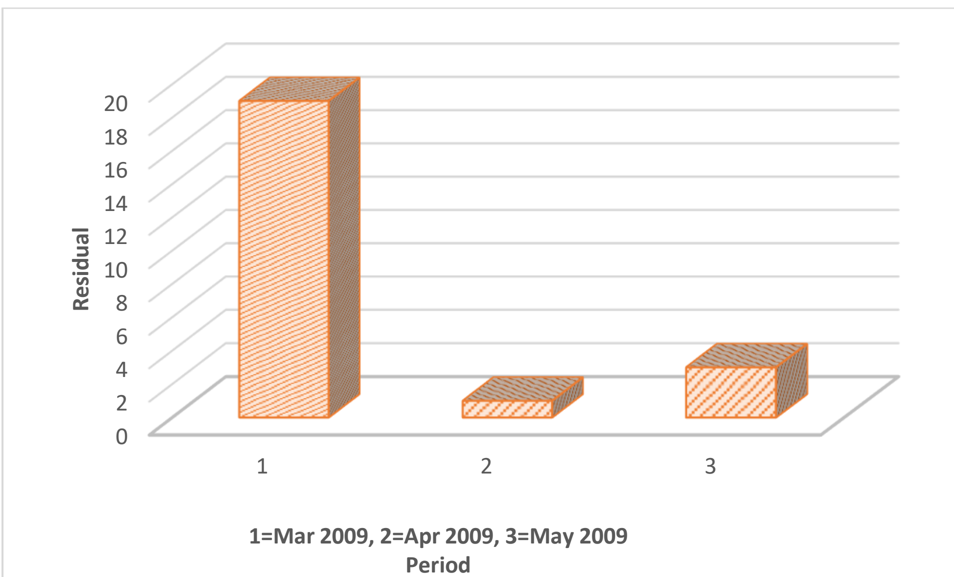

Figure 9: Impulse Response Function

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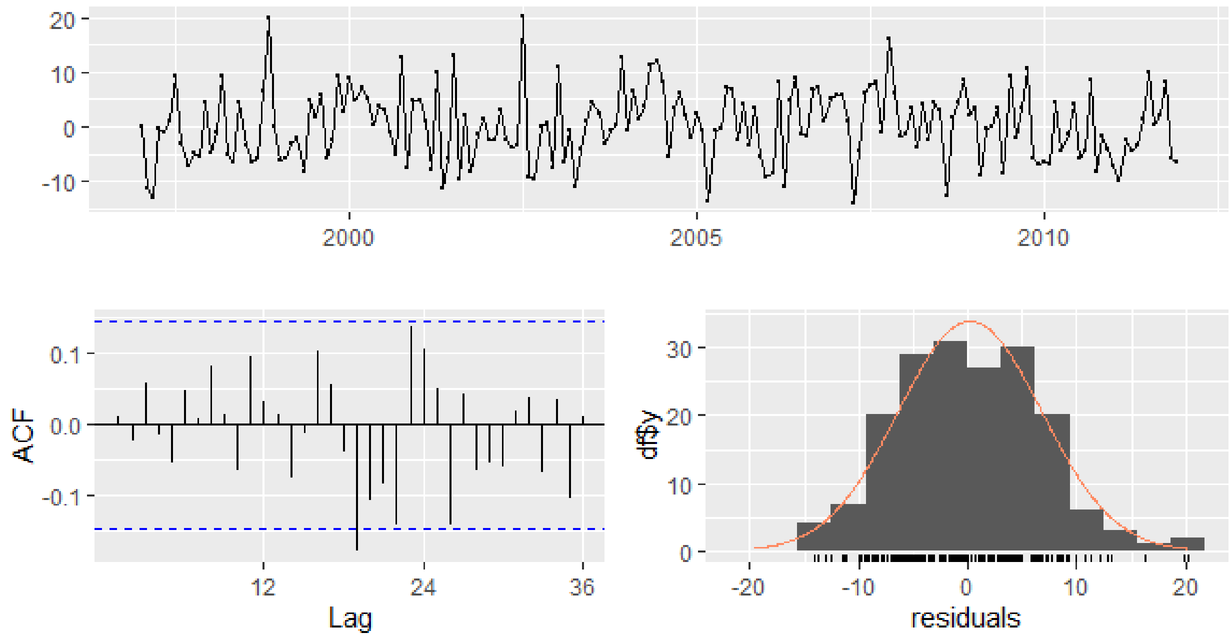

Figure 10: Fitted Model Residuals

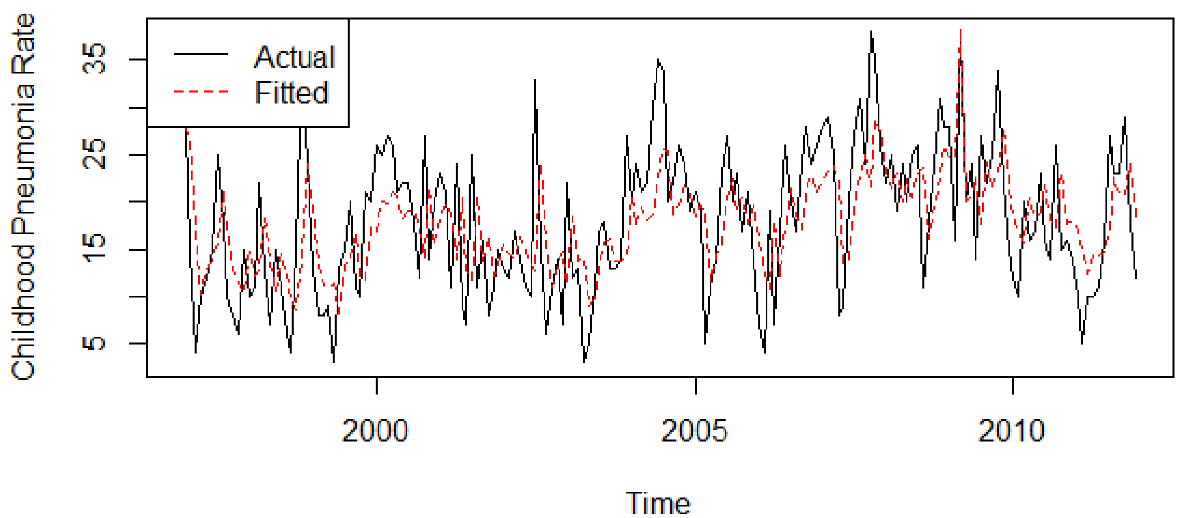

Figure 11: Plot of Fitted Model Value Vs Actual Values

Table 7: Estimation of the Full Model

Parameter	Est.	Standard Error	Zvalue	Prob. Value
π_1	0.469299	0.077540	6.0524	1.427e-09 ***
ν_1	-0.965794	0.029532	-32.7034	< 2.2e-16 ***
$\ni$	19.528485	5.893130	3.3138	0.0009205 ***
ϱ	0			

Table 8: Ljung-Box Test of Intervention Model

Q* = 30.807
Degrees of freedom: 22
Prob. Value: 0.1001
Model degrees of freedom: 2
Total lags used: 24

4. Conclusion

To evaluate the effect of the government's intervention on childhood pneumonia prevalence, the Box–Tiao intervention modelling approach was applied. March 2009 was designated as the intervention point, and the intervention was modelled as a pulse function. Over the study period, 3,243 youngsters between the ages of zero and fourteen years were diagnosed with pneumonia. An $ARIMA(1,1,1)$ model was fitted using pre-intervention data and was found to be adequate for capturing the underlying dynamics. The impact parameter was estimated at 19.5285 ($p - value = 0.001 < 0.05$), indicating that the intervention did not fully achieve its intended effect, as hospital admissions continued to rise post–intervention, ranging between 10 and 34 cases. With a growth rate of 0, the initial effect of the intervention equalled its long-term effect of 20, explaining the immediate and abrupt nature of the intervention impact.

Residual diagnostics of Figure 6 and Table 8 confirmed the statistical adequacy of the fitted model. Comparison of fitted versus observed values (Figure 7) demonstrated a close alignment, further validating the model's goodness of fit. Forecasts from the model in equation (16) also fell within the 95 percent prediction interval and closely matched the actual observations, suggesting its utility for predicting future pneumonia cases and informing control strategies. In line with the theme of 2023 World Pneumonia Day, "Every Breath Counts: Stop Pneumonia in Its Tracks" (Pace Hospital, 2023), the results underscore the importance of timely prevention, diagnosis, and treatment. Given that pneumonia is largely preventable and treatable, further investment in accessible, high–quality healthcare facilities is essential to reduce avoidable childhood mortality.

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Conflict of Interest

The authors state that there are no conflicts of interest concerning this research.

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