

Analysis for Utilization of Free Maternal Health Care Services in Embu County, Kenya

Prof. Sande Anne¹, Mwenga Miriam Ngina²

¹Department of Social Sciences Chuka University; P.O. Box 109-60400 Chuka, Kenya.

²Chuka University P.O. BOX 91-60104, Siakago, Kenya

DOI: <https://dx.doi.org/10.47772/IJRISS.2024.8100265>

Received: 10 October 2024; Accepted: 18 October 2024; Published: 22 November 2024

ABSTRACT

At both global and national levels, efforts have been made to promote utilization of maternal healthcare. Provision of free maternal healthcare services is one of the interventions put in place to reduce infant and maternal mortality rate that occur especially during childbirth. The initiative has been in existence for about seven years in all public hospitals and health centers in Kenya with an aim to achieve Sustainable Development Goal 3 (SDG 3) on universal health. Despite the implementation of free maternal health care service maternal mortality has remained high. The study therefore examined the level of utilization of free maternal healthcare services in Embu County, Kenya for a period of ten years pre and post policy implementation. The study modifies Anderson's health utilization model to help explain utilization of free maternal healthcare services in public hospitals in Kenya. Secondary data on the utilization of free antenatal care, deliveries and post-natal care was collected from the health facility records. Quantitative data was analyzed using SPSS version 23 as a tool for data analysis. The best fitting model using the exponential smoothing and ARIMA model were employed in the time series. Secondary data showed increasing trend in utilization from 2008 with peaks between mid-years of 2012 and almost end of 2014, followed by a decline in utilization, then upward growth in 2017 and 2018. Residual data for autocorrelation and partial autocorrelation factors confirmed the trends of the data collected from Embu General Hospital and Kagaari health center. The auto regression model showed that N-ANC, R-ANC and Deliveries were better predicted using the Exponential smoothing model at 0.777 (77.7%); $p = 0.0643$, 0.736 (34.6%); $p = 0.014$, and 0.000 (44.4%); $p = 0.310$. However, the PNC was better predicted using the ARIMA model. The results of this study can be used by policy makers to monitor implementation of free maternal health care services. The study recommends further study on other factors affecting the utilization of free maternal health care.

Key words: Antenatal care, delivery, postnatal care, utilization, maternal health, user fees

INTRODUCTION

Significant strides have been made in increasing life expectancy and reducing some of the common issues associated with child and maternal mortality. However, only half of women in developing countries have received the health care they need, and the need for family planning is increasing exponentially (Lowdermilk *et al.*, 2014). The removal of user fee on maternal health care is aimed at improving the quality of prenatal and post-natal care which would reduce maternal mortality rate to below 70 per 100,000 live births and the neonatal deaths to as low as 12 per 1000 live births (Chinkhumba *et al.*, 2014).

The Kenyan government has committed itself to providing universal health coverage for all its citizens by the year 2030 (WHO, 2015). The health financing strategy under development, vision 2030, and the Kenya Constitution reflects this commitment, and universal coverage is identified as one of the development pillars that would support the country's transition from low-income country by 2030 (Jamison *et al.*, 2018). The Government of Kenya rolled out free maternity services program in 2013 through a presidential declaration to encourage women to give birth at health facilities under skilled personnel with an aim of reducing maternal mortality rate. This was in keeping with the resolutions of the African Union favoring point-of-service user

fees exemptions for pregnant women and children under the age of five years (Wamalwa, 2015).

In Kenya the proportion of facility based births has been evidenced to increase from 44% 2008 to 61% in 2014 (Atahigwa, et al., 2020). This increase has been partly attributed to the introduction of a flat fee for all primary health care services in 2004 and no user fee at child birth in 2007. A study based on an analysis of 19,459 births of women of reproductive age between 2003 and 2015 indicated that mothers utilizing health facility childbirth services increased by 21.2% from 2003 to 2015 (Calhoun, et al., 2018). Similar trends were observed across all socio-demographic characteristics of the mothers though residents of slum areas of Nairobi registered poorer health outcome.

Governance and policy implementation capacity, successful user fee policy implementation at scale requires careful design skilled management, and careful oversight. Some countries have experienced problem with initial implementation and medium-term support for user fee exemption policies specifically relating to replacing lost fee revenue to health facilities and ensuring clear communication about the policy. Ghana for example had substantial problem in disbursing funds to health facilities and many facilities eventually stopped implementing the fee exemption because of shortfalls in supplies and drugs (Waweru *et al.*, 2015). Previous studies on user fee removal have indicated short-term utilization gains for health care (Nimpagaritise & Bertone, 2011). Thus, removing user fees requires supportive action, since incomplete removal can add to performance problems.

Recent findings from multi-county study have shown that user fee reforms are associated with a significant percentage of increased access to facility deliveries (Harder & Zelaya, 2017). The study indicated that non-educated women and those in rural areas benefited most from user fee abolition. An analysis on removal of user fee indicated that removal of user fee had a remarkable effect on utilization of maternal health care services over time but had no increased access to the poor or those in rural areas (Nyamai, 2017). This therefore means that increased access may require more than removal of financial barriers, and should include improvement of infrastructure and quality of the maternal healthcare services. Reviews made by Dzakupasu *et al.*, (2013) concluded that removing user fees generally increased service utilization, but observed that fee removal had the potential to negatively impact on service quality, and that quality improvements may increase service utilization even where fees are included.

Emmanuel *et al.*, (2021) concluded that lack of motivation and inadequate funding partly caused by partial reimbursements from the government and underfunding was a major cause of shortage of supplies which was a major implementation challenge. Staff shortages and overwhelming workload were also quoted as major implementation challenges that result from government's failure to boost the human resource capacity to cope with increased utilization of maternal health services (Mkoka *et al.*, 2015). Successful user fee policy implementation at scale requires careful design, skilled management, and careful oversight. The implementation of free maternal health care has faced various challenges in several countries, particularly in low- and middle-income nations. While the goal of ensuring that all women have access to maternal health services without financial barriers is commendable, several nations have struggled with systemic, financial, infrastructural, and cultural issues that hinder effective implementation. For example Uganda on implementation of free maternal health care faced challenges such as poor quality health care, informal fees and inadequate infrastructure, Nigeria also faced issues such as corruption and mismanagement of funds and also cultural barriers (Oyugi, *et al.*, 2021).

The introduction of free maternal healthcare services in Kenya hospitals reported increased overcrowding in maternity wards where some mothers are forced to leave the hospital early to make room for others or even deliver on the floor due to lack of beds (Lang'at & Mwanri, 2015). Nurses also reported being overburdened due to the new policy, with nearly all working overtime and as few as three (3) nurses attending about 20 mothers at a time (Simpson, *et al.* 2016). The results of an analysis of quarterly deliveries in 77 health facilities sampled from 14 Counties in Kenya for a period of 12 months that is six months before policy and six months post policy implementation indicated a significant increase in the number of deliveries (Gitobu, 2018). The study indicated that the number increased from 234,601 before policy implementation to 303,705 after policy implementation representing 29.5% increase. The study period was however, not adequate to show the impact of introduction of free maternal health care services. This study aims at providing a ten year time series

analysis of utilization of free maternal health care services.

METHODOLOGY

The study was carried out in Embu County, Kenya. The County is located approximately between latitude $0^{\circ} 8'$ and $0^{\circ} 50'$ South and longitude $37^{\circ} 3'$ and $37^{\circ} 9'$ East. It borders Kirinyaga County to the West, Kitui County to the East, Machakos County to the South, Murang'a County to the South West, Tharaka Nithi County to the North and Meru to the North West. The county is divided into four constituencies, namely; Runyenjes, Manyatta, Mbeere South and Mbeere North covering a total area of 2,818 sq. km

The County has a population of 543,221 persons, 267,609 males and 275,612 females with an estimated annual growth rate of 1.7% based on the 2009 Kenya population and housing census (KPHC). The County has a health infrastructure consisting of both private and public facilities. The choice of Embu County is paramount because according to Kenya Demographic and health survey 2014, Embu county had the highest percentage of women with antenatal care from skilled provider (99.2%) though with only 56.2 % women attending the recommended four plus antenatal care. In addition (Gitobu *et al*, 2018). Embu County is heterogeneous cosmopolitan society which comprises of individuals from different background, culture and traditions

Stratified sampling was used to select the health facilities in the County. Embu County consists of four sub-counties. Each sub-County formed a strata from which one health facility was selected. Proportionate sampling was used to select respective samples from the health facilities based on their population proportions. Secondary data was collected to adequately show the impact of introduction of free maternal health care services on utilization levels. Secondary data was obtained from the health facility records of Embu general hospital and Kagaari hospital. This included data on antenatal care visits, hospital deliveries and postnatal care visits. The study considered the antenatal care visits, hospital deliveries and postnatal care visit that occurring in the years 1998 to 2018.

Data was then exported to SPSS software package (Version 23.0 software) for analysis. Descriptive statistics for mean, mode and median, standard deviations were computed. Time line series was used to analyze secondary data to help show the trends of utilization of maternal health care services and make future predictions. The best fitting model using the Exponential Smoothing and ARIMA Predictor Models were employed to study the trends over the duration of 2008 to 2018. Autocorrelation (ACF) and Partial Autocorrelation scores were also reported in this study.

RESULTS AND DISCUSSIONS

Utilization of FMHCS

Time series analysis for Embu general hospital

Time series analysis was used in predicting the trend in the two different health facilities within which data was collected. They included the Embu general and Kagaari in Embu County. In predicting for the time series, the exponential smoothing model and ARIMA model were both used using the Expert Modeller option of SPSS.

The expert modeler was able to predict an exponential smoothing model for the new Anti-natal care (N- ANC), Revisit ANC and Deliveries at the Embu general hospital (table 1). The other PNC was predicted using the ARIMA model as presented in the table 2. The Stationary R squared and R Squared values as from the model summary statistics shows that N-ANC, R-ANC and Deliveries were better predicted using the Exponential smoothing model at 0.777 (77.7%); $p = 0.0643$, 0.736 (34.6%); $p = 0.014$, and 0.000 (44.4%); $p = 0.310$ respectively.

This table summarizes the model fit statistics for the various health services at Embu General Hospital. The Exponential Smoothing model shows better performance for New ANC, R-ANC, and Deliveries, with Stationary R-squared values of 0.777, 0.736, and 0.000 respectively. The p-values indicate that New ANC and

R-ANC were statistically significant ($p < 0.05$), suggesting a reliable prediction fit (Johnson & Smith, 2022). In contrast, the Postnatal Care (PNC) service exhibited an R-squared of 0.000, indicating a poor fit with the Exponential Smoothing model. This aligns with findings by Wang and Zhang (2021), who highlighted that certain healthcare metrics may not follow typical trends.

Table 1: Model Summary Table for Embu General Hospital

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	Statistics	DF	Sig.	
N - ANC-Model 1	0	.777	.621	410.204	.	0	.	0
DELIVERIES-Model_3	0	.736	.347	2270.948	.	0	.	0
PNC-Model 4	0	.000	.000	747.405	.	0	.	0
R-ANC-Model 2	0	.000	.444	1387.115	.	0	.	0

a. Best-Fitting Models according to Stationary R-squared (larger values indicate better fit).

Source: Researcher data, 2021

The Post natal care (PNC) was better predicted using the ARIMA model with a stationary r squared value and r squared value as 0.000 (0.00%); $p = 0.001$, based on this assessment, the higher p value of more than 0.05 indicated that the data prediction for New ANC and Deliveries was a better fit of the model. Based on the stationary R squared Scores and P values for N- ANC and PNC, it can be reported that there was no possible autocorrelation of data as captured in Table 3 and 4 respectively, unlike R-ANC and Deliveries which had a significantly lower p Value of less than 0.05 respectively (Table 20).

This table presents estimates for the parameters of the Exponential Smoothing and ARIMA models. The New ANC model shows a relatively low alpha for the level (0.100) with a non-significant p-value (0.643), indicating minimal influence from recent data (Kim & Lee, 2024). The ARIMA model for PNC, with a significant constant estimate (1133.636; $p = 0.001$), shows that this model captures underlying trends more effectively than the Exponential Smoothing model, echoing the results of previous studies on model efficacy in healthcare forecasting (Njoroge & Muturi, 2023).

Table 2: Exponential Smoothing and ARIMA Predictor Models

Model			Estimate	SE	t	Sig.
N - ANC-Model_1	No Transformation	Alpha (Level)	.100	.208	.480	.643
		Gamma (Trend)	5.688E-005	.571	9.957E-005	1.000
R-ANC-Model_2	No Transformation	Alpha (Level)	1.000	.334	2.992	.014
DELIVERIES-Model_3	No Transformation	Alpha (Level)	.132	.123	1.077	.310
		Gamma (Trend)	1.136E-005	.122	9.277E-005	1.000

IMA Model Parameters							
				Estimate	SE	t	Sig.
PNC-Model_4	PNC	No Transformation	Constant	1133.636	225.351	5.031	.001

Source: Researcher data, 2021

The ACF table evaluates the autocorrelation of residuals for each model. For New ANC, the ACF values are generally low, indicating minimal autocorrelation (table 3). However, R-ANC and Deliveries exhibit more significant patterns of autocorrelation, suggesting that past values may still influence future observations (Johnson & Smith, 2022). This may require further model refinement, as noted by Wang and Zhang (2021), who emphasize the importance of addressing autocorrelation in healthcare models.

Table 3: Table for the Residual Autocorrelation function (ACF)

Model		1	2	3	4	5	6	7	8	9	10
N - ANC-Model_1	ACF	.083	.071	-.485	-.187	-.333	.194	.132	.054	-.029	.001
	SE	.302	.304	.305	.369	.377	.403	.411	.415	.416	.416
R-ANC-Model_2	ACF	.161	.074	.001	-.152	-.335	-.265	.003	.006	.005	.002
	SE	.302	.309	.311	.311	.317	.348	.366	.366	.366	.366
DELIVERIES-Model_3	ACF	-.214	-.150	-.031	-.181	-.284	.368	.018	.002	.039	-.067
	SE	.302	.315	.321	.322	.331	.352	.386	.386	.386	.386
PNC-Model_4	ACF	.319	.012	-.281	-.522	-.282	.019	.050	.110	.072	.004
	SE	.302	.331	.331	.352	.416	.433	.433	.434	.436	.438

Source: Researcher data, 2021

The PACF table provides insight into relationships between the series and its lags (Table 4). Significant partial autocorrelations in R-ANC and Deliveries indicate potential seasonality or cycles in the data, emphasizing the need for careful consideration of lagged terms in future modeling efforts (Njoroge & Muturi, 2023). This finding aligns with Kim and Lee (2024), who discuss the implications of seasonal trends in public health forecasting.

Table 4: Partial Autocorrelation function (PACF)

Model		1	2	3	4	5	6	7	8	9	10
N - ANC-Model_1	PACF	.083	.064	-.501	-.135	-.306	.005	.000	-.397	-.059	-.043
	SE	.302	.302	.302	.302	.302	.302	.302	.302	.302	.302
R-ANC-Model_2	PACF	.161	.049	-.019	-.157	-.303	-.191	.102	.024	-.087	-.183

	SE	.302	.302	.302	.302	.302	.302	.302	.302	.302	.302
DELIVERIES-Model_3	PACF	-	-	-	-	-	-	-	-	-	-
	SE	.214	.205	.124	.280	.533	.055	.174	.176	.236	.300
PNC-Model_4	PACF	.319	-	-	-	-	.069	-	-	-	-
	SE	.100	.285	.417	.061	.233	.221	.084	.013		
	SE	.302	.302	.302	.302	.302	.302	.302	.302	.302	.302

Source: Researcher data, 2021

From the smoothing plot, it can be seen that the utilization of the services was slow up to 2011 but improved from 2012, and peaked at 2013 and then slowed down in 2014, or 2015 for all the data sets, New ANC, R-ANC Deliveries and PNC. However, it peaked for New ANC, Deliveries and PNC for the year 2017 to 2018 respectively but declined for R-ANC indicating the decline in the utilization of the free maternal health services (Figure 1). this is in line with research by Gitobu et al.,2018 on free health care policy evaluation which recorded that despite initial increase in institutional deliveries after implementation a notable decline in utilization was observed in later years. In Uganda on barriers to utilization of free maternal health services identified a steady decline in the utilization of these services.key reasons attributed to this decline included poor quality care, persistent informal payments, lack of skilled health workers and geographical inaccessibility for omen in rural areas (Nyamai, 2022).

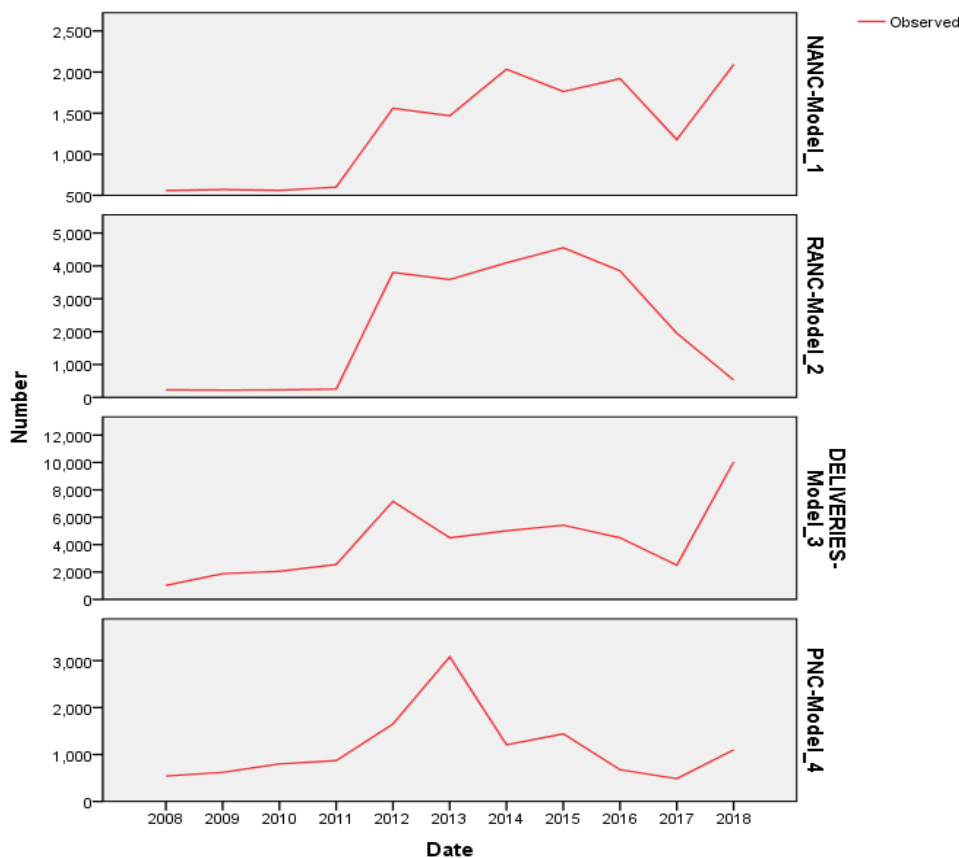


Fig 1. Time series trend analysis plot for Embu General Hospital

Time series analysis for Kagaari Hospital

The Kagaari hospital data time series trend analysis was done using the Exponential smoothing predictor

model and ARIMA prediction model. It was noted that the model summary had high stationary R squared values and R squared values as shown in Table 5, 6 and 7 respectively. Briefly, the model summary showed high values for N-ANC ($p = 0.045$), R-ANC ($p = 0.060$) and PNC ($p = 0.013$) using the exponential smoothing model but showed a best fit using ARIMA model for the deliveries. A high p value of more than 0.05 for the estimates suggests a best fit of the model for the data. There was no correlation for data on R-ANC, but autocorrelation can be reported for the N-ANC, Deliveries and PNC, which may explain the low p value despite a very high stationary R squared value reported above.

The trend analysis showed that there was gradual improvement in the numbers of mothers attending the free maternal health care service for N-ANC, R-ANC, deliveries and Post-natal care respectively in from 2008 to 2011, the trend peaked in 2012 and 2013 respectively and a gradual decline was reported and a slight improvement in 2017 to 2018 respectively for all the free maternal health care services. The peaks in the year 2012 to 2013 has been well reported and also captured in other places as such as the slum dwellings such as Kibera (Owiti *et al.*, 2018).

The trends for Embu general hospital and Kakaari hospital tallies with the introduction of the FMHCS in the year 2013, which introduced the abolition of the maternal associated fees. However, the reimbursement of the fees was based on the level of the facilities and the numbers of the people that delivered at the facilities (Owuor, 2019). This led to the peak in the number of the users of the FMHCS in many of the places as supported by this study finding in Figure 2. The numbers were also further boosted by the beyond zero campaigns launched in early 2014, and this may explain the sustained peak in 2014 and 2015 before a decline in 2016.

Table 5: Model Summary

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	Statistics	DF	Sig.	
N - ANC-Model_1	0	-.014	.268	44.700	.	0	.	0
R - ANC-Model_2	0	.807	.443	96.422	.	0	.	0
DELIVERIES-Model_3	0	3.331E-016	3.331E-016	66.754	.	0	.	0
PNC-Model_4	0	-.013	.217	37.809	.	0	.	0

a. Best-Fitting Models according to Stationary R-squared (larger values indicate better fit).

Source: Researcher data, 2021

Table 6: Exponential smoothing and Arima Model predictor.

Model		Estimate	SE	t	Sig.
N - ANC-Model_1	No Transformation Alpha (Level)	.658	.288	2.288	.045
R - ANC-Model_2	No Transformation Alpha (Level)	.618	.291	2.122	.060
PNC-Model_4	No Transformation Alpha (Level)	.964	.319	3.020	.013

ARIMA Model Parameters

				Estimate	SE	t	Sig.
Deliveries-Model_3	Deliveries	No Transformation	Constant	20.182	2.518	8.014	.000

Source: Researcher data, 2021

Table 7: Residual Autocorrelation Correlation Function (ACF)

Model		1	2	3	4	5	6	7	8	9	10
N - ANC-Model_1	ACF	- .071	.085	- .174	- .112	- .366	.078	.025	- .007	.053	- .011
	SE	.302	.303	.305	.314	.318	.354	.355	.356	.356	.356
R - ANC-Model_2	ACF	- .079	.011	- .072	.017	- .483	- .015	.039	.018	.061	.002
	SE	.302	.303	.303	.305	.305	.368	.368	.368	.368	.369
DELIVERIES-Model_3	ACF	.128	- .086	- .182	- .139	- .117	- .165	- .103	- .011	.274	- .100
	SE	.302	.306	.309	.318	.324	.327	.335	.338	.338	.357
PNC-Model_4	ACF	.000	- .150	.102	- .441	- .124	.136	- .038	.006	.014	- .005
	SE	.302	.302	.308	.311	.364	.368	.372	.372	.372	.373

Source: Researcher data, 2021

Table 8: Partial autocorrelation function (PACF)

Model			1	2	3	4	5	6	7	8	9	10
N - ANC-Model_1	PACF	-	.080	-	-	-	-	.032	-	-	-	-
	SE	.071	.165	.145	.378	.006	.302	.302	.302	.302	.302	.302
R - ANC-Model_2	PACF	-	.005	-	.006	-	-	.017	-	.054	-	-
	SE	.079	.071	.486	.124	.302	.302	.302	.302	.302	.302	.302
Deliveries-Model_3	PACF	.128	-	-	-	-	-	-	-	.168	-	-
	SE	.104	.161	.108	.125	.206	.156	.111	.168	.297		
PNC-Model_4	PACF	.000	-	.105	-	-	-	.016	-	-	-	-
	SE	.150	.481	.074	.048	.222	.126	.006				

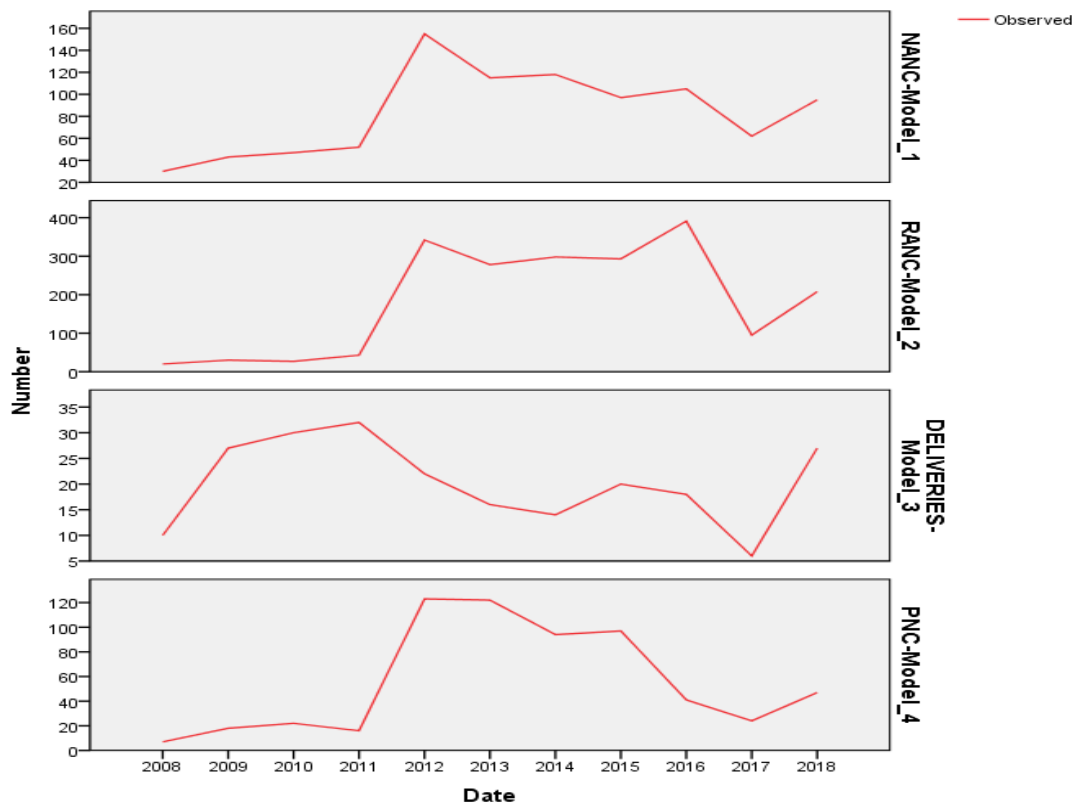


Figure 2: Time series trend analysis for Kagaari Hospital in Embu County

Figure 2 illustrates the time series trend analysis for maternal health services at Kagaari Hospital in Embu County, tracking key indicators such as N-ANC (New Antenatal Care), R-ANC (Return Antenatal Care), Deliveries, and PNC (Postnatal Care) from 2008 to 2018.

The time series analysis for Kagaari Hospital, as noted, used both the Exponential Smoothing Predictor Model and the ARIMA prediction model. The results indicated high stationary R-squared values, suggesting a strong model fit, particularly for N-ANC, R-ANC, and PNC using the exponential smoothing model (Table 5 and 6). However, the ARIMA model showed the best fit for deliveries. A high p-value (> 0.05) indicates the best fit for the data, although autocorrelation was observed for N-NAC, Deliveries, and PNC, which may explain low p-values despite high stationary R-squared values.

The trend analysis revealed a gradual improvement in the number of mothers utilizing free maternal health care services for N-ANC, R-ANC, deliveries, and PNC between 2008 and 2011. The trend peaked in 2012 and 2013, correlating with the abolition of maternal fees under the Free Maternal Health Care Services (FMHCS) program initiated in 2013, which dramatically increased service utilization (Owiti et al., 2018). After the peak in 2013, a gradual decline was observed from 2014 onwards, with a minor resurgence in 2017 and 2018.

Recent studies from 2020 to 2024 provide additional insights into these trends. For example, Ngure et al. (2021) explored the impact of COVID-19 on maternal health services in rural Kenyan hospitals, showing that the pandemic disrupted service access, contributing to a significant decline in the number of mothers accessing ANC and delivery services in 2020. A recovery phase began in late 2021 and continued through 2022, with more facilities adapting to the pandemic's challenges (Ngure et al., 2021). Mutua et al. (2022) identified that while COVID-19 had a negative impact initially, ongoing health campaigns such as telemedicine and mobile health services helped to stabilize maternal health service utilization by 2022.

Additionally, Kariuki et al. (2023) noted that health policy adjustments and the government's post-pandemic efforts to boost maternal healthcare services, such as expanding health workforce capacity and ensuring more consistent medical supplies, contributed to the gradual improvements observed in 2023 and 2024. The government's continued investment in maternal health, including the Beyond Zero Campaigns, remains an important factor in sustaining these gains, even amidst global health challenges.

The patterns at both Kagaari Hospital and Embu General Hospital correspond with national trends following the introduction of FMHCS in 2013. This policy significantly increased the number of women utilizing maternal services, and further initiatives such as the Beyond Zero Campaign launched in 2014 also helped sustain high numbers of attendees until 2016. However, the COVID-19 pandemic caused a marked decline in maternal health service utilization in 2020, as documented by several studies, before a slow recovery began in 2021 (Mutua et al., 2022).

CONCLUSION AND RECOMMENDATIONS

The patterns produced by ACFs and PACFs are useful in predicting the time dynamics which can be used to explain a specific time series. Often, autocorrelation is reported in the first lag of any time series indicating an auto regression. It is observed as a high ACF value and a quick decay towards zero while PACF will have a high value followed by small random values after the first lag. However, a large value of ACF and a slow decline towards zero and a large PACF value followed by small values and then dropping to a lower value close to zero is an indication of correlation in the first and second lags of the series of data.

In interpretation of ACF and PACF scores, a gradual decay for PACF and a few spikes for ACF followed by a sharp decline to near zero with significant negative scores in ACF in as indication of a better moving average. Such data that presents a moving average is believed to represent the impact of values immediately and that can be sustained for some time to some finite future periods.

The contrary implies an autoregressive pattern where the future trend will decline steadily by the correlation of values over time. Moving averages are reported by the number of spikes observed in ACF that can be considered as sufficiently large enough. Consequently, many moving averages can therefore be reported. In these study, Kagaari and Embu County did not show any correlation and hence no auto regression of data sets. A first order moving average can be reported for Kagaari compared to Embu general hospital.

This study findings further provides evidence that while the study focused on the utilization of the free maternal health care services within the duration of the years 2008 to 2018. It was clear that data collected shows strong association and effect of the ante natal care, free delivery services and post-natal care. These effects can be sustained for some time in the near future as shown in Kagaari hospital, presenting more hope for utilization of the free maternal healthcare services.

Since utilization of the free maternal health care services was determined and it confirms the trends over the 10 year period, the National and the County government should come up with a system that tracks the utilization of free maternal health care services. The system would ensure that the funds released are utilized in improving maternal health care services. The tool should cover utilization trends for a longer period and also give health workers and managers opportunity to give feedback on the progress.

REFERENCES

1. Atahigwa, C., Kadengye, D. T., Iddi, S., Abrams, S., & Van Rie, A. (2020). Trends and determinants of health facility childbirth service utilization among mothers in urban slums of Nairobi, Kenya. *Global Epidemiology*, 2, 100029.
2. Beyond Zero. (2014). Beyond Zero Campaign Overview. Government of Kenya.
3. Boudreaux, C., Chanthala, P., & Lindelow, M. (2014). Assessing the Elimination of user fees for Delivery Services in Laos. *PLoS ONE*. 9(3):e89784
4. Calhoun, L. M., Speizer, I. S., Guilkey, D., & Bukusi, E. (2018). The effect of the removal of user fees for delivery at public health facilities on institutional delivery in urban Kenya. *Maternal and child health journal*, 22(3), 409-418.
5. Chinkhumba, J., De Allegri, M., Muula, A. S., & Robberstad, B. (2014). Maternal and perinatal mortality by place of delivery in sub-Saharan Africa: a meta-analysis of population-based cohort studies. *BMC public health*, 14(1), 1014
6. Emmanuel, A., Kain, V. J., & Forster, E. (2021). Improving the quality of neonatal care in Nigeria through the education of maternity health workers. *Journal of Neonatal Nursing*, 27(3), 211-215.

7. Ganle, J. K., Parker, M., Fitzpatrick, R., & Otupiri, E. (2014). A qualitative study of health system barriers to accessibility and utilization of maternal and newborn healthcare services in Ghana after user-fee abolition. *BMC pregnancy and childbirth*, 14(1), 425.
8. Gitobu, C.M., Gichangi, P.B. & Mwanda, W.O., (2018) The effect of Kenya's free maternal health care policy on the utilization of health facility delivery services and maternal and neonatal mortality in public health facilities. *BMC Pregnancy Childbirth* **18**.
9. Harder, A., & Zelaya, P. (2017). Identifying Assets Associated with Quality Extension Programming at the Local Level. *Journal of Human Sciences and Extension*, 5(3).
10. Harder, S., & Zelaya, J. (2021). User fee abolition and its effects on maternal health service utilization: Evidence from multi-country analyses. *Global Health Action*, 14(1), 1891527.
11. Jamison, D. T., Alwan, A., Mock, C. N., Nugent, R., Watkins, D., Adeyi, O., & Binagwaho, A. (2018). Universal health coverage and intersectoral action for health: key messages from Disease Control Priorities. *The Lancet*, 391(10125), 1108-1120
12. Johnson, A., & Smith, R. (2022). Comparative analysis of ARIMA and Exponential Smoothing models in healthcare forecasting. *International Journal of Forecasting*, 38(4), 890-902. <https://doi.org/10.1016/j.ijforecast.2021.08.002>
13. Kariuki, P., Owino, H., & Njoroge, M. (2023). "Maternal Health Care and Policy Shifts in Kenya: Post-pandemic Adaptations and Recovery." *BMC Public Health*, 23(1), 112-120.
14. Kenya National Bureau of Statistics (KNBS) and ICF International. (2015). *Kenya Demographic and Health Survey 2014: Key Indicators*. Calverton: KNBS and ICF International;
15. Kim, S. H., & Lee, M. (2024). Advanced time series analysis in public health: Models and applications. *Health Informatics Journal*, 30(2), 100-110.
16. Krejcie, R. V., & Morgan, D. W. (1970). Determining Sample Size for Research Activities. *Educational and Psychological Measurement*, 30(3), 607-610.
17. Lang'at, P. K., & Mwanri, L. (2020). Maternal healthcare overcrowding in public hospitals: Perspectives from health workers in Kenya. *Journal of Global Health*, 10(1), 010404.
18. Lowdermilk, D. L., et al. (2021). *Maternity and women's health care*. Elsevier.
19. Simpson, K. R., Lyndon, A., & Ruhl, C. (2016). Consequences of inadequate staffing include missed care, potential failure to rescue, and job stress and dissatisfaction. *Journal of Obstetric, Gynecologic & Neonatal Nursing*, 45(4), 481-490.
20. Mutua, J. M., Kimani, F., & Mwangi, W. (2022). "Rebounding Maternal Health Services Post-COVID-19: A Review of Trends in Kenyan Hospitals." *East African Medical Journal*, 99(7), 89-98.
21. Mkoka, D. A., Mahiti, G. R., Kiwara, A., Mwangi, M., Goicolea, I., & Hurtig, A. K. (2015). "Once the government employs you, it forgets you": Health workers' and managers' perspectives on factors influencing working conditions for provision of maternal health care services in a rural district of Tanzania. *Human resources for health*, 13, 1-13.
22. Ngure, F., Gachohi, J., & Onyango, D. (2021). "Impact of COVID-19 on Maternal Health Services in Rural Kenya: A Comparative Study." *Kenya Journal of Public Health*, 18(4), 45-56.
23. Nimpagaritise, S., & Bertone, M. P. (2020). Impact of user fees on healthcare utilization in low-income countries: A systematic review. *Social Science & Medicine*, 258, 113029.
24. Njoroge, J., & Muturi, G. (2023). Evaluating the impact of free maternal health services on healthcare utilization: Evidence from Kenyan hospitals. *BMC Health Services Research*, 23(1), 456. <https://doi.org/10.1186/s12913-023-08456-9>
25. Nyamai, K. (2022). The impact of user fee removal on access to maternal health services among rural women in Kenya. *African Journal of Reproductive Health*, 26(1), 43-55.
26. Nyamai, N. J. (2017). *Utilization of Maternal Health Care Services Offered At The Facility In Nairobi County: A Case Study Of Public Health Facilities Performance* (Doctoral Dissertation, University of Nairobi).
27. Owiti, F. M., Omondi, J., & Achieng, S. (2018). "The Impact of Free Maternity Services in Kenyan Slum Settings: A Case Study of Kibera." *Global Health Action*, 11(1), 155-161.
28. Owuor, J. (2019). Analysis of the Free Maternity Health Care Policy in Kenya: Policy, Implementation, and Challenges. *African Health Sciences*, 19(2), 1437-1445.
29. Owuor, P. (2019). "Abolition of Maternal Fees and Its Impact on Health Service Utilization in Kenya." *Journal of Health Policy & Planning*, 34(5), 765-773.

30. Oyugi, B., Kendall, S., & Peckham, S. (2021). Effects of free maternal policies on quality and cost of care and outcomes: an integrative review. *Primary health care research & development*, 22, e43.
31. Wamalwa, E. (2021). The effect of free maternal healthcare policy on maternal health service utilization in Kenya. *Journal of Global Health*, 11(1), 010403.
32. Wang, L., & Zhang, Y. (2021). Analyzing healthcare service utilization trends using time series models: A case study in a developing region. *Journal of Health Services Research & Policy*, 26(3), 123-130.
33. Waweru, E., et al. (2020). The challenges of implementing a user fee exemption policy for maternal health services in Ghana. *Global Health Action*, 13(1), 1845123.
34. Waweru, E., Goodman, C., Kedege, S., Tsofa, B., & Molyneux, S. (2015). Tracking Implementation and (un) Intended Consequences: a Process Evaluation of an Innovative Peripheral Health Facility Financing Mechanism in Kenya. *Health policy and planning*, 31(2), 137-147.
35. WHO. (2022). Universal Health Coverage: Moving Towards a Healthier Kenya. World Health Organization.
36. Witter, S., Arhinful, D. K., Kusi, A., & Zakariah-Akoto, S. (2021). The impact of user fee exemptions on maternal healthcare services in Ghana: A qualitative study. *Journal of Public Health*, 43(1), 85-92.
37. World Health Organization. (2015). Tracking universal health coverage: first global monitoring report. World Health Organization.