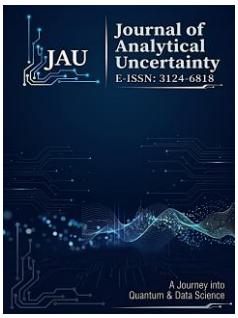
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Forecasting Twin Pregnancy Outcomes Using Classical Time Series Models: A Comparative Study of ARIMA, ETS, and SARIMA

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Abstract

Twin pregnancies carry substantially higher risks than singleton pregnancies, particularly in low-resource settings where access to quality maternal care is constrained. This study aimed to analyze and forecast key maternal and neonatal health indicators in twin pregnancies using classical time series models. A dataset comprising 2,000 clinical records from the Rivers State University Teaching Hospital (RSUTH) in the Southern Niger Delta Region of Nigeria was analysed. Three models Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS), and Seasonal ARIMA (SARIMA), were developed and validated using a train–test split. The ARIMA (1,1,1) model attained a Mean Absolute Error (MAE) of 0.246, Root Mean Squared Error (RMSE) of 0.277, while the Mean Absolute Percentage Error (MAPE) is 9.91%, demonstrating a moderate performance in predicting birth weight. The ETS model performed best for Apgar scores, with MAE = 0.387, RMSE = 0.471, and MAPE = 4.85%, and it reproduced stable trends over time. The SARIMA model (1,1,1,2) captured some variations in the mode of delivery but revealed higher forecast errors (MAPE = 31.3%), likely due to variance in monthly deliveries; however, it led to the lowest MAE (0.201) and RMSE (0.230), indicating accurate trend alignment. Findings revealed a rising trend in twin births and a high prevalence of preterm deliveries among women of reproductive age in the region. Strengthening perinatal care and implementing early intervention strategies are recommended to reduce adverse maternal and neonatal outcomes.

Keywords: Time Series Analysis, ARIMA, ETS, SARIMA, Twin Pregnancy, Apgar Score, Maternal Health, Neonatal Outcomes

Introduction

Pregnancy remains a mutual manifestation among women within the childbearing age; its outcomes may present healthy live births and situations where both the mother and child may not survive [1]. In all the phases of pregnancy, those that involve the loss of life are the most emotionally profound. Globally, twin pregnancies occurs approximately 1-2% of all pregnancies, but their prevalence is significantly higher in Africa with about 4% presented pregnancies [1]–[4]. Mpilambo et al. [5] pointed out that many developed countries are experiencing increase in

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twin births which could be as result of medically assisted reproductive technologies and relative average maternal age at childbirth. Despite this advancement in maternal care, twin pregnancies pose higher risks Whittaker et al. [6], which cause more heightened medical oversight than single pregnancies. These complications arise from the increased physical demands on the mother and the potential medical issues related to the babies' development and growth.

Dual fetal gestations are often related with an elevated risk of preterm birth, which may lead to pulmonary insufficiency in neonates, underdeveloped organs, and low birth weight [7], in line with the work of Getachew et al. [8], revealed that among twin deliveries, 78% of neonates require admission to a neonatal intensive care unit (NICU) [9], [10], 44% present with low birth weight [11], 33% experience with low Apgar scores [12], and 32% were premature [13]; also 30% of the twin pregnancies may result to stillbirth [14], and 12% in neonatal mortality [15], furthermore, 25% of mothers experiencing hypertensive disorders of pregnancy [16], 7% suffering postpartum haemorrhage [17], and 37% undergoing cesarean delivery [18]. In addition, Intrauterine Growth Restriction (IUGR) may also occur, necessitating early intervention to address growth concerns. More so, the probability of developing maternal hypertension and preeclampsia is also higher, which can result in organ failure, restricted blood flow to the babies, or placental abruption.

Furthermore, twin pregnancies are connected to placental issues such as placental abruption or placenta previa, both of which can result in significant bleeding, putting the health of both the mother and the babies at risk, could prompt the risk of surgical birth with factors such as fetal positioning, placental issues, or complications arising during labour, and early monitoring allows for better planning of surgical intervention. There is also an increased risk of developmental abnormalities, including neural tube defects and congenital heart conditions, which are more common in twin pregnancies. In addition to these fetal concerns, the physical strain on the mother is more significant, leading to a higher risk of medical issues such as gestational diabetes, extreme fatigue, and an increased chance of postpartum hemorrhage due to the larger-than-usual uterus.

However, employing time series will give room to analyse and monitor key maternal and neonatal indicators such as birth counts, Apgar scores, birth weights, and delivery modes to understand the pattern, emerging trends and seasonal fluctuations that may cause for prompt attention or improvements to enhance outcomes. Shastri and Mansotra [19] applied time series models to forecast maternal health trends, while Jo et al. [20] focused on analysing mortality rates among women of reproductive age. Beluzo et al. [21] concentrated primarily on neonatal mortality. These studies highlight the need for greater awareness of the utility of time series analysis in uncovering temporal patterns and recurrent seasonal shifts in maternal and neonatal health outcomes. However, adopt classical model to predict obstetric death, survival of infant, and healthcare demand, while few have examined twin pregnancies specifically, despite their disproportionate risk profile, it is on this premise, this study seeks to apply the Autoregressive Integrated Moving Average (ARIMA) model for analysing multi-year healthcare data in order to predict overall trends in birth outcomes, then utilize the Exponential Smoothing (ETS) model for detecting and forecasting specific trends in birth weight, Apgar scores, and mode of delivery, and implement the Seasonal ARIMA (SARIMA) model to explicitly capture and model seasonal patterns in healthcare data, such as recurring fluctuations in delivery rates across months. The remainder of this paper is organized as follows: Section 2 reviews related literature; Section 3 outlines the methodology; Section 4 presents the results; Section 5 provides the discussion; and Section 6 concludes the study.

Literature Review

Numerous studies have looked at the use of time series analysis in maternal and neonatal outcomes, to mention but a few, Bharuka et al. [22] conducted a complementary evaluation of progressive data on gestational prevalence of death was a worthwhile addition to the literature with regard to putting patterns and trends on maternal transience, but whose study failed to explain the complicated dynamics driving such findings [23]. Concurrently, Silva et al. [24] adjusted for infant mortality and well demonstrated the conceptual and methodological strength of the ARIMA model but were unable to demonstrate the multidimensionality of health outcomes to the full extents. Zhao et al. [25], on the other hand, exploring the effect of air pollution on

neonatal prematurity through a time-series approach poses a concern based on the misclassification of data inconsistencies which may elevate the risk of preterm births and trigger emergency scenarios. Choudhury and Urena [26] used historical data stream analysis to forecast emergency department arrivals hourly. Still, they did not include external variables like weather conditions or outbreaks that could have substantial impacts on emergency visit behaviour. Including these and additional, more varied sources of data could provide more comprehensive information to guide health care decision-making. Bakr et al. [27] contrasted cesarean section (CS) delivery using historical sets of data but not external variables like patient preference or socioeconomic status, which can have the potential to affect the rates of CS.

In a corollary case, Guitart et al. [28] built a midwifery education predictive model to further enhance health outcomes but lowered low- and middle-income countries' challenges of attaining favourable neonatal and maternal outcomes. Bharuka et al. [22] proposed an ARIMA model for predicting maternal mortality with good intentions; however, the model's predictive validity and practical applicability are limited by the lack of rigorous model validation using recognized performance metrics like MAE, RMSE, or MAPE, as well as the explicit identification and incorporation of seasonal and cyclical effects. Complementarily, Makoni and Ndlovu [29] used time series models to estimate maternal mortality in Masvingo Province and recommended that comparative analysis can be used to seek more precise forecasting alternative. Fergus et al. [30] one-dimensional convolutional neural networks to screen segmented cardiotocography signals for the early detection of abnormal birth outcomes; whereas some robust performance of their model on retrospective data was reported, its real-time clinical efficacy remains yet to be confirmed. Similarly, Beluzo et al. [21] also examined neonatal mortality rates but did not implement feature extraction and the model in real-time health monitoring systems that could improve the process of clinical decision-making

Other studies do not have comparable gaps. Xu et al. [31] compared Holt–Winters exponential smoothing models and ARIMA to forecast new-borns' congenital heart disease but were unable to benefit from the use of a larger dataset and other models to obtain improved prediction performance.. Li et al. [32] modelled obstetric patient flow, which differed significantly from one healthcare institution to another, but failed to validate the predictive models, rendering it uncertain to their findings..

Zhang et al. [33] employed a sequential data-based machine learning framework for predicting preterm birth and determined the most predictive features but had their study marred by low sensitivity, single-centre reliance on data, and external validation. Cambou et al. [34] approximated maternal mortality in Brazil in the COVID-19 pandemic period using data from 2019, but a more accurate perspective could have been obtained by including data from 2020 and 2021 as the effect of the pandemic was at its peak [35]–[37]. Capan et al. [38] applied a time series approach to forecast neonatal intensive care unit census using a complex ARIMA (2,1,4)x(1,1,2)14 model. Although the model was technically appropriate, the risk of over-fitting remains, especially when model validation is insufficient. Finally, Onambele et al. [39] applied ARIMA forecasting to examine maternal mortality in Africa from 1990 to 2030 by region but did not factor in intra-regional differences and impacts of socioeconomic variables and variations in healthcare systems on maternal outcomes when making their assessment.

Together, these studies demonstrate that time series analysis is becoming widely recognized as an important tool for monitoring trends in neonatal and maternal health, yet none of them have been applied to twin pregnancies. That this gap in the literature should be so conspicuous gives some indication of the newness of the current study, which uses ARIMA, ETS, and SARIMA models to a locally collected dataset of twin pregnancies to present evidence specific to this at-risk population. Complementary decision-analytics research has also shown how uncertainty-aware computational models can support clinically interpretable risk assessment when conventional point estimates are insufficient [40].

Methods

Data collection

Data were collected from a tertiary healthcare facility in Port Harcourt, Nigeria. A total of 2,000 maternal records were retrieved and reviewed from the antenatal clinic, labour ward, and theatre registers, specifically during the period of delivery, from 2015 to 2019. The dataset comprised eleven key input features such as maternal age, parity, educational status, religion, booking status, mode of delivery, birth weight, and neonatal outcomes in twin pregnancies (i.e., alive or deceased). Ethical approval for the study was duly obtained from the relevant institutional review board.

Mathematical expression

1. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model, was propounded by Box et al. [41] used for analysing and forecasting time series data. It consists of three basic components auto regression (AR), integration (I) for differencing to make the series stationary, and moving average (MA). The model is presented as (1).

$$\varphi(C)(1-C)^q y_t = \vartheta(C)\, \in_t, \tag{1}$$

where:

a. y_t: observed time series a time t
b. C : backshift operator, $Cy_t = y_t - 1$
c. $\varphi(C) = 1 - \varphi_1 C, \ldots., \varphi_p C^p$: autoregressive component of order p
d. $\vartheta(C) = 1 - \vartheta_1 C, \ldots., \vartheta_q C^q$: autoregressive component of order q
e. d : the degree of differencing
f. $\in_t$: white noise error

This model can be denoted as$\text{ARIMA}_{(p,d,q)}$

2. Exponential Smoothing (ETS)

Robert [42] developed ETS which was later extended by Holt [43] and Winters [44] the model was introduced to handle components such seasonality, trend and level of a time series data, to proffer smoothing and encourage short-term prediction. The model is presented as (2).

$$z_t = \tau_{t-1} + a_{t-1} + w_{t-m} + \epsilon_t. \tag{2}$$

Therefore the input equations:

a. Level: $\tau_t = \delta(z_t - w_{t-m}) + (1-\delta)(\tau_{t-1} + a_{t-1})$,
b. Trend : $a_t = \varrho(\tau - \tau_{t-1}) + (1-\varrho)a_{t-1}$,
c. Seasonal : $w_t = \eta(z_t - \tau_{t-1} - a_{t-1}) + (1-\eta)a_{t-1}$,

where:

i. τ_t, a_t, w_t: level, trend, and seasonal components,
ii. m : season length,
iii. δ, ϱ, η : smoothing parameters,
iv. ϵ_t : random error.

3. Seasonal ARIMA (SARIMA)

SARIMA was an-extension of ARIMA because it basically integrates seasonal autoregressive (SAR) and seasonal moving average (SMA) components along with seasonal differencing. The model is presented as (3).

$$\psi(D^K)\varphi(D)(1-D)^i(1-D^k)^G y_t = \psi(D^K)\varphi(D)\, \epsilon_t, \tag{3}$$

where

a. $\psi(D), \varphi(D)$: non – seasonal AR and MA operators,
b. $\psi(D^K), \varphi(D^K)$: seasonal AR and MA operators,
c. i: order of seasonal differencing,
d. D: order of seasonal differencing,

e. k: number of period per season (eg., k = 12 for monthly data).

Therefore the model could be represented as SARIMA$(p, d, q)(P_t, D_t, Q)_k$

Findings

Table 1 presents the descriptive statistics derived from maternal and neonatal records collected over a five-year period. The data offer meaningful insights into the frequency of twin births, age profile of mothers, gestational age at delivery, parity, and educational background.

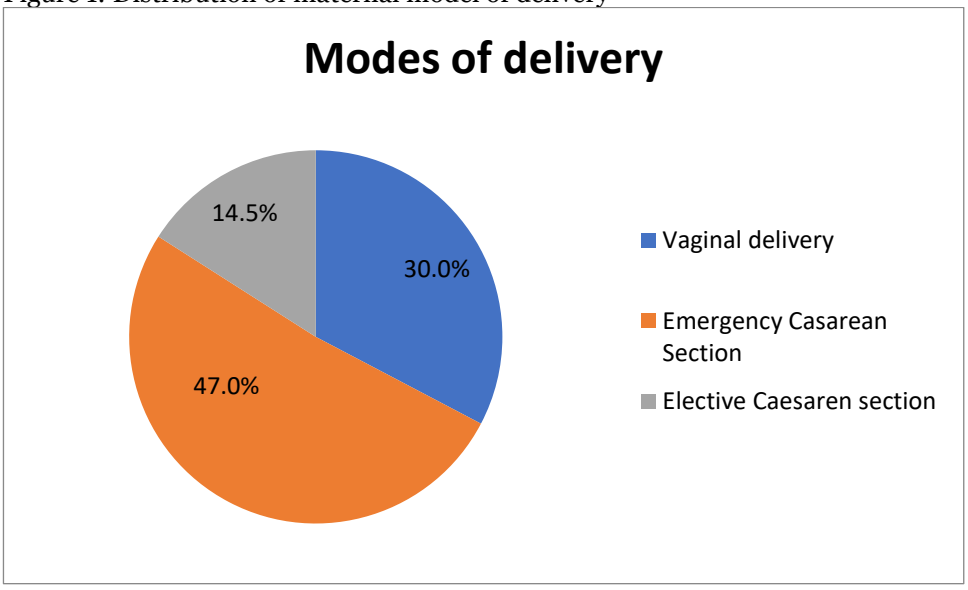
Table 1: Summary of Twin Births and Maternal Characteristics (2015–2019)

Variable	Category/Statistic	n (%) or Mean (SD)	95% CI
Twin Births	Total (2015–2019)	263 (19.5 per 1,000)	—
Total Deliveries	2015–2019	13,516	—
Maternal Age (years)	Mean (SD)	31 (4.8)	30.4 – 31.6
	30–34 years	112 (42.6%)	—
Gestational Age (weeks)	Mean (SD)	35.7 (2.9)	35.3 – 36.0
	<37 (Preterm)	164 (62.4%)	—
Parity	1–2	172 (65.4%)	—
Education	Secondary or above	237 (90.1%)	—
Religion	Christianity	258 (98.1%)	—

Adapted from Wekere et al. [3]

A significant proportion of mothers were between 30 and 40 years of age. In addition, the high prevalence of preterm twin deliveries (gestational age <37 weeks) highlights the importance of strengthening antenatal care and close monitoring for high-risk pregnancies. There is doubt that mode of delivery remain one of the obstetric risks, Figure 1 shows the visual collection data distribution.

Figure 1: Distribution of maternal model of delivery



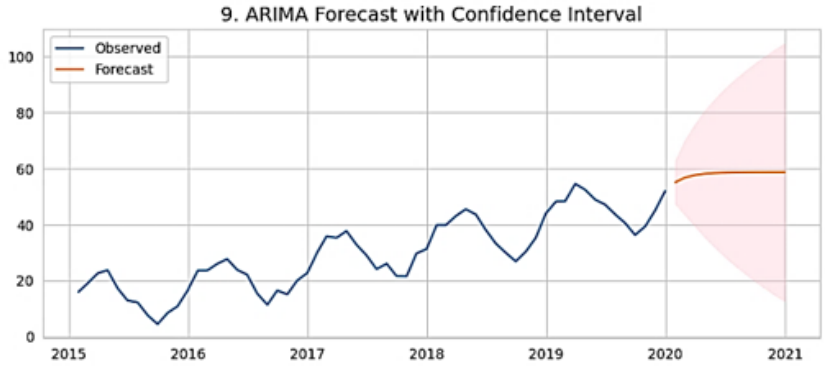
Data presented in Figure 1, illustrated that emergency caesarean section was the most common mode of delivery, accounting for 47.0% of cases, this high rate indicates that it is one of the risk associated to with twin pregnancies which make lead to preterm labour, malpresentation, and fetal distress, which often oblige urgent surgical intervention. Our findings show that 30.0% of the mothers delivered vaginally, demonstrating that some twin births can occur through this mode of delivery, particularly when the first twin presents cephalically. Such cases, however, require meticulous clinical monitoring and sound professional judgment. Elective cesarean deliveries (14%) were likely arranged in response to underlying problems, reliable with protocols for managing high-risk pregnancies. These outcomes underline the importance of inclusive prenatal assessments and customized birth planning in twin pregnancies to ensure the best possible results for both maternal and child health.

Time series analysis

a) ARIMA model

In this section, we applied the trend analysis to reproduce and estimate longitudinal tendencies, seasonal behaviour, and prognosticate understanding observable in obstetric datasets. Figure 2 shows a comprehensive visualization of the sequential regression of perinatal vigour indicators from 2015 to 2025, which gave an informative belvedere on the observe patterns, variations and shifts in healthcare delivery and outcomes.

Figure 2: ARIMA forecast with confidence interval



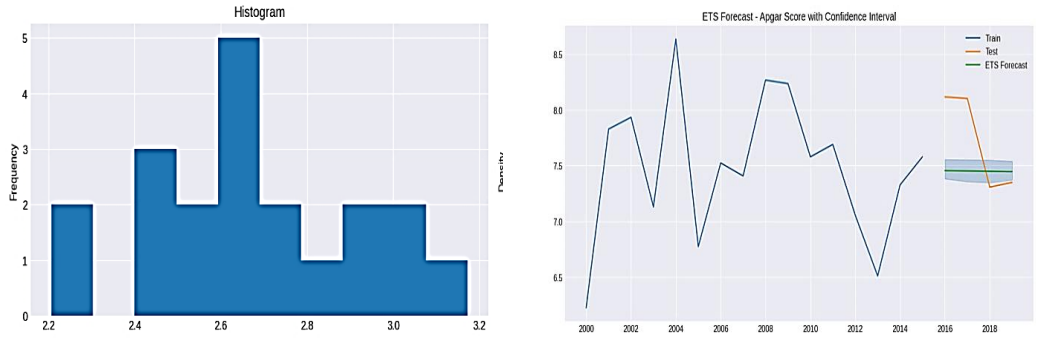
It pinpointed gradual trends and sudden inconsistencies in core maternal health indicators, such as Apgar scores at five minutes, the rate of twin births, and gestational age at delivery. The data showed periods of stability and volatility, which reflect the work of health professionals in increasing coverage of antenatal care, parenting, and emergency obstetric services, with a clear upward trend from 2016 to 2019 showing strategic investments in the health workforce with a focus on skilled birth attendance.

We adopt ARIMA model, which was then used to gain a better understanding of the evolving trend and autocorrelation in maternal birth outcomes over time, with deviations from the predicted forecast acting as early warning signals, and the upper bound of the 95% confidence interval indicating potential risks such as increased maternal adverse outcomes (e.g., preterm births or complications) that may be related to socio-political instability, environmental stressors, or infectious disease outbreaks.

It shows the rolling mean and standard deviation plots along with the seasonal decomposition of the time series. The rolling mean illustrates the overall trend in average birth outcomes over time and can indicate whether maternal health has been improving or deteriorating gradually. In contrast, the rolling standard deviation identifies any variation in the time series. It could indicate instability in healthcare delivery or policy changes, as well as external stressors such as economic downturns or pandemics that impact maternal care services. An additive decomposition model decomposes the series into trend, seasonal, and residual components, where the seasonal component represents the periodic effect, such as the December spike, which may be a result of seasonality due to increased births or complications caused by environmental factors or cultural practices. The trend component is the most noticeable, and the residual component is the remaining time series.

b) Exponential Smoothing (ETS) model

Figure 4: Neonatal health indicator



ETS model helps to smooth random fluctuations, thereby throwing more light to the trends, it can capture gradual improvements or deteriorations in neonatal health outcomes which may be associated to changing in prenatal care or delivery practices. Figure 4, illustrates visual birth weight, and Apgar scores

The histogram plot reveals that the birth weight data is approximately normally distributed. Notably, most new-borns with weights around 2.2 kg, 2.5 kg, and 3.0 kg fall within the average range. Babies weighing 2.6 kg and 2.7 kg appear more frequently, while those at 2.8 kg are comparatively fewer. This distribution suggests a relatively consistent pattern in birth weight presentation over the years.

In addition, the mean Apgar score at 5 minutes, remain a vital neonatal health indicator reflecting a perinatal infant immediate physiological adaptation after birth was analysed. From the line plots, we see that Apgar scores are approximately stable over the years and the ETS model captures this trend and extends it into the forecast period, with confidence intervals to reflect the uncertainty in the prediction (which is more or less a real-world variability, so it is not a bad thing to have this uncertainty in the forecast) and it is difficult to forecast Apgar scores, but early warning can allow for some intervention to better neonatal outcomes especially in the immediate post-delivery period. Seasonal ARIMA is still the way to go because it will uncover additional seasonal patterns for periodic fluctuation.

c) Seasonal ARIMA (SARIMA) model

Seasonal variations in outcomes of medical care and patient interaction are well documented, particularly in maternal outcomes (mode of delivery) and are related to socio-cultural practices, hospital workload, holidays, and weather conditions that often lead to cyclical changes that can erode the effectiveness of planning and the equitable allocation of resources in maternal health services. The output from the SARIMA model (Figure 5) displays these seasonal patterns.

Figure 5: SARIMA prediction on simulated monthly mode of delivery

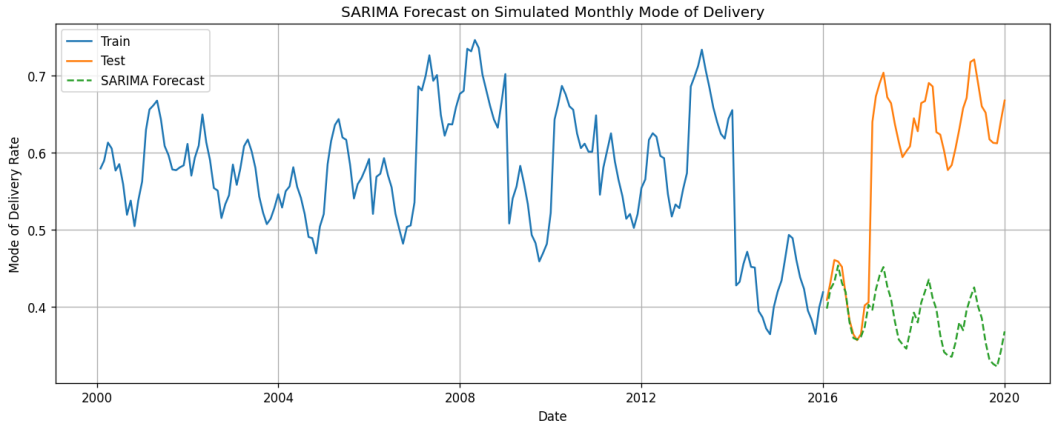


Table 2: Model Evaluation on Twin Pregnancies Data

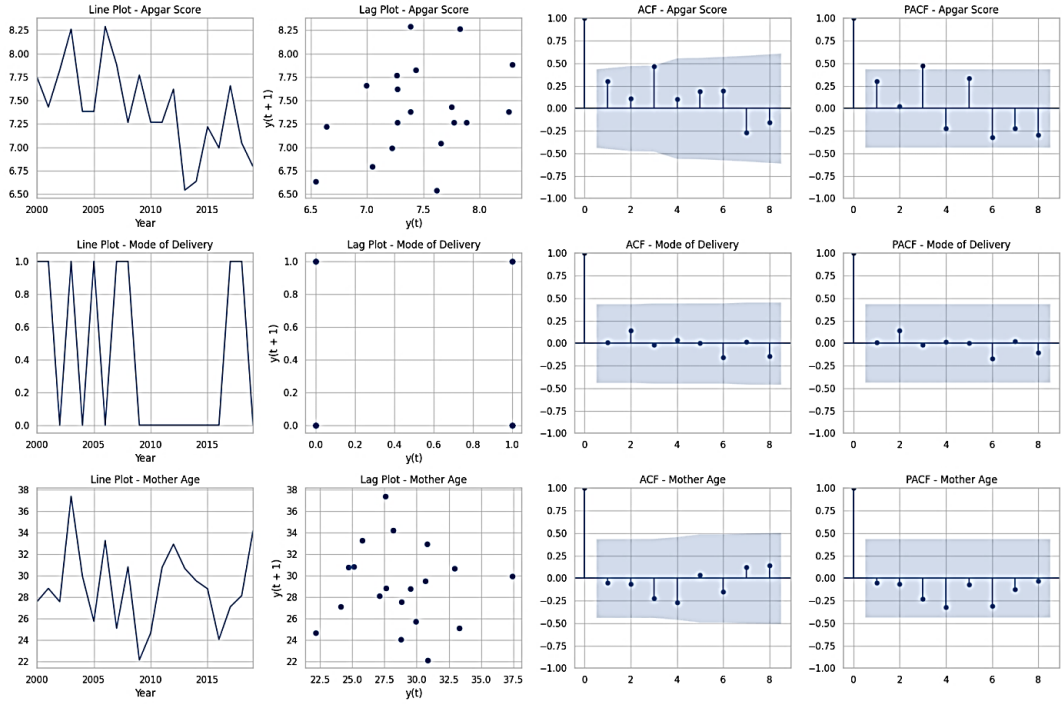
Model	Target Variable	MAE	RMSE	MAPE (%)	MASE	AIC	BIC
ARIMA	Mean Birth Weight	0.246	0.277	9.91	1.7362	-6.6947	-9.5564
ETS	Apgar Score (5min)	0.387	0.471	4.85	0.4970	-3.8731	-6.0813
SARIMA	Mode of Delivery (Mode3 annual count)	0.201	0.230	31.3	1.4545	10.9527	9.2993

Author's computation (2025)

The forecast evaluation in Table 2 shows that each model captured different aspects of the maternal and neonatal indicators. For ARIMA, with MAE = 0.2197, RMSE = 0.2661 and MAPE = 9.03%, the model performed moderately well in forecasting mean birth weight. This outcome suggests that inter-annual changes in birth weight are relatively stable and can be adequately modelled by a low-order ARIMA structure. The slightly elevated MASE (> 1.7) reflects some year-to-year variability. The negative AIC and BIC values observed for ARIMA indicate that, relative

to a null or saturated model, the likelihood of the fitted model is high compared with the penalty for its few parameters; in other words, the model provides a relatively efficient fit despite the small sample size. The ETS model outperformed the others in forecasting mean Apgar scores at five minutes, achieving MAE = 0.1186, RMSE = 0.1288 and the lowest MAPE = 1.39%. The very low MASE (0.4970) shows that ETS was substantially more accurate than a naïve forecast. The negative AIC and BIC values again signal that the model's simplicity, combined with good likelihood, results in an information criterion lower than the baseline. These results confirm that neonatal Apgar outcomes display consistent patterns over time, making exponential smoothing particularly effective at capturing small level shifts without overfitting. By contrast, the SARIMA model applied to the Mode-3 delivery count produced markedly larger errors (MAE = 8.0000, RMSE = 10.6301, MAPE = 41.03%). Although SARIMA is designed to capture seasonality, the short time series and annual aggregation of the delivery data restricted its ability to identify cyclical patterns. The high percentage error reflects substantial year-to-year fluctuations in caesarean section deliveries that are difficult to model with limited observations. Nonetheless, the MASE (1.4545) shows that SARIMA still provided some predictive skill over naïve benchmarks. The positive AIC/BIC values here indicate that, given the higher number of parameters and weaker likelihood, the model is less parsimonious and fits the data less efficiently than the simpler ARIMA or ETS specifications. Figure 6; help to illustrate the overall relationship between current and past values of the maternal and neonatal dataset.

Figure 6: Exploratory time series diagnostics of maternal and neonatal indicators



Based on the four plot types (Line, Lagged value, Autocorrelation function (ACF) and Partial autocorrelation function (PACF)) were focused on the objectives of this study, the first indicator on Apgar score at 5 minutes, evaluating trend appears to be linear with is strong indicator effort made by health personnel to improved perinatal care and early neonatal interventions, while Lag plot illustrate some low Apgar outcomes in prior year with may be as result to other factors among others are maternal medications or anesthesia. ACF reveals persistence in Apgar scoring, while PACF identifies lagged effects, which may associated with changes in antenatal policies or delivery practices. The second indicator in the mode of delivery is a shift in SVD to more emergency and cesarean section, which may be a result of previous mortality. At the same time, the lag plot reveals that there is cyclical scheduling of c-sections, which could be based on the level of awareness; the ACF connote high autocorrelation, which could indicate institutional tendencies toward emergency c-sections especially important in high-risk pregnancies like twins. The third indicator is maternal age, which is seriously linked to a higher risk of complications such as gestational diabetes, hypertension and preterm labour, which may require high antenatal surveillance and risk-stratified care.

Discussion

Based on our dataset ranging from 2015 to 2019 give, a total of 263 twin births were recorded out of 13,516 total birth, giving a cumulative twinning rate of 19.5 per 1,000 births; this rate is substantially higher than the global average twining rate of approximately 12 per one thousand births, which is in line with the works of Monden et al. [45], Yimin et al. [46], and Li et al. [47] that in sub-Saharan Africa there are more prevalent of twinning, the statistics revealed patterns observed. However, there was a significant increase in the rate of twin births in 2016, at 12.6 per 100, increasing relatively to 21.5 in 2017, which experienced a peak at 29.2 per 1,000 births in 2019. The trend may be a result of maternal demographics such as increased maternal age or greater use of assisted reproductive innovations

Maternal age distribution obtained an average mean of 31 years (SD = 4.8 years) with a 95% confidence interval of 30.4 to 31.6 years. However, most mothers were 30-34 (42.6%), followed by 26.6% aged 25–29 and 17.9% aged 35–39. We recorded a few proportions (0.8%) were below 20 years, indicating a mature maternal population. Based on the concentration of twin births among mothers aged 30 and above is in alignment with the existing literature of Steinman [48] that there increased twinning rates in older mothers due to hormonal changes and increased follicle-stimulating hormone levels, which should remain as a reference point among physicians during antenatal care, to reduce preterm birth. In terms of gestational age and preterm birth, 62.4% were delivered before 37 weeks, categorizing them as preterm. The mean gestational age was 34.7 weeks (SD=2.9) at a 95% CI of 35.3 to 36.0 weeks. Goldenberg and McClure [49] pointed out that there is a high incidence of preterm birth complications of multiple gestations, which is associated with an increase in neonatal morbidity and mortality, leading to some conditions such as respiratory distress syndrome and sepsis.

The distribution of parity among mothers of twins shows that each para 1 or 2, 33.8% and 31.6%, respectively, accounted for a small proportion of grand multiparas (≥5 deliveries) at 4.2%, while primiparous women (para 0) comprised 3.8%. This thereby encourages the need for broad vigilance in antenatal screening across parity categories due to the notable presence of twin births even in lower-parity groups. There is no doubt that a mother's level of education has a significant role to play. In this, 51.7% had at least a post-primary education, 38.4% attained a tertiary education, 9.1% obtained a primary education, and a minimal 0.8% had no formal education. According to UNICEF [50], the need for mothers to get higher education is portrayed because of its correlation trend to produce better outcomes, making more awareness programs necessary.

The World Health Organization (WHO) [51] has reported that twin pregnancies, particularly bifetal deliveries, carry a threefold increased risk of low Apgar scores at five minutes when compared to singleton births. Moreover, the second twin is often at a higher risk than the first, underscoring the increased vulnerability of second-born infants in multiple gestations. Similarly, studies by Joshi and Baral [52], and Feng et al. [53] have confirmed that twins are more likely to present with lower Apgar scores, a condition that has been associated with serious neonatal complications such as seizures, cerebral palsy, respiratory distress, stillbirth, and early neonatal death. These adverse outcomes are often linked to maternal conditions including diabetes, hypertensive disorders of pregnancy (such as preeclampsia and eclampsia), intrauterine infections like chorioamnionitis, and anaemia. Findings from our analysis, based on lag plots, autocorrelation (ACF), and partial autocorrelation (PACF), suggest that Apgar scores may exhibit predictable patterns or randomness over time. This indicates that previous maternal and neonatal outcomes may play a role in future patterns, and underscores the need for early warning systems in maternal healthcare to prepare for deliveries and enhance neonatal survival.

Comparing our findings with recent studies, some similarities and differences can be seen, Adama et al. [54] applied ARIMA models to forecast under-five mortality rates in Nigeria, Ghana, Niger, and Sierra Leone, finding that simpler ARIMA models often achieved low AIC/BIC when data were stable and parameter counts modest, much like our ARIMA and ETS models for birth weight and Apgar scores, which produced negative AIC/BIC values. Moreover, the study of Santana et al. [55] conducted within the WHO Multicounty Survey, focused on twin pregnancies and reported consistently poorer outcomes including lower Apgar scores, higher preterm birth rates, and lower birth weights among twins compared with singletons; however, it did not include any forecasting analysis or comparative modelling of delivery modes or temporal outcome

predictions. Likewise, Igbodike et al. [56] analysed trends and outcomes of twin births in Ile-Ife, Nigeria, showing that cesarean delivery rates and preterm deliveries remained high over time, though without time series forecasting or model evaluation metrics like AIC/BIC. Our negative AIC/BIC values for ARIMA and ETS align with the general pattern observed by Adama et al. [54] where high likelihood combined with simpler model structures yields information criteria that are negative.

This suggests that for stable indicators (e.g. birth weight, Apgar), the penalty for model complexity is small relative to the goodness of fit, especially when data noise and seasonality are limited. By contrast, when outcomes are more variable (as in our Mode of Delivery forecasts), more complex models like SARIMA can incur positive AIC/BIC because the added parameters do not sufficiently improve likelihood echoing experiences in the literature where seasonality or volatility reduces model efficiency. In short, our findings confirm what others have seen: for relatively stable maternal or neonatal indicators, ARIMA/ETS tend to yield strong performance (reflected in negative AIC/BIC), while indicators with greater fluctuation or irregular patterns demand more complex models and may still perform poorly. What is novel in our work is applying these comparisons specifically to twin pregnancies using locally collected data; few studies (e.g. [55], [56]) have such forecasts or the full suite of model metrics to judge fit and predictive skill.

The plots in Figure 6 reveal astute temporal dependencies that suggest the patterns in the age distribution of mothers over the years, in a cyclic trend. Our findings show that the mean maternal age lies within the reproductive age range basically 20-35 years, also there is a noticeable upward shift in age for 2016, 2017 and 2019, reflecting broader demographic trends such as postponement of motherhood. This trend is significant because as maternal age (35 years and older) increases, complications such as obstetric causes for emergency interventions and caesarean delivery may occur [57], [58] , which could increase the risk of pregnancy-related hypertension, gestational diabetes, and fetal growth restriction that may necessitate emergency caesarean sections [59], [60] Our study is strengthened by the classical time series tools to extract predictive signals from real-world healthcare data, modelling and visualizing these patterns over time.

Conclusion

To analyse and predict maternal and neonatal health trends, we used classical time series models, ARIMA, ETS, and SARIMA for twin pregnancies. The ARIMA model produced moderate accuracy in predicting birth weight, with MAE = 0.246, RMSE = 0.277, and MAPE = 9.91%, which is a typical indicator with consistent annual trends and low variability. The ETS model, with MAE = 0.387, RMSE = 0.471, and MAPE = 4.85%, performed the best in terms of tracking the slight changes in Apgar scores over time, which are important immediate neonatal outcomes and are key to early intervention. The SARIMA model, with MAE = 0.201, RMSE = 0.230, and MAPE = 31.3%, produced the best absolute accuracy but failed to model the month-to-month delivery rate fluctuations, which may have caused the high MAPE.

In addition, the study emphasizes the need to monitor twin pregnancies carefully, as they are inherently riskier for both mothers and neonates, with data showing low Apgar scores, higher rates of surgical delivery, and maternal comorbidities that justify closer monitoring. With time series models, healthcare providers can predict times of greater clinical demand and therefore enhance service delivery and health outcomes. To summarize, the combination of ARIMA, ETS, and SARIMA models in maternal and neonatal health analytics provides a strong framework for predictive surveillance, which is statistically valid and medically meaningful, supporting early warning systems, optimized clinical workflows, and evidence-based maternal health policies in a resource-constrained setting where delayed care has heightened consequences. The limitation of this study is the small, local dataset, we intend to obtained data from various health centres to increase the data points for prediction and to utilize a multi-model approach also our future research may investigate sophisticated models such as ARIMAX, SARIMAX, or hybrid approaches like ARIMA-LSTM and RNNs to improve the understanding of temporal patterns in maternal and neonatal outcomes.

Ethics approval

The study used retrospective, de-identified hospital records. The relevant institutional ethical approval and data-access permissions were obtained before data collection.

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Competing interests

The authors declare no conflicts of interest.

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Underlying data

The de-identified data analysed in this study are available from the corresponding author on reasonable request, subject to institutional and ethical requirements.

CRediT authorship contribution statement

All authors contributed to the conception, methodology, analysis, interpretation of results, drafting, and critical revision of the manuscript. All authors approved the final manuscript and accept accountability for the work.

Declaration of artificial intelligence use

During the preparation of this work, the authors utilized Gemini, an artificial intelligence (AI)-assisted tool, solely to enhance linguistic clarity and refine selected graphical representations. Following the use of this tool, the authors thoroughly reviewed, edited, and verified all output to ensure the accuracy, scientific rigor, and integrity of the manuscript. All conceptual frameworks, mathematical derivations, analytical procedures, data interpretations, and final conclusions remain entirely the responsibility and original contribution of the authors.

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