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Assessment of Maternal Mortality in Federal Medical Centre Jalingo Using ARIMA Model

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Abstract

Nigeria bears a disproportionate burden of global maternal mortality, contributing approximately 10% of all maternal deaths worldwide. This study adopts a multi-theoretical and empirical approach to analyze the complex interplay of socio-cultural, economic, and systemic determinants influencing maternal mortality in Nigeria. Grounded in models such as the Three Delays Model, Health Belief Model, Social Determinants of Health, Andersen's Behavioral Model, and the Cultural and Structural Competency Framework, the research highlights the multifaceted barriers impeding timely and effective maternal care. Empirical findings based on Autoregressive Integrated Moving Average (ARIMA) modeling reveal persistent, though insufficient, declines in maternal and child mortality over recent decades. Additionally, socioeconomic variables such as low levels of female education, high fertility rates, poverty, and inadequate access to antenatal care significantly correlate with maternal mortality rates. The study critiques existing interventions as poorly coordinated and unsustainable, with limited community involvement and cultural adaptation. Recommendations emphasize a multilevel prevention strategy—

ranging from primordial to quaternary levels—integrating structural reforms, community-based education, capacity-building among healthcare providers, and a reconfiguration of national health policy. The findings contribute to the growing body of knowledge on maternal health by providing a comprehensive, culturally-informed, and data-driven analysis aimed at guiding future research, policy, and practice.

Keywords; Maternal; Mortality; ARIMA; Forecasting; Antenatal

INTRODUCTION

Maternal mortality is a sensitive indicator of a country's health system performance, social equity, and the effectiveness of its reproductive health services. Globally, substantial progress has been made in reducing maternal deaths. However, this progress is uneven, with Sub-Saharan Africa, particularly Nigeria, lagging significantly. Nigeria accounts for one of the highest maternal mortality ratios (MMRs) globally, estimated at 512 deaths per 100,000 live births (Ronsmans & Graham, 2006). With more than 58,000 maternal deaths annually, the country represents a global hotspot for maternal health failure (WHO, 2013)

Despite decades of targeted interventions and international assistance, Nigeria has failed to meet successive global maternal health targets (Sharma, *et al.*, 2017). The causes are complex and interconnected, from weak healthcare infrastructure, inadequate human resources for health, and underfunded facilities, to socio-cultural barriers such as harmful traditional practices, gender inequality, and widespread poverty. Government policies and donor-funded programs have largely failed to address grassroots realities. In an attempt to address this situation, experts in public health related issues made some recommendations and Nigeria's federal ministry of health in 2013 granted those recommendations, that all maternal health institutions across the country should from time to time conduct a maternal death review, surveillance and response using the technical guidance document as recommended by the world health organization, (WHO, 2013). The entire program was updated in 2016 to include prenatal death reviews and the plan was given the title maternal and perinatal death surveillance and response (MPDSR). This initiative will capture the high rates of stillbirth, neonatal and perinatal deaths in the country, (Idowu, et al., 2017). From the inception of the program till this day, Nigeria's Federal Ministry of Health has made the suggestion that states within the federation assume a unified etiquette for carrying

out the review. The Taraba State Ministry of health is one of Nigeria 36 federating states and as such, it is expected that the state has started implementing those recommendations and protocols. (Idowu, *et al.*, 2017). This research aims to identify and analyze the major determinants of maternal mortality, employ ARIMA modeling to evaluate temporal trends and project future maternal mortality patterns and propose an integrated, multilevel framework for the prevention of maternal mortality by considering Federal Medical Centre, Jalingo, as case study. Oyedepo (2023) studied the trends and patterns of maternal mortality in Nigeria and to determine whether it has any association with economic growth using Ordinary least squares regression findings showed that a significant increase in female life expectancy and economic growth leads to a reduction in maternal mortality. Ewere and Donalben (2020) conducted a research on time series analysis and forecast of infant mortality rate in Nigeria and to determine if it has long been a public health menace in Nigeria by utilizing the Auto-Regressive Integrated Moving Average (ARIMA) model for to make forecast of infant mortality in Nigeria up to the year 2030. The time plot of the forecast showed a downward movement suggesting that there would be a continuous decrease in infant mortality rate. David and Raheem (2023) studied a time series modeling and forecasting of under-5 mortality rate in Nigeria and to examine the trend in the Under-5 mortality rate in Nigeria. The study revealed that the most adequate model for the under-5 mortality rate is ARIMA (1,1,0). Odambele et al.(2023) investigates the trends, projections, and regional disparities of mortality in Africa using an ARIMA approach, the results found a decline in maternal mortality in Africa. Abdullahi et al. (2021) conducted a researched on analysis and forecasting of maternal mortality in Nigeria and to determine whether it has any association with the economic and sociological development of any community. ARIMA model was used on maternal mortality data from 1990-2015 to forecast the maternal mortality ratio from 2016-2025. The results showed that education, particularly female education, is negatively connected to maternal difficulties and mortality. Orgingene et al. (2022) investigated factors affecting maternal and neonatal mortality in Northern NIGERIA. The authors employed the use of time series data from 2012 to 2021. Multiple Linear Regression and Multivariate Logistic Regression analysis were used to estimate predictor variables that determine maternal and neonatal mortalities in the region. Results from the study revealed a negative relationship between antenatal care and neonatal mortality implying that an increase in the number of women attending antenatal care will lead to a reduction in neonatal mortality by about 43%.

METHODS

Stationarity in Time series

The first step in time series is to obtain the time plot and examine the series for stationarity before fitting an appropriate Box-Jenkins model to the series analysis (David & Raheem, 2023).

Autoregressive processes

The autoregressive process of order p is denoted AR(p), and defined

$$Xt = \sum \varphi r Xt-r + p\ r=1\ \epsilon t \quad (2.1)$$

where $\varphi 1,...,\varphi r$ are autoregressive coefficients and $\{\epsilon t\}$ is a sequence of independent (or uncorrelated) random variables with mean 0 and variance $\sigma 2$. That is, ϵt is a white noise. Consider an (1) process, defined by;

$$Xt = \varphi 1 Xt-1 + \epsilon \quad (2.2)$$

Obtaining the Mean, the Variance and Covariance functions of (2.1) Consider re-writing (2.1) as a function of the residuals

$$Xt = \epsilon t + \varphi 1(\epsilon t-1 + \varphi 1(\epsilon t-2 + \cdots)) = \epsilon t + \varphi 1\,\epsilon t-1 + \varphi 1\ 2\epsilon t-2 + \cdots \quad (2.3)$$

The fact that $\{Xt\}$ is second order stationary follows from the observation that $(Xt) = 0$ and that the autocovariance function can be calculated as follows:

$$\gamma 0 = [(\epsilon t + \varphi 1\,\epsilon t-1 + \varphi 2\ 2\epsilon t-2 +)]2 = (1 + \varphi 2 + \varphi 4 + \ldots)\sigma 2 \quad (2.4)$$

$$= \sigma 2\ (1-\varphi 1\ 2-\varphi 2\ 2-\cdots) \quad (2.5)$$

$$\gamma k = Cov\ (Xt,-k) \equiv Cov\ (Xt,Xt+k) = E(Xt.Xt-k)\ \gamma k = E\{(\sum\ \varphi 1\ r\varphi t-r\infty\ r=0 \sum\ \varphi 1\ s\varphi t-s+k\ \infty\ s=0\ )\} =\ \sigma 2\varphi 1\ k\ 1-\varphi k\ 2 \quad (2.6)$$

For example, the mean for (1) is 0, while its variance is

$$\gamma 0 = \sigma 2\ (1-\varphi 1\ 2) \quad (2.7)$$

Thus, its autocovariance at lag k is; $\gamma k = \varphi 1\,\gamma k-1, \quad \forall\ k = 1,2,...$ (2.8)

Investigating the stationarity of the process Consider the AR(p) $Xt = \varphi 1 Xt-1 + \varphi 2 Xt-2 + \cdots + \varphi p Xt-p + \epsilon\ t$ (2.9)

Multiplying (2.9) by $Xt-k$; take the expectation and divide by $\gamma 0$, to produce the Yule-Walker equation

$$\rho k = \varphi 1 \rho k-1 + \varphi 2 \rho k-2 + \cdots + \varphi p \rho k-p, \forall\ k = 1,2 \quad (2.10)$$

These are linear recurrence relations, with the general solution of the form

$$\rho k = C1 w1\ |k|\ + \cdots + Cpwp\ |k| \quad (2.11)$$

where $\omega 1,...,\omega p$ are the roots of the characteristic equation $\omega\ p$

$$-\ \varphi 1 \omega p-1 - \varphi 2 \omega p-2 - \cdots - \varphi p = 0 \quad (2.12)$$

and $C1,...,Cp$ in (2.11) are determined by setting $\rho 0 = 1$ for $k = 1,...,p - 1$. It is natural that $\gamma k \to 0\ as\ k \to \infty$, in which case the inverse roots must lie within the unit circle; that is, $|\omega i| < 1$. Thus one can conclude that the process is covariance stationary for any chosen value of $\varphi 1,...,$.

Moving Average Process

The moving average process of order q is denoted MA(q) and defined by;

$$Xt = \sum \theta s \epsilon t-s\ q\ s=0 \quad (2.13)$$

where $\theta 1,...,\theta q$ are fixed constants, $\theta 0 = 1$, and $\{\varepsilon t\}$ is a sequence of independent (or uncorrelated) random variables with mean 0 and variance $\sigma 2$. It is clear from the definition that this is a second-order stationarity and that

$$\gamma k = \{0 \qquad \forall\ |k| > q\ \sigma 2 \sum \theta s \theta s+k\ q-|k|\ s=0 \quad \forall\ |k| \le q \quad (2.14)$$

We remark that two moving average processes can have the same autocorrelation function. For instance, $Xt = \epsilon t + \theta \epsilon t-1$ (2.15)

$$Xt = \epsilon t + (1\ \theta) \epsilon t-1 \quad (2.16)$$

both have $\rho 1 = \theta\ (1+\theta 2)$, $\quad \rho k = 0, |k| > 1$ (2.17)

However, re-writing the first (in (2.15) as an inverse function of error terms (in terms of Xt)

gives $\in t = Xt - \theta \epsilon t-1\ = Xt - \theta = Xt - \theta Xt-1 + \theta 2 Xt-2$ (2.18)

The (2.18) is called Invertible process, with $|\theta| < 1$ for the process to be stationary. No two invertible processes have the same autocorrelation function.

ARMA processes

The autoregressive moving average model provides a parsimonious description of a weakly stationary stochastic process compared to the autoregressive and the moving average processes. It is usually referenced as the $ARMA\ (p,)$ model, consisting of the p-lags of autoregressive (AR) terms and q-lags of moving average (MA) terms, mathematically expressed as:

$$Xt - \sum \varphi r Xt - r\ p\ r=1 = \sum \theta s \epsilon t - s\ q\ s=0 \quad (2.19)$$

where again $\{\epsilon t\}$ is white noise.

ARIMA processes

When the original series $\{Yt\}$ is not stationary, we then explore differencing the series, starting with first-order differencing until the series becomes stationary. For example, the first order differenced series is achieved using:

$$Xt' = \nabla Yt = Yt - Yt-1 \quad (2.20)$$

The d-order differenced process

$$Xt\ d = \nabla dYt = (\nabla d-1) \quad (2.21)$$

While differencing a series, we test for the stationarity and once the stationarity if achieved, the differenced series is adopted in fitting an appropriate ARMA model.

The process $\{Yt\}$ is said to be an autoregressive integrated moving average process, $A(p,d,q)$, $such\ that\ Xt = \nabla dYt$. In the meantime, having ensured stationarity of the series, by testing for the presence or otherwise of the unit root using Augmented Dickey and Fuller (1979) test statistic; next is to obtain the correlogram, where both the autocorrelation (ACF) and partial autocorrelation (PACF) functions have to be inspected for possible model(s) that best reproduce the original series. Next is the model estimation and selection, using (corrected) Akaike information criterion proposed by Akaike (1974) or Schwarz Bayesian information criterion elaborated by Bumham and Anderson (2002). The model with the lowest AIC or BIC value is usually favored. After that, the fitted model is examined to ensure no serial correlation in the residuals, using the Durbin Watson Statistic.

RESULTS

Descriptive Statistic

Table 1: Descriptive Statistic

Measures	Values
N	40
Minimum	0.00
Maximum	4.00
Mean	0.7250
Standard Deviation	1.1762
Variance	1.384
Skewness	1.564
Kurtosis	1.503

Time Series Plot

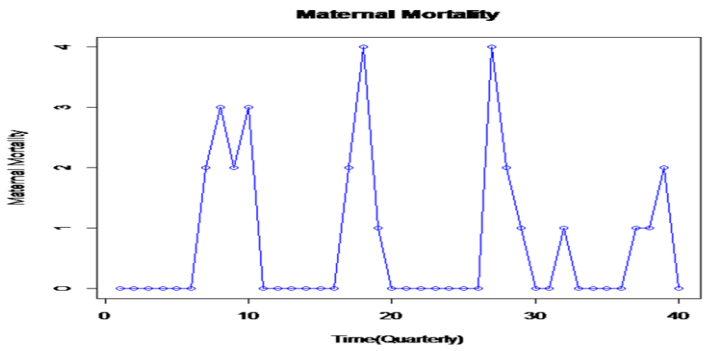

Figure 1: Quarterly Time Series Plot for Maternal Mortality Rate

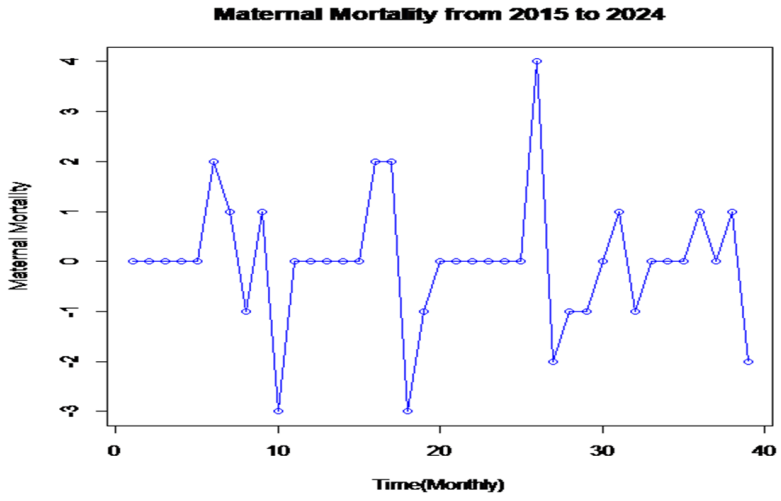

Figure 2: Quarterly Time Series Plot for Maternal Mortality Rate after differencing I(1)

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plot

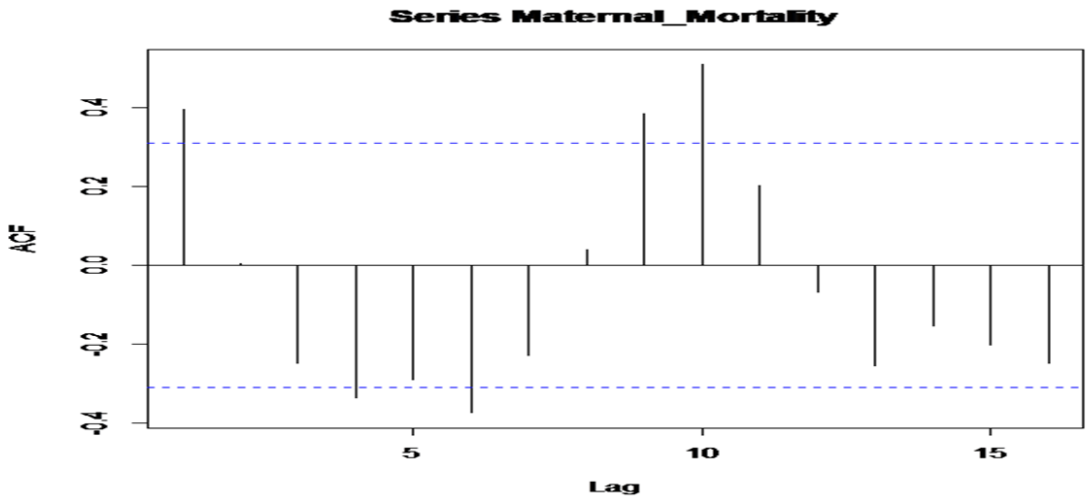

Figure 3: Autocorrelation Function (ACF) Plot for Maternal Mortality Rate

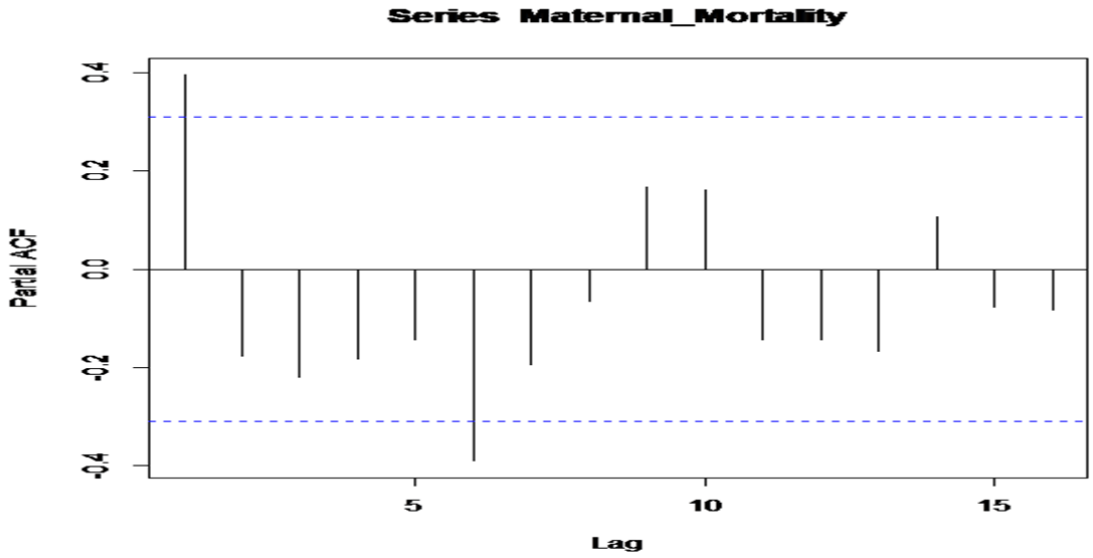

Figure 4: Partial Autocorrelation Function (ACF) Plot for Maternal Mortality Rate

Stationary test

Table 2: Unit root test

Data	Augmented Dickey-Fuller (ADF) tests		Philips-Perron (PP) Test		Remark
	t-value	P-value	t-value	P-value	
Maternal Mortality	-4.3175	0.0100	-38.122	0.010	Stationary at level I(1)

Model Selection

Table 3: Model Selection

S/N	Model	AIC
1.	ARIMA (1,1,0)	149.73
2.	ARIMA (1,1,1)	134.61
3.	ARIMA (2,1,2)*	121.22
4.	ARIMA (1,1,2)	130.07
5.	ARIMA (2,1,1)	135.98
6.	ARIMA (3,1,1)	136.85
7.	ARIMA (3,1,2)	132.05

Interpretation of the best model:

Table 4: Autoregressive Moving Average with p=2, d=1 and q=2 (ARIMA (2,1,2))

	Coefficient	Standard Error	t-value	P-value
Constant	0.8343	0.2899	2.88	0.004
AR (1)	0.5502	0.1661	3.31	0.0009
AR (2)	-0.1566	0.1662	-0.94	0.347
MA (1)	-1.9869	0.1145	-17.35	0.0001
MA(2)	1.0000	0.1143	8.75	0.0001

Forecasting:

Table 5: Forecasting from 2025 to 2027 (Quarterly) for maternal mortality

Year	Quarterly	Values
2025	1st	2
	2nd	0
	3rd	1
	4th	2
2026	1st	0
	2nd	1
	3rd	2
	4th	0
2027	1st	0
	2nd	1
	3rd	2
	4th	2

DISCUSSION

The descriptive statistics presented in Table 1 provide a detailed summary of a dataset consisting of 40 observations. The minimum value is 0.00, while the maximum value is 4.00, suggesting that the data points are spread across this range. The mean of the dataset is 0.7250, which indicates that, on average, the values tend to be relatively low. This is further supported by the standard deviation of 1.1762, which measures the amount of variability or dispersion of the data from the mean. A higher standard deviation suggests a wide spread of values, and in this case, it highlights significant variation within the data points.

The variance, calculated at 1.384, provides another measure of the data's spread. The skewness value of 1.564 indicates a positive skew in the data, meaning that the distribution has a longer tail on the right side, and there are more values clustered toward the lower end of the scale. This positive skew suggests that a larger portion of the data falls on the lower side of the range, with fewer high values.

The kurtosis value of 1.503 indicates that the data distribution is platykurtic, meaning it is relatively flat compared to a normal distribution. A kurtosis value below 3 implies that the data has fewer extreme values (outliers) and is more spread out than a normal distribution.

In this case, the kurtosis suggests that the distribution is somewhat flatter and less peaked than a typical bell-shaped curve, further indicating that the data lacks significant outliers or extreme values.

Figure 1 shows quarterly data on maternal mortality (MM) from 2015 to 2024 reveals notable fluctuations, reflecting both challenges and potential improvements in maternal health over the years. In 2015, the year began with no reported maternal deaths, but a significant increase occurred in the third quarter with 2 cases, followed by 3 in the fourth quarter. This surge highlights potential gaps in maternal healthcare during that period. The trend in 2016 showed a continued rise, starting with 2 cases in the second quarter and peaking at 3 in the fourth quarter. This pattern emphasizes the need for enhanced maternal health interventions during these periods. In 2017, the first half of the year experienced 2 and 3 cases in the first and second quarters, respectively, but a decline to zero in the third and fourth quarters. This decrease may suggest the impact of targeted health initiatives or seasonal factors affecting healthcare access. The year 2018 saw a return to zero cases across all quarters, possibly indicating successful health interventions or improved healthcare access.

However, 2019 experienced a resurgence with 2 cases in the first quarter, 4 in the second, and 1 in the third, before returning to zero in the fourth quarter. This fluctuation underscores the ongoing challenges in achieving consistent maternal health improvements. The subsequent years, 2020 and 2021, began with zero cases, followed by a spike to 4 cases in the third quarter of 2021 and 2 in the fourth quarter. These variations highlight the need for continuous monitoring and responsive health strategies. In 2022, maternal deaths were reported in the first and fourth quarters, with zero cases in the intervening periods. This pattern may reflect specific challenges or successes in particular seasons. The years 2023 and 2024 concluded the decade with a mix of zero and low cases, suggesting potential stabilization or improvements in maternal health services.

Figure 3 and 4 for the time series on maternal mortality for the ACF plots are stationary, since there exists quick decay in the series for all lag values in the plot. Likewise, the PACF plot shows a significant spike after lag 2 with marginal spikes in some few lags of the series as shown in Figure 3. It is noticeable that the graph of ACF and PACF of the time series values cuts off quickly, then the times series under study is considered stationary at differencing.

The results presented in Table 2 show the outcomes of two unit root tests, the Augmented Dickey-Fuller (ADF) test and the Philips-Perron (PP) test, applied to the dataset on maternal mortality. Both tests are used to determine the stationarity of the time series data, with stationarity meaning that the statistical properties of the data (such as mean and variance) do not change over time.

For the Augmented Dickey-Fuller (ADF) test, the t-value is reported as -4.3175, with a corresponding p-value of 0.010. Since the p-value is less than the commonly used significance level of 0.05, we can reject the null hypothesis of a unit root, indicating that the time series is stationary at first differencing, or I(1). This means that the series does not require differencing to achieve stationarity.

Similarly, the Philips-Perron (PP) test provides a t-value of -38.122 and a p-value of 0.010. Again, the p-value is less than 0.05, which allows us to reject the null hypothesis of a unit root and confirms that the series is stationary at first differencing, or I(1). Both tests show consistent results, affirming that the maternal mortality data is stationary at the first differencing, or I(1).

Table 3 presents the results of the model selection process for the ARIMA (AutoRegressive Integrated Moving Average) models, where different combinations of autoregressive (AR), differencing (I), and moving average (MA) terms are compared. The models are evaluated based on their Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, which are used to assess the goodness of fit and model complexity. Lower values of both AIC and BIC suggest a better fit, as they indicate the model's ability to explain the data while avoiding overfitting.

Among the listed models, ARIMA(2,1,2) stands out as the most favorable, marked with an asterisk to denote it as the best fit. This model has the lowest AIC (121.22) and a competitive BIC (141.4030), suggesting it offers the best balance between goodness of fit and parsimony.

The other models, such as ARIMA(1,1,1), ARIMA(1,1,2), and ARIMA(2,1,1), while having varying AIC and BIC values, do not surpass the performance of the ARIMA(2,1,2) model. For instance, ARIMA(1,1,1) has an AIC of 134.61 and a BIC of 141.5225, both higher than those of ARIMA(2,1,2).

Therefore, the ARIMA(2,1,2) model is recommended for forecasting in this study, as it minimizes both AIC and BIC, thereby providing an optimal balance between model fit.

The intercept term in Table 4 suggests that when all other variables are zero, the expected value of the differenced series is 0.8343. The t-value of 2.88 and p-value of 0.004 indicate that this coefficient is statistically significant, implying a meaningful contribution to the model.

The first autoregressive term indicates that the current value of the differenced series is positively influenced by the immediately preceding value. A one-unit increase in the previous value is associated with a 0.5502-unit increase in the current value. With a t-value of 3.31 and a p-value of 0.0009, this coefficient is highly significant.

The second autoregressive term suggests a negative relationship with the value two periods prior. However, the t-value of -0.94 and p-value of 0.347 indicate that this coefficient is not statistically significant, implying a negligible effect.

The first moving average term reflects a strong negative association with the immediate past forecast error. A one-unit positive error in the previous forecast leads to a 1.9869-unit decrease in the current value. The high t-value of -17.35 and a p-value of 0.0001 confirm its statistical significance.

The second moving average term indicates a positive relationship with the forecast error from two periods ago. A one-unit positive error two periods prior results in a one-unit increase in the current value. With a t-value of 8.75 and a p-value of 0.0001, this coefficient is also highly significant.

The statistical significance of the constant, AR (1), MA (1), and MA (2) coefficients suggests that these terms meaningfully contribute to modeling the time series data. The lack of significance for AR (2) implies that it may not provide substantial explanatory power and could be considered for removal in model refinement.

Therefore, the ARIMA(2,1,2) model effectively captures the temporal dependencies in the data, with significant contributions from the specified terms.

From Table 5, the quarterly forecasts of maternal mortality from 2025 to 2027 suggest a cyclical pattern, with fluctuations between 0 and 2 deaths per quarter. Notably, the first and fourth quarters often predict higher mortality rates, potentially due to seasonal factors affecting maternal health. These projections are crucial for healthcare planning, enabling targeted interventions during anticipated peak periods to enhance maternal health outcomes.

CONCLUSION

The analysis provides valuable insights into the temporal dynamics of maternal mortality, revealing both persistent patterns and periods of fluctuation. The ARIMA (2,1,2) model's effectiveness in capturing these trends offers a reliable tool for forecasting future Maternal Mortality rates. However, the observed fluctuations, especially the anticipated increases in late 2027, highlight ongoing challenges in maternal health that require continuous attention.

Based on the findings, we recommend the Implementation of targeted interventions during periods identified with higher Maternal Mortality rates, particularly in the third and fourth quarters of 2027, to mitigate potential increases. Establish robust surveillance systems to monitor maternal health trends, enabling timely responses to emerging patterns and ensuring the effectiveness of interventions. Develop multifaceted approaches that address underlying factors contributing to maternal mortality, including access to quality prenatal care, skilled birth attendance, and emergency obstetric services. Engage policymakers and communities in efforts to improve maternal health outcomes, fostering collaboration to implement sustainable solutions and raise awareness about the importance of maternal care.

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