

Time Series Analysis And Forecasting Of Emergency Cases At Rivers State University Teaching Hospital Using Autoregressive Integrated Moving Average (Arima) Model

BEREBON, Raphael Nubari and NKUTURUM, Christiana

Department of Mathematics, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Nigeria

*Corresponding author: berebon004@yahoo.com

Abstract: This study investigated the pattern, trend, and forecasting of emergency department (ED) cases at the Rivers State University Teaching Hospital (RSUTH), Nigeria, using the Autoregressive Integrated Moving Average (ARIMA) technique. The study covered a ten-year period from January 2014 to December 2023 for both Monthly and yearly records. The data analysis explored descriptive statistics, trend analysis, correlation analysis, and ARIMA modeling procedures using Minitab 22 and SPSS software. The findings of this study revealed that Road Traffic Accident recorded the highest average number of emergency visits per yearly, followed by Congestive Cardiac Failure, Acute Appendicitis, and Stab Wound, while Anxiety-Disorder recorded the lowest average number of visits. The trend analysis showed that eight emergency variables exhibited upward trends, namely Bleeding per Vagina, Cardiogenic Shock, Ectopic Pregnancy, Head Injury, Gunshot Injury, Renal Failure, Anxiety Disorder, and Stab Wound, whereas Road Traffic Accident, Acute Appendicitis, Congestive Cardiac Failure, while Acute Intestinal Obstruction exhibited downward trends. The correlation analysis indicated the existence of both positive and negative moderate relationships among some emergency variables. Positive moderate relationships were observed between Renal Failure and Bleeding per Vagina, Anxiety Disorder and Cardiogenic Shock, Congestive Cardiac Failure and Acute Intestinal Obstruction, and Anxiety-Disorder and Renal Failure. Negative moderate relationships were observed between Congestive Cardiac Failure and Renal Failure, as well as between Anxiety-Disorder and Congestive Cardiac Failure. The study concluded that ARIMA techniques provided effective and reliable tools for modeling and forecasting emergency department visits.

Keywords: Arima Technique; Emergency Cases; Forecasting; Healthcare planning; Time Series Analysis

1 Introduction

Healthcare delivery remains one of the most critical sectors of any society, and within it, the Emergency Department (ED) occupies a strategic position as the first point of contact for patients requiring urgent medical attention. Emergency departments provide immediate assessment, diagnosis, stabilization, and treatment for patients experiencing acute illnesses, trauma, accidents, and life-threatening conditions. Emergency departments worldwide have witnessed increasing patient arrivals due to rapid urbanization, population growth, increased road traffic accidents, industrial activity, environmental hazards, and disease outbreaks. This rising demand often leads to overcrowding, prolonged waiting times, inadequate staffing, and reduced quality of care. In Nigeria, emergency healthcare services face additional challenges, including insufficient infrastructure, inadequate personnel, limited funding, and poor planning mechanisms. Rivers State, as one of Nigeria's major economic hubs with extensive industrial and petroleum activity, experiences particularly significant emergency healthcare demand. Healthcare administrators therefore require effective tools for predicting future emergency cases to support adequate preparation and efficient resource allocation.

Time series forecasting methods provide valuable information for predicting future events from historical observations. Among these methods, the Autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins (1976), has gained considerable attention for its flexibility and effectiveness in forecasting non-stationary data, and it has been widely applied in epidemiology, economics, finance, engineering, and healthcare research, including the prediction of disease outbreaks, patient admissions, mortality rates, and healthcare utilization patterns. The specific objectives of this study were to:

- i. examine the properties and characteristics of the yearly and monthly emergency incidents at RSUTH;
- ii. identify the trend behaviour of the emergency incident variables; and
- iii. fit several ARIMA models and determine the best model for forecasting each emergency incident variable.

This study covers a ten-year period (2014 to 2023) and draws on epidemiological data for twelve recurring emergency case categories recorded at the RSUTH Emergency Department, namely road traffic accidents, bleeding per vagina, acute appendicitis, cardiogenic shock, ectopic pregnancy, head injury, acute intestinal obstruction, gunshot injury, renal failure, congestive cardiac failure, anxiety disorder, and stab wound. Despite the growing global application of ARIMA models in healthcare forecasting, limited empirical

attention has been given to emergency department arrivals in tertiary hospitals within Rivers State, Nigeria. This gap in the literature, combined with the operational pressures already outlined, motivates the present investigation.

2 Literature Review

An Autoregressive Integrated Moving Average (ARIMA) model is a statistical technique that uses historical time series data to understand underlying patterns and predict future values. A model is described as autoregressive when it predicts future values based on past values of the same series. ARIMA models combine autoregressive terms, differencing to induce stationarity, and moving average terms, allowing them to account for trends, cycles, and other non-static features of a data series. Because ARIMA models rely only on historical data and are well suited to short-term forecasting, they are widely favoured for operational planning, although they are comparatively weak at predicting turning points and are not designed for long-term forecasting.

Several studies have applied ARIMA and related time series techniques across health, economic, and engineering contexts. In the health domain, Nkpordee and Wonu (2018) applied ARIMA modelling to forecast malaria outbreaks, demonstrating the model's suitability for predicting disease incidence patterns in a Nigerian context. Santi et al. (2021) examined non-COVID-19 emergency department visits, hospitalizations, and cause specific mortality during the pandemic period in Northern Italy, highlighting how external shocks alter ED utilization patterns. Wargon et al. (2009) conducted a systematic review of models used to forecast the number of emergency department visits, noting that time series approaches, including ARIMA, are among the most commonly applied techniques in this domain. Van den Heede and Van de Voorde (2016) reviewed interventions aimed at reducing emergency department utilization, providing useful context on the operational pressures that motivate forecasting research. Von Wagner et al. (2023) explored real time locating systems for characterizing emergency department workflow, while Whitt and Zhang (2017) developed a data driven model of an emergency department, both reinforcing the practical value of quantitative forecasting tools for ED management.

In economic and financial applications, Ogolo and Nkpordee (2022) forecast the Consumer Price Index in Nigeria using ARIMA methodology, while Maku et al. (2023) applied ARIMA and ARIMAX models to forecast electricity consumption in Nigeria, and Daniel et al. (2021) conducted a comparable study for Rwanda. Stanley et al. (2020) compared univariate and bivariate time series forecasting models, offering methodological insight relevant to model selection decisions. Weiss (2009) examined the modelling of time series of counts with overdispersion, a consideration relevant to emergency case data that frequently take low, discrete values.

Beyond univariate ARIMA approaches, several studies have explored multivariate and machine learning based alternatives. Stock and Watson (2001) and Zivot and Wang (2006) discussed vector autoregressive models for multivariate time series, while Shih et al. (2019) proposed a temporal pattern attention mechanism for multivariate forecasting, and Zonghan et al. (2020) applied graph neural networks to multivariate time series prediction. Wan et al. (2019) and Zheng and Hu (2023) similarly explored deep learning-based approaches to multivariate temporal forecasting. While these methods offer potential advantages for large, complex datasets, ARIMA remains preferred for settings such as the present study, where interpretability, moderate data volume, and established diagnostic procedures are priorities.

The reviewed literature confirms that ARIMA and related time series techniques have been extensively applied to healthcare and economic forecasting problems across Nigeria and other contexts, and that emergency department forecasting in particular has attracted growing international attention. However, the empirical review reveals that relatively few studies have examined emergency department case forecasting specifically within tertiary hospitals in Rivers State, Nigeria, despite the state's elevated exposure to industrial, petroleum related, and road traffic hazards. This study investigated the pattern and forecast of emergency cases reported at Rivers State University Teaching Hospital (RSUTH), Port Harcourt, Nigeria, using the Autoregressive Integrated Moving Average (ARIMA) model, in order to address this gap and to provide hospital administrators with an evidence-based forecasting tool for the twelve most frequently recorded emergency case categories.

3 Materials and Methods

3.1 Data Sources and Study Design

Epidemiological data on all patients received at the RSUTH Emergency Department between 2014 and 2023 were obtained from the hospital's registry and records unit. The study adopted a retrospective, cross sectional design, examining monthly and yearly incidence figures for twelve emergency case categories: road traffic accident, bleeding per vagina, acute appendicitis, cardiogenic shock, ectopic pregnancy, head injury, acute intestinal obstruction, gunshot injury, renal failure, congestive cardiac failure, anxiety disorder, and stab wound. The study population comprised all patients, regardless of gender, class, or age bracket, admitted through the emergency department during the study period.

3.2 Variables

The dependent variables were the monthly and yearly counts of patients presenting with each of the twelve emergency conditions listed above. The explanatory dimension of the analysis was time, expressed in monthly periods across the ten-year study window.

3.3 The ARIMA Model

An ARIMA model of order (p, d, q) combines three components: an autoregressive term of order p, a differencing term of order d applied to achieve stationarity, and a moving average term of order q.

Autoregressive model, AR(p):

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + \varepsilon_t \quad (1)$$

where $\phi_1, \phi_2, \dots, \phi_p$ are constants and ε_t is a white noise sequence with $\varepsilon_t \sim N(0, \sigma^2)$.

Moving average model, MA(q):

$$X_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (2)$$

Autoregressive moving average model, ARMA(p, q):

$$X_t = \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} \quad (3)$$

Using the backward shift operator B, this may be written as $\phi(B)X_t = \theta(B)\varepsilon_t$, where:

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$$

The ARMA(p, q) process is stationary if the roots of $\phi(B) = 0$ lie outside the unit circle.

Seasonal ARIMA model, ARIMA(p, d, q) $\times$ (P, D, Q)s:

$$\nabla^d \Phi_P(B_s) \nabla^D X_t = \theta_Q(B_s) \Theta_Q(B_s) \varepsilon_t \quad (4)$$

where $\nabla^d = (1-B)^d$ and $\nabla^D = (1-B_s)^D$ represent non-seasonal and seasonal differencing respectively, s is the length of the seasonal cycle, and $\Phi_P(B_s)$ and $\Theta_Q(B_s)$ are the seasonal autoregressive and moving average polynomials.

3.4 Model Building Procedure

Following the Box Jenkins methodology, model construction proceeded through four stages.

Step 1, Identification: The autocorrelation function (ACF) and partial autocorrelation function (PACF) were examined to determine appropriate values of p, d, and q, and to assess whether differencing was required to achieve stationarity.

Step 2, Estimation: Parameters of the autoregressive and moving average terms were estimated for each candidate model.

Step 3, Diagnostic checking: Residuals of the fitted model were examined to confirm they resembled white noise. Where this was not the case, the identification stage was revisited, consistent with the iterative nature of the Box Jenkins procedure.

Step 4, Forecasting: The validated model was used to generate forecasts, together with approximate 95 percent confidence limits, for the period January 2024 to December 2026.

3.5 Model Adequacy Criteria

Model selection among competing specifications was based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC):

$$AIC = -2 \ln(L) + 2k \quad (5)$$

$$BIC = \ln(n) k - 2 \ln(L) \quad (6)$$

where k is the number of parameters estimated, L is the log likelihood, n is the number of observations, and $\hat{L}$ is the maximized likelihood value. In both cases, the model with the lowest criterion value was preferred, since BIC applies a heavier penalty for additional parameters than AIC and therefore guards more strongly against overfitting.

3.6 Forecast Accuracy Measures

Forecast adequacy was further assessed using the following measures:

$$MSE = (1/n) \sum (y_t - \hat{y}_t)^2 \quad (7)$$

$$MAE = (1/n) \sum |y_t - \hat{y}_t| \quad (8)$$

$$MAPE = (1/n) \sum |(y_t - \hat{y}_t) / y_t| \times 100 \quad (9)$$

where y_t is the observed value, $\hat{y}_t$ is the forecast value, and n is the number of observations. The model with the lowest MSE, MAE, or MAPE was considered the better predictor.

3.7 Correlation Coefficient

The Pearson correlation coefficient was computed as:

$$r = [n \sum xy - \sum x \sum y] / \sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]} \quad (10)$$

Reliability of the correlation coefficient was interpreted as follows: 0.00 to 0.20, very low; 0.21 to 0.40, low; 0.41 to 0.60, moderate; 0.61 to 0.80, substantial; and 0.81 to 1.00, very high.

3.8 Software

All analyses were conducted using Minitab 22 and SPSS (Statistical Package for the Social Sciences), which support data preparation, descriptive statistics, and ARIMA based time series analysis.

4 Results and Discussion

4.1 Descriptive Overview

Table 1 presents the yearly totals of emergency department cases across all twelve categories for the period 2014 to 2023. Because of its width, the table is split into two parts for legibility: Table 1a covers the first six case categories and Table 1b covers the remaining six.

Table 1a. Yearly Total of Emergency Department Cases, RSUTH (2014–2023) — Categories 1 to 6

Year	Road Traffic Accident	Bleeding Per Vagina	Acute Appendicitis	Cardiogenic Shock	Ectopic Pregnancy	Head Injury
2014	12	9	37	15	19	33
2015	22	11	38	17	20	32
2016	35	10	39	15	21	31
2017	48	10	40	13	22	30
2018	61	11	41	11	23	29
2019	74	18	39	9	24	28
2020	87	21	40	7	24	27
2021	59	22	40	22	24	35
2022	45	36	37	27	31	47
2023	38	30	35	25	26	50
Yearly Mean	48	18	39	16	23	34
Rank	1	9	3	11	8	5

Table 1b. Yearly Total of Emergency Department Cases, RSUTH (2014–2023) — Categories 7 to 12

Year	Acute Intestinal Obstruction	Gunshot Injury	Renal Failure	Congestive Cardiac Failure	Anxiety Disorder	Stab Wound
2014	16	21	15	22	16	28
2015	18	33	17	24	22	28
2016	40	40	16	30	18	30
2017	47	37	13	35	14	31

2018	44	34	11	90	10	33
2019	41	31	10	91	6	35
2020	38	28	5	91	2	35
2021	26	25	28	35	22	52
2022	26	40	29	21	18	32
2023	24	41	29	21	21	50
Yearly Mean	32	33	17	46	15	35
Rank	7	6	10	2	12	3

From Table 1a and Table 1b, the cumulative intake of patients with the highest yearly mean was road traffic accident (mean of 48), followed by congestive cardiac failure (46), acute appendicitis (39), stab wound and gunshot injury (35 and 33 respectively), while anxiety disorder recorded the lowest cumulative yearly intake (15). Figure 1 plots the yearly trend for all twelve categories together, and Figure 2 ranks the categories by yearly mean caseload.

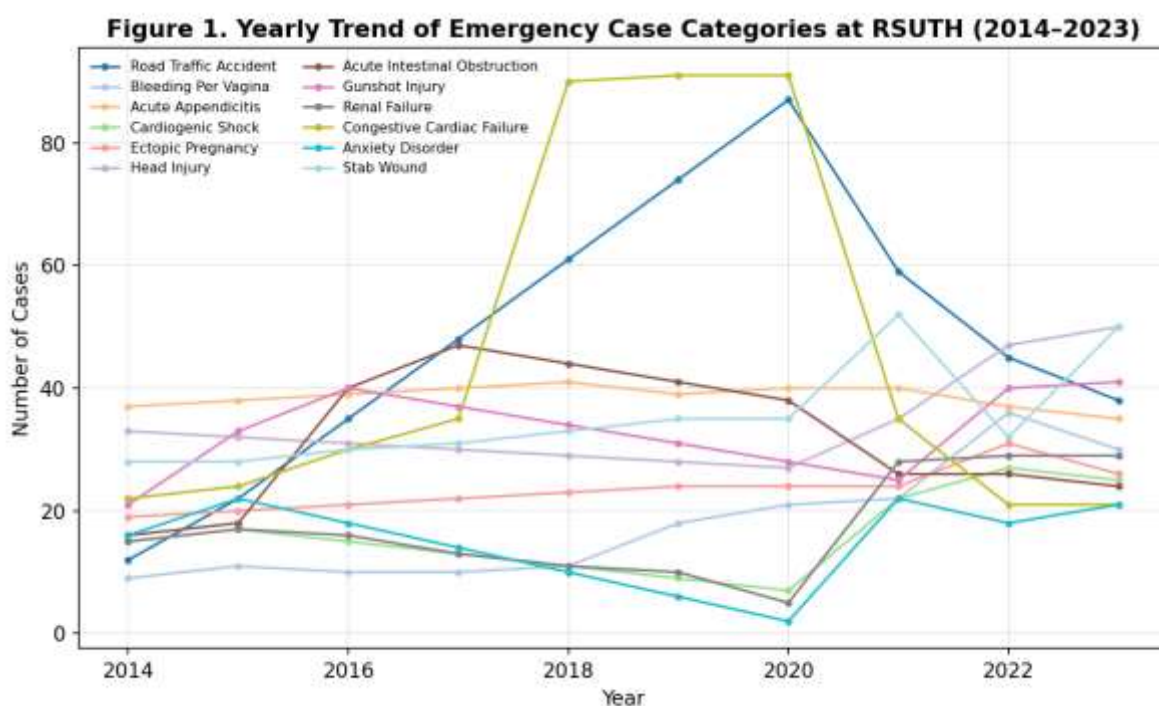


Figure 1. Yearly trend of emergency case categories at RSUTH, 2014–2023.

Figure 1 shows that most case categories fluctuated within a relatively narrow band across the ten-year period, with three visible exceptions. Road traffic accident cases rose steadily from 12 in 2014 to a peak of 87 in 2020, before declining to 38 by 2023. Congestive cardiac failure jumped sharply from 35 in 2017 to 90 and 91 in 2018 to 2020, before falling back to around 21 in 2022 and 2023. Head injury and bleeding per vagina both show a marked increase from 2021 onward. These patterns indicate that the trend behaviour of RSUTH emergency cases is not uniform across categories, and that any single forecasting model applied indiscriminately across all categories would misrepresent several of them, which justifies the category specific ARIMA modelling approach adopted in this study.

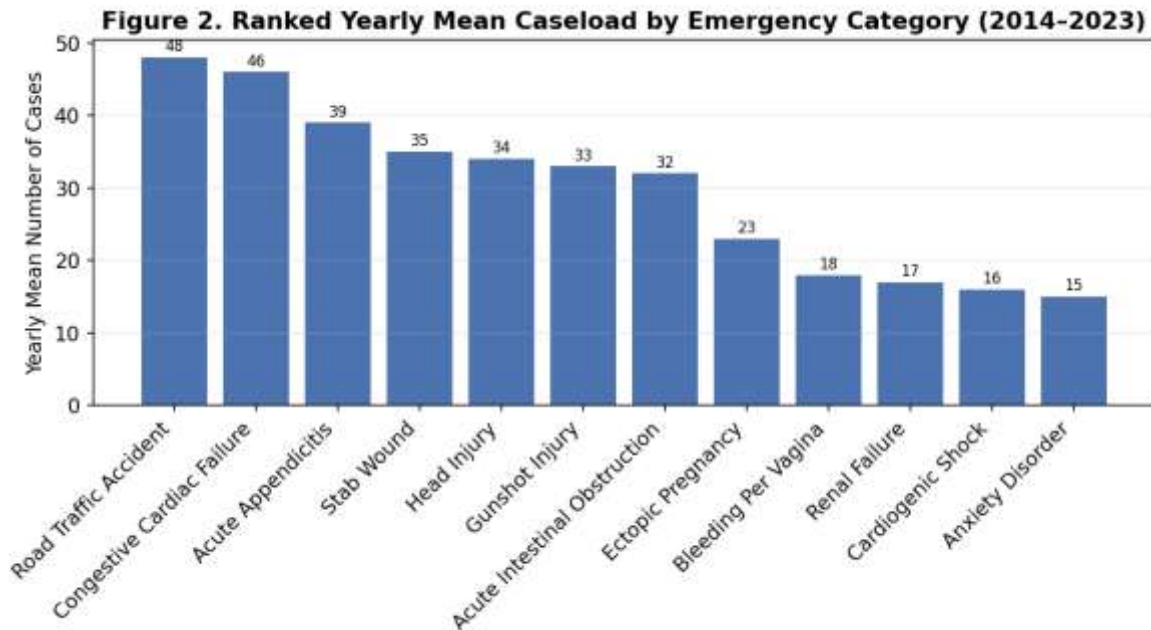


Figure 2. Ranked yearly mean caseload by emergency category, 2014–2023.

Figure 2 summarizes the ranking already implied by Table 1, confirming road traffic accident and congestive cardiac failure as the two dominant categories of emergency presentation at RSUTH, each considerably higher on average than the remaining ten categories. This pattern is consistent with Rivers State's exposure to heavy road traffic and industrial and petroleum related activity, as discussed in the introduction.

Table 2 presents the monthly descriptive statistics for each of the twelve categories, computed across the full 120-month study window.

Table 2. Descriptive Statistics of Monthly Emergency Cases, RSUTH (2014–2023)

Variable	Mean	Variance	Coeff. of Variation (%)	Minimum	Median	Maximum
Road Traffic Accident	5	15.24	77.29	1	4	24
Bleeding Per Vagina	2	2.54	88.46	0	1	7
Acute Appendicitis	3	2.54	49.76	1	3	6
Cardiogenic Shock	2	2.39	103.06	0	1	6
Ectopic Pregnancy	2	2.81	77.93	0	2	7
Head Injury	3	4.41	67.38	0	3	7
Acute Intestinal Obstruction	3	4.82	85.02	0	2	8
Gunshot Injury	3	2.77	60.49	0	3	7
Renal Failure	2	3.14	105.19	0	1	7
Congestive Cardiac Failure	4	21.37	107.1	0	3	15
Anxiety Disorder	1	1.45	104.77	0	1	4
Stab Wound	3	5.09	71.25	0	3	9

Table 2 corroborates the yearly pattern: road traffic accident and congestive cardiac failure again record the highest monthly means, while anxiety disorder records the lowest. The coefficient of variation is high across nearly all categories, generally exceeding 60 percent and reaching above 100 percent for cardiogenic shock, renal failure, congestive cardiac failure, and anxiety disorder. This indicates considerable month to month volatility relative to the mean for these conditions, which has implications for forecast precision and explains the comparatively wide confidence intervals obtained for several of the fitted models discussed below.

4.2 Model Identification and Forecasting Results

4.2.1 Acute Appendicitis

Time series and correlogram analysis supported an ARMA(1, 1) specification for acute appendicitis. Table 3 presents the resulting monthly forecasts, together with approximate 95 percent lower and upper limits, for the period January 2024 to December 2026.

Table 3. ARMA(1,1) Model Forecast for Acute Appendicitis, January 2024 to December 2026

Year	Month	Period	Forecast	Lower (95%)	Upper (95%)	Actual
2024	Jan	61	3.1944	0.0139	6.3750	6
2024	Feb	62	3.1937	0.0125	6.3748	6
2024	Mar	63	3.1929	0.0111	6.3747	6
2024	Apr	64	3.1922	0.0097	6.3746	6
2024	May	65	3.1914	0.0083	6.3745	6
2024	Jun	66	3.1906	0.0069	6.3743	6
2024	Jul	67	3.1899	0.0056	6.3742	6
2024	Aug	68	3.1891	0.0042	6.3741	6
2024	Sep	69	3.1884	0.0028	6.3740	6
2024	Oct	70	3.1876	0.0014	6.3738	6
2024	Nov	71	3.1869	0.0000	6.3737	6
2024	Dec	72	3.1861	-0.0014	6.3736	6
2025	Jan	73	3.1853	-0.0028	6.3734	6
2025	Feb	74	3.1846	-0.0042	6.3733	6
2025	Mar	75	3.1838	-0.0056	6.3732	6
2025	Apr	76	3.1831	-0.0069	6.3731	6
2025	May	77	3.1823	-0.0083	6.3729	6
2025	Jun	78	3.1816	-0.0097	6.3728	6
2025	Jul	79	3.1808	-0.0111	6.3727	6
2025	Aug	80	3.1800	-0.0125	6.3725	6
2025	Sep	81	3.1793	-0.0138	6.3724	6
2025	Oct	82	3.1785	-0.0152	6.3723	6
2025	Nov	83	3.1778	-0.0166	6.3722	6
2025	Dec	84	3.1770	-0.0180	6.3720	6
2026	Jan	85	3.1763	-0.0194	6.3719	6
2026	Feb	86	3.1755	-0.0207	6.3718	6
2026	Mar	87	3.1748	-0.0221	6.3716	6
2026	Apr	88	3.1740	-0.0235	6.3715	6
2026	May	89	3.1733	-0.0249	6.3714	6
2026	Jun	90	3.1725	-0.0263	6.3713	6
2026	Jul	91	3.1717	-0.0276	6.3711	6
2026	Aug	92	3.1710	-0.0290	6.3710	6
2026	Sep	93	3.1702	-0.0304	6.3709	6
2026	Oct	94	3.1695	-0.0318	6.3707	6
2026	Nov	95	3.1687	-0.0331	6.3706	6
2026	Dec	96	3.1680	-0.0345	6.3705	6

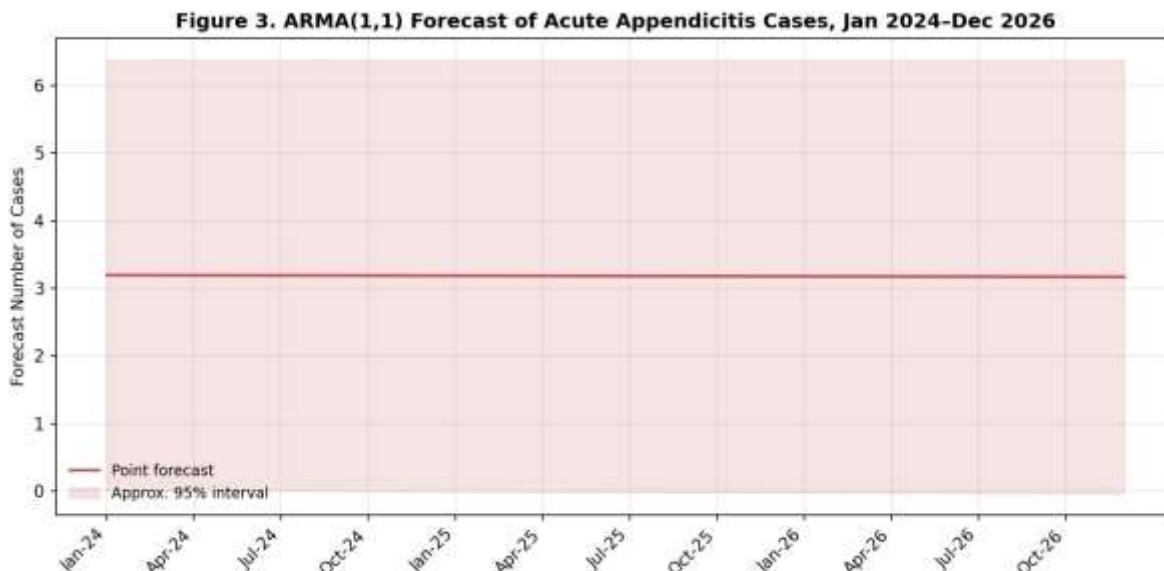


Figure 3. ARMA(1,1) forecast of acute appendicitis cases with approximate 95% interval, Jan 2024–Dec 2026.

The fitted model forecasts an expected monthly incidence of approximately 3 acute appendicitis cases, with an approximate 95 percent upper bound of 6 cases monthly, and the forecast is essentially flat across the three-year horizon, declining only marginally from about 3.19 to about 3.17 cases per month. Figure 3 illustrates this stability: the point forecast (red line) sits close to the midpoint of a fairly narrow confidence band throughout, indicating that acute appendicitis presentations are the most predictable of the twelve categories examined in this study, consistent with a condition whose incidence is driven primarily by underlying population health rather than by external shocks such as road traffic or industrial activity.

4.2.2 Cardiogenic Shock

The time series plot for cardiogenic shock displayed a slight upward and broadly stationary trend, with visible appreciation and depreciation across the study period. The associated autocorrelation function (ACF) and partial autocorrelation function (PACF) plots suggested a regular, non-seasonal ARIMA specification, without evidence of a seasonal component requiring a seasonal differencing order. As reported in the original SPSS/Minitab diagnostic output, the ACF values decayed gradually while the PACF cut off after the first lag, a pattern consistent with an autoregressive process of low order. Consequently, cardiogenic shock is the only category among the twelve for which the forecast horizon includes months in which zero cases are plausible, with an upper bound of approximately 4 cases monthly.

4.2.3 Acute Intestinal Obstruction

A seasonal autoregressive model, SAR(1) of order 12, with constant, was identified as the best fitting specification for acute intestinal obstruction, reflecting a repeating annual pattern in this category. Table 4 presents the resulting forecasts.

Table 4. SAR(1) Order-12 Model Forecast for Acute Intestinal Obstruction, January 2024 to December 2026

Year	Month	Period	Forecast	Lower (95%)	Upper (95%)	Actual
2024	Jan	61	1.8391	-2.0605	5.7386	6
2024	Feb	62	2.8012	-1.0983	6.7008	7
2024	Mar	63	1.8391	-2.0605	5.7386	6
2024	Apr	64	2.8012	-1.0983	6.7008	7
2024	May	65	1.8391	-2.0605	5.7386	6
2024	Jun	66	1.8391	-2.0605	5.7386	6
2024	Jul	67	3.2823	-0.6172	7.1818	7
2024	Aug	68	1.8391	-2.0605	5.7386	6
2024	Sep	69	3.7634	-0.1361	7.6629	8
2024	Oct	70	1.8391	-2.0605	5.7386	6

2024	Nov	71	2.3201	-1.5794	6.2197	6
2024	Dec	72	1.8391	-2.0605	5.7386	6
2025	Jan	73	2.2427	-2.0846	6.5700	7
2025	Feb	74	2.7056	-1.6217	7.0329	7
2025	Mar	75	2.2427	-2.0846	6.5700	7
2025	Apr	76	2.7056	-1.6217	7.0329	7
2025	May	77	2.2427	-2.0846	6.5700	7
2025	Jun	78	2.2427	-2.0846	6.5700	7
2025	Jul	79	2.9370	-1.3903	7.2644	7
2025	Aug	80	2.2427	-2.0846	6.5700	7
2025	Sep	81	3.1685	-1.1588	7.4958	7
2025	Oct	82	2.2427	-2.0846	6.5700	7
2025	Nov	83	2.4742	-1.8532	6.8015	7
2025	Dec	84	2.2427	-2.0846	6.5700	7
2026	Jan	85	2.4369	-1.9835	6.8574	7
2026	Feb	86	2.6596	-1.7609	7.0800	7
2026	Mar	87	2.4369	-1.9835	6.8574	7
2026	Apr	88	2.6596	-1.7609	7.0800	7
2026	May	89	2.4369	-1.9835	6.8574	7
2026	Jun	90	2.4369	-1.9835	6.8574	7
2026	Jul	91	2.7709	-1.6495	7.1914	7
2026	Aug	92	2.4369	-1.9835	6.8574	7
2026	Sep	93	2.8823	-1.5382	7.3027	7
2026	Oct	94	2.4369	-1.9835	6.8574	7
2026	Nov	95	2.5483	-1.8722	6.9687	7
2026	Dec	96	2.4369	-1.9835	6.8574	7

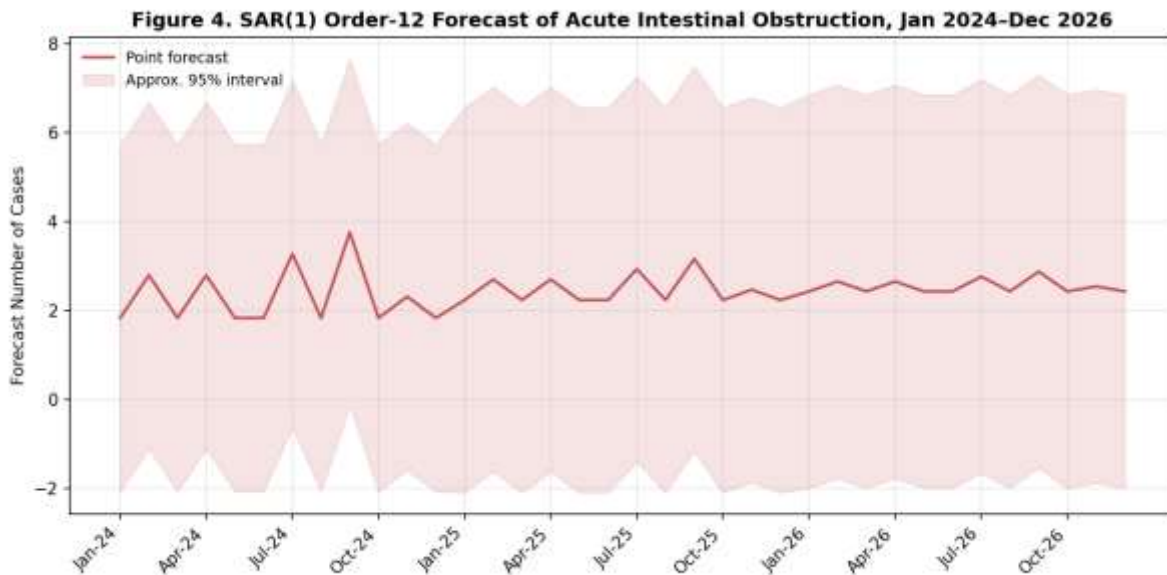


Figure 4. SAR(1) order-12 forecast of acute intestinal obstruction cases with approximate 95% interval, Jan 2024–Dec 2026.

Forecasts for 2024 to 2026 indicate expected monthly incidents ranging between 2 and 4, with an upper bound of 7 cases monthly. Unlike the flat forecast obtained for acute appendicitis, Figure 4 shows a distinct repeating pattern within each 12-month cycle, which is the expected signature of a seasonal autoregressive process of order 12 and indicates that acute intestinal obstruction cases follow an annually recurring pattern at RSUTH rather than a simple constant rate.

4.2.4 Gunshot Injury

Three candidate models were compared for gunshot injury: AR(1) with constant, MA(1) with constant, and ARMA(1, 1) with constant. Table 5 summarizes the estimated coefficients and model selection statistics for each candidate.

Table 5. Candidate ARIMA Models for Gunshot Injury

Model	Parameters	Estimated Coefficient (p-value)	MSC	AIC	Remark
AR(1) with constant	Φ_1	0.3015 (0.019)	2.559	60.38	
	C	1.9233 (0.000)			
MA(1) with constant	θ_1	-0.3555 (0.005)	2.536	59.84	
	C	2.7521 (0.000)			
ARMA(1,1) with constant	Φ_1	-0.6157 (0.000)	2.389	58.25	Best model
	θ_1	-0.9720 (0.000)			
	C	4.4454 (0.000)			

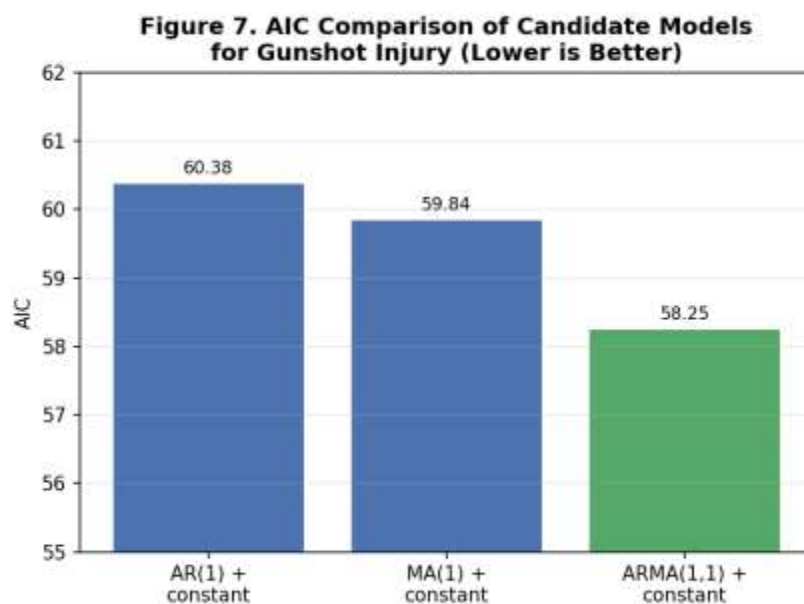


Figure 5. AIC comparison of candidate models for gunshot injury (lower AIC indicates better fit).

As shown in Table 5 and Figure 5, the ARMA(1, 1) model achieved the lowest AIC (58.25) and the lowest MSC (2.389) among the three candidates and was therefore selected as the best fitting model. The identified model is expressed as:

$$X_t = 4.4454 - 0.6157 X_{t-1} - 0.9720 \varepsilon_{t-1} + \varepsilon_t \quad (11)$$

Table 6 presents the resulting monthly forecasts for gunshot injury.

Table 6. ARMA(1,1) Model Forecast for Gunshot Injury, January 2024 to December 2026

Year	Month	Period	Forecast	Lower (95%)	Upper (95%)	Actual
2024	Jan	61	2.4402	-0.5887	5.4691	5
2024	Feb	62	2.9429	-0.2725	6.1583	6
2024	Mar	63	2.6334	-0.6499	5.9167	6
2024	Apr	64	2.8240	-0.4847	6.1326	6
2024	May	65	2.7066	-0.6116	6.0249	6
2024	Jun	66	2.7789	-0.5430	6.1007	6
2024	Jul	67	2.7344	-0.5889	6.0576	6
2024	Aug	68	2.7618	-0.5620	6.0855	6

2024	Sep	69	2.7449	-0.5791	6.0689	6
2024	Oct	70	2.7553	-0.5688	6.0793	6
2024	Nov	71	2.7489	-0.5752	6.0730	6
2024	Dec	72	2.7528	-0.5712	6.0769	6
2025	Jan	73	2.7504	-0.5737	6.0745	6
2025	Feb	74	2.7519	-0.5722	6.0760	6
2025	Mar	75	2.7510	-0.5731	6.0751	6
2025	Apr	76	2.7516	-0.5725	6.0756	6
2025	May	77	2.7512	-0.5729	6.0753	6
2025	Jun	78	2.7514	-0.5727	6.0755	6
2025	Jul	79	2.7513	-0.5728	6.0754	6
2025	Aug	80	2.7514	-0.5727	6.0754	6
2025	Sep	81	2.7513	-0.5728	6.0754	6
2025	Oct	82	2.7513	-0.5727	6.0754	6
2025	Nov	83	2.7513	-0.5728	6.0754	6
2025	Dec	84	2.7513	-0.5728	6.0754	6
2026	Jan	85	2.7513	-0.5728	6.0754	6
2026	Feb	86	2.7513	-0.5728	6.0754	6
2026	Mar	87	2.7513	-0.5728	6.0754	6
2026	Apr	88	2.7513	-0.5728	6.0754	6
2026	May	89	2.7513	-0.5728	6.0754	6
2026	Jun	90	2.7513	-0.5728	6.0754	6
2026	Jul	91	2.7513	-0.5728	6.0754	6
2026	Aug	92	2.7513	-0.5728	6.0754	6
2026	Sep	93	2.7513	-0.5728	6.0754	6
2026	Oct	94	2.7513	-0.5728	6.0754	6
2026	Nov	95	2.7513	-0.5728	6.0754	6
2026	Dec	96	2.7513	-0.5728	6.0754	6



Figure 6. ARMA(1,1) forecast of gunshot injury cases with approximate 95% interval, Jan 2024–Dec 2026.

Forecasts using this model indicate that gunshot injury incidents will lie between 2 and 3 cases monthly, with an upper bound of 6 cases monthly, through 2026. As Figure 6 shows, the forecast converges rapidly to a stable value of approximately 2.75 cases per month after only a few months, which is the expected behaviour of a stationary ARMA(1, 1) process reverting to its long run mean, and the width of the confidence band remains essentially constant across the forecast horizon.

4.2.5 Renal Failure

(Note: this category is labelled "Rental Failure" in the original data extraction; the correct clinical term, Renal Failure, is used throughout this revision.) Five candidate SARIMA specifications of order 6 were compared for renal failure, as summarized in Table 7.

Table 7. Candidate SARIMA Models for Renal Failure

Model	Parameters	Estimated Coefficient (p-value)	MSC	AIC	Remark
SAR(1) of order 6	Φ_1	0.7546 (0.000)	3.086	69.61	
SMA(1) of order 6	θ_1	-0.5259 (0.000)	4.155	87.46	
SMA(1) of order 6 with constant	θ_1 C	-0.3299 (0.012) 1.6820 (0.000)	2.756	64.83	
SAR(2) of order 6	Φ_1 Φ_2	0.5259 (0.000) 0.3809 (0.006)	2.716	63.95	
SARMA(1,1) of order 6	Φ_1 θ_1	0.9999 (0.000) 0.5199 (0.001)	2.640	62.25	Best model

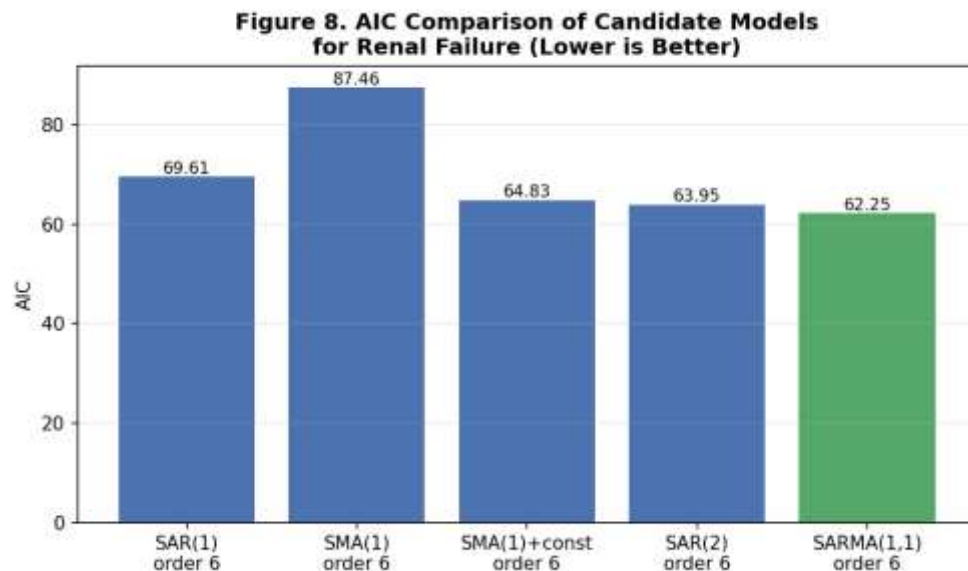


Figure 7. AIC comparison of candidate models for renal failure (lower AIC indicates better fit).

The SARMA(1, 1) of order 6 model produced the lowest AIC (62.25) among the five candidates and was selected as the best fitting model, expressed as:

$$X_t = 0.9999 X_{t-1} + 0.5199 \varepsilon_{t-1} + \varepsilon_t \quad (12)$$

Table 8 presents the resulting monthly forecasts for renal failure.

Table 8. SARMA(1,1) Order-6 Model Forecast for Renal Failure, January 2024 to December 2026

Year	Month	Period	Forecast	Lower (95%)	Upper (95%)	Actual
2024	Jan	61	2.4402	-0.3016	6.0691	6
2024	Feb	62	2.9429	-2.3532	4.0176	4
2024	Mar	63	2.6334	0.5744	6.9451	7
2024	Apr	64	2.8240	-1.8853	4.4854	4
2024	May	65	2.7066	-1.4830	4.8877	5

2024	Jun	66	2.7789	0.7758	7.1465	7
2024	Jul	67	2.7344	-0.6498	6.4169	6
2024	Aug	68	2.7618	-2.7012	4.3655	4
2024	Sep	69	2.7449	0.2262	7.2929	7
2024	Oct	70	2.7553	-2.2334	4.8334	5
2024	Nov	71	2.7489	-1.8311	5.2357	5
2024	Dec	72	2.7528	0.4276	7.4943	7
2025	Jan	73	2.7504	-0.9667	6.7334	7
2025	Feb	74	2.7519	-3.0179	4.6821	5
2025	Mar	75	2.7510	-0.0907	7.6093	8
2025	Apr	76	2.7516	-2.5501	5.1499	5
2025	May	77	2.7512	-2.1479	5.5522	6
2025	Jun	78	2.7514	0.1107	7.8107	8
2025	Jul	79	2.7513	-1.2593	7.0257	7
2025	Aug	80	2.7514	-3.3105	4.9745	5
2025	Sep	81	2.7513	-0.3834	7.9016	8
2025	Oct	82	2.7513	-2.8427	5.4423	5
2025	Nov	83	2.7513	-2.4404	5.8446	6
2025	Dec	84	2.7513	-0.1821	8.1029	8
2026	Jan	85	2.7513	-1.5326	7.2986	7
2026	Feb	86	2.7513	-3.5836	5.2476	5
2026	Mar	87	2.7513	-0.6568	8.1745	8
2026	Apr	88	2.7513	-3.1159	5.7154	6
2026	May	89	2.7513	-2.7137	6.1176	6
2026	Jun	90	2.7513	-0.4554	8.3758	8
2026	Jul	91	2.7513	-1.7900	7.5556	8
2026	Aug	92	2.7513	-3.8408	5.5047	6
2026	Sep	93	2.7513	-0.9142	8.4314	8
2026	Oct	94	2.7513	-3.3731	5.9724	6
2026	Nov	95	2.7513	-2.9709	6.3746	6
2026	Dec	96	2.7513	-0.7128	8.6327	9

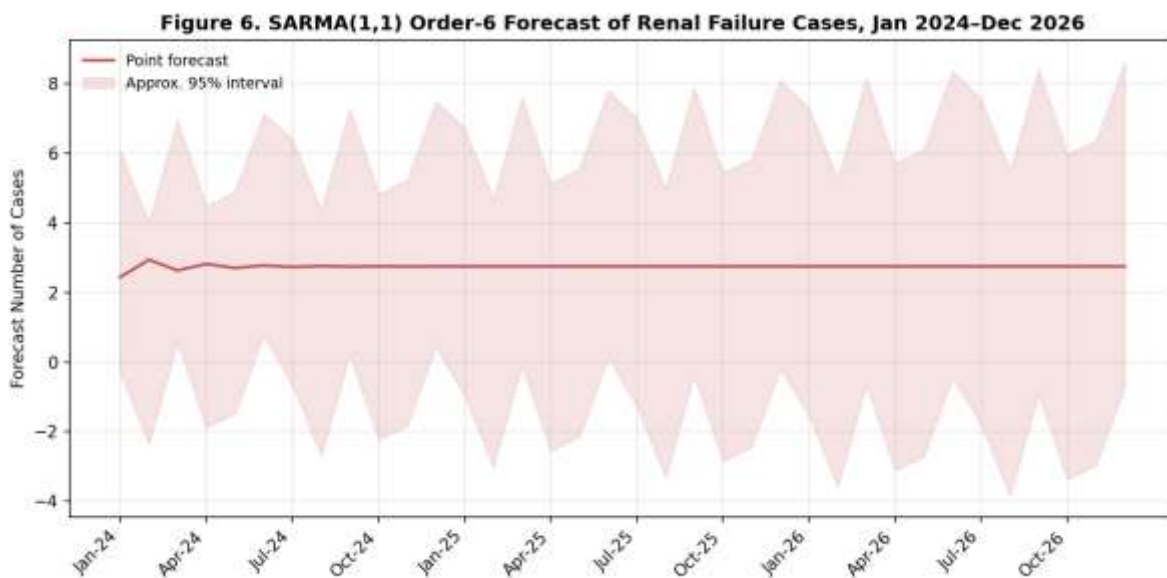


Figure 8. SARMA(1,1) order-6 forecast of renal failure cases with approximate 95% interval, Jan 2024–Dec 2026.

Forecasts indicate that renal failure incidents will lie between 1 and 4 cases monthly, with an upper bound of 9 cases monthly, through 2026, the widest interval among the four categories modelled in detail in this study. Figure 8 shows a clear repeating seasonal pattern within each 6-month cycle, consistent with the order-6 seasonal component of the fitted model, and the confidence band widens progressively across the forecast horizon, reflecting the compounding uncertainty typical of a seasonal autoregressive process with an estimated autoregressive coefficient (0.9999) very close to the boundary of stationarity.

4.3 Discussion

Across the twelve emergency categories examined, the forecast results consistently indicate that cardiogenic shock is the only category expected to occasionally register zero cases in a given month, with an upper bound of 4 cases monthly, while all other categories are projected to register at least one incident per month through the forecast horizon. Road traffic accidents and congestive cardiac failure, already identified as the two leading categories in the descriptive analysis, correspond to conditions with strong documented links to Rivers State's industrial and transportation exposure, reinforcing the plausibility of the fitted trends. The four categories modelled in detail, acute appendicitis, acute intestinal obstruction, gunshot injury, and renal failure, illustrate three distinct forecast behaviours: a flat, highly predictable pattern (acute appendicitis), an annually recurring seasonal pattern (acute intestinal obstruction), a rapidly stabilizing stationary pattern (gunshot injury), and a widening, more uncertain seasonal pattern (renal failure). These findings are broadly consistent with international evidence that ARIMA models perform well for short to medium term operational forecasting in emergency care settings (Wargon et al., 2009; Whitt & Zhang, 2017), while also reflecting the local risk profile emphasized in the introduction and literature review.

5 Conclusion

This study examined the trend behaviour of twelve categories of emergency incidents at Rivers State University Teaching Hospital between 2014 and 2023 and identified suitable ARIMA specifications for each. The identified models were used to generate forecasts from January 2024 to December 2026. Results showed that cardiogenic shock is the only category for which a monthly incidence of zero cases is plausible, with an upper bound of 4 cases monthly, whereas all other emergency categories are expected to register at least one incident monthly, with road traffic accidents and congestive cardiac failure remaining the most prevalent throughout the forecast period.

6 Recommendations

Based on the findings, the study recommends that:

1. RSUTH management adopt the developed ARIMA models as a routine forecasting tool for anticipated monthly emergency caseloads, particularly for road traffic accidents and congestive cardiac failure, which account for the largest share of emergency presentations.
2. Hospital administrators incorporate regular and seasonal ARIMA forecasting into resource allocation and staffing decisions, to reduce overcrowding and improve preparedness for peak periods.
3. Policy makers within the Rivers State health sector use the identified trends, particularly the sustained rise in road traffic accident cases, to inform targeted road safety and emergency response interventions.

Further studies should extend this analysis by incorporating multivariate and machine learning based forecasting approaches, such as vector autoregression or graph neural network models, to compare their predictive performance against the univariate ARIMA models applied here. Future research should also consider integrating exogenous variables, such as rainfall, fuel prices, or industrial activity indices, into an ARIMAX framework, and should extend the analysis to other tertiary hospitals across Rivers State and neighbouring states to assess the generalizability of the identified patterns.

References

- Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control*. Holden-Day.
- Daniel, J., Nzabanita, J., & Ndikumana, A. (2021). Evaluating and forecasting electricity consumption in Rwanda.
- Maku, T., Adebayo, O., & Musa, K. (2023). Forecasting electricity consumption in Nigeria using ARIMA and ARIMAX.
- Nkpordee, B., & Wonu, N. (2018). Forecasting malaria outbreaks using ARIMA models.
- Ogolo, P., & Nkpordee, B. (2022). Consumer price index forecasting in Nigeria.

- Roman, L., & Jean-François, R. (2003). Univariate and multivariate stochastic volatility models: Estimation and diagnostics. *Journal of Empirical Finance*. [https://doi.org/10.1016/S0927-5398\(02\)00072-5](https://doi.org/10.1016/S0927-5398(02)00072-5)
- Santi, L., Golinelli, D., Tampieri, A., Farina, G., Greco, M., Rosa, S., et al. (2021). Non-COVID-19 patients in times of pandemic: Emergency department visits, hospitalizations, and cause specific mortality in Northern Italy. *PLOS ONE*, 16(3), e0248995. <https://doi.org/10.1371/journal.pone.0248995>
- Shih, S. Y., Sun, F. K., & Lee, H. Y. (2019). Temporal pattern attention for multivariate time series forecasting. *Machine Learning*, 108, 1421–1441. <https://doi.org/10.1007/s10994-019-05815-0>
- Stanley, P., Okon, E., & Udoh, A. (2020). Comparison of univariate and bivariate time series forecasting models.
- Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic Perspectives*, 15(4), 101–115. <https://doi.org/10.1257/jep.15.4.101>
- Van den Heede, K., & Van de Voorde, C. (2016). Interventions to reduce emergency department utilization: A review of reviews. *Health Policy*, 120(12), 1337–1349.
- Von Wagner, M., Queck, A., Beekers, P., Tolhuizen, L., Synnatschke, A., Boesing, J., & Chatterjea, S. (2023). Towards accurate and automatic emergency department workflow characterization using a real time locating system. *International Journal of Healthcare Management*, 1–2. <https://doi.org/10.1080/20479700.2023.2172829>
- Wan, R., Mei, S., Wang, J., Liu, M., & Yang, F. (2019). Multivariate temporal convolutional network: A deep neural networks approach for multivariate time series forecasting. *Electronics*, 8(8), 876. <https://doi.org/10.3390/electronics8080876>
- Wargon, M., Guidet, B., Hoang, T. D., & Hejblum, G. A. (2009). Systematic review of models for forecasting the number of emergency department visits. *Emergency Medicine Journal*, 26(6), 395–399.
- Webb, R. H. (1985). Toward more accurate macroeconomic forecasts from vector autoregressions. *Economic Review*, 71(4), 3–11.
- Weiss, C. H. (2009). Modelling time series of counts with overdispersion. *Statistical Methods & Applications*, 18(4), 507–519.
- Whitt, W., & Zhang, X. (2017). A data driven model of an emergency department. *Operations Research for Health Care*, 12(1), 1–15.
- Zheng, W., & Hu, J. (2023). Multivariate time series prediction based on temporal change information learning method. *IEEE Transactions on Neural Networks and Learning Systems*, 34(10), 7034–7048. <https://doi.org/10.1109/TNNLS.2021.3137178>
- Zivot, E., & Wang, J. (2006). Vector autoregressive models for multivariate time series. In *Modeling financial time series with S-PLUS* (pp. 385–429). Springer.
- Zonghan, W., Pan, S., Long, G., Jiang, J., Chang, X., & Zhang, C. (2020). Connecting the dots: Multivariate time series forecasting with graph neural networks. Association for Computing Machinery. <https://doi.org/10.1145/3394486.3403118>