Neonatal Mortality Estimates and Associated Risk Factors in Nine Counties in Kenya

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Abbreviations

AIC	Akaike information criterion
ANC	antenatal care
AOR	adjusted odds ratio
ARIMA	autoregressive integrated moving average
CI	confidence interval
D4I	Data for Impact
DHS	Demographic and Health Survey
ETS	error, trend, and seasonality
KDHS	Kenya Demographic and Health Survey
KHIS	Kenya Health Information System
KPHC	Kenya Population and Housing Census
MCH	maternal and child health
NMR	neonatal mortality rate
OR	odds ratio
RMSE	root mean square error
SDG	Sustainable Development Goal
SSA	sub-Saharan Africa
UN-IGME	United Nations Interagency Group for Child Mortality Estimation
USAID	United States Agency for International Development

Executive Summary

Addressing neonatal mortality remains a key priority globally. In Kenya, the neonatal mortality rate (NMR) estimated by the United Nations Interagency Group for Child Mortality Estimation (UN-IGME) was 20 per 1000 live births in 2020, which demonstrates suboptimal decline. Although more still needs to be done, the Government of Kenya and its stakeholders have put strategies in place to achieve Sustainable Development Goal 3 to ensure healthy lives and promote well-being for all ages and have targeted ending preventable deaths of newborns and children. Although risk factors associated with neonatal mortality are known, there is a paucity of data when it comes to disaggregation by counties and projected estimates to support planning and implementation of interventions.

The overall goal of this project was to conduct a secondary analysis to provide quality and easily accessible estimates of neonatal mortality in nine counties in Kenya for decision-making purposes, and to improve program planning, implementation, and policies.

The study involved a desk review and secondary analysis of available data on neonatal mortality in nine counties in Kenya: Homa Bay, Kakamega, Kisumu, Kwale, Nairobi, Nakuru, Trans-Nzoia, Turkana, and Vihiga. This was achieved through a literature review to identify data sources for estimating neonatal mortality, followed by the development and comparison of estimates of neonatal mortality. We used Kenya Demographic and Health Survey (KDHS) data and Kenya Health Information System (KHIS) data from the nine counties. Time series forecasting techniques were employed to build projection models, whereas a multilevel logistic regression model was used to determine factors associated with neonatal mortality.

A total of 15 data sources were reviewed, of which 9 were found to have data on neonatal mortality indicators, 3 were found to be suitable for secondary analysis, and only 2 were used since the census data was not disaggregated. When compared with the KDHS estimates, the KHIS estimates were lower in all counties except Kisumu and Nairobi. We also noted that for the two counties whose estimates were higher, the KDHS estimates for NMR were not within the confidence interval limits for the KHIS estimates. As for trends, we observed a striking decline in rates in 2017 in almost all counties, followed by an increase the following year. Some counties, such as Kakamega and Vihiga, showed moderately constant rates over the years. All counties except Nakuru and Turkana demonstrated virtually constant rates in the projected period. For point forecasts, Kisumu and Trans-Nzoia led with about 15, Kakamega and Nairobi closely followed with slightly more than 10, and the rest ranged between 6 and 8.

Factors associated with lower odds of neonatal mortality were never married, middle wealth quintile, singleton births, birth order of above two children, immediate initiation of breastfeeding after delivery or within 24 hours, and attendance of more than four antenatal care (ANC) visits. A factor associated with higher odds of neonatal mortality was county of residence, with Nakuru having higher odds compared with Nairobi.

NMRs remain high and projections show trends that remain constant over time, hence the need for programs and policies focusing specifically on neonatal mortality because there has been little change over time. There is a need to enhance reporting mechanisms to improve the KHIS data and

ensure improved estimates of NMR. Measures should also be put in place to support data availability in the KHIS, even when shocks occur to the health system such as healthcare worker strikes and election uncertainties.

Factors associated with neonatal mortality showed similarity with known risk factors from other studies in similar settings, even at the county level. Initiatives to support women to attend ANC and skilled birth attendance are key to reducing neonatal mortality. There is a need to improve the quality and availability of services undertaken during ANC visits because more women are attending clinics. High-quality ANC services have been shown to reduce neonatal morbidity and mortality through early identification and management of complications of pregnancy and other preexisting conditions. It is also important to address poverty as a risk factor to ensure that women have sufficient resources to support their pregnancy and delivery. Primigravida women need to be supported throughout their pregnancy to ensure that they have safe and successful deliveries. Continued efforts for exclusive breastfeeding initiatives need to be strengthened in all counties. A need also exists to enhance programmatic initiatives by organizations, such as the United States Agency for International Development (USAID), that have been shown to lead to declining trends in neonatal mortality. Lastly, there is a need to provide support for counties to ensure enough facilities, and a skilled workforce to manage high-risk births where there is a large number of pregnancies.

Introduction

The neonatal mortality rate (NMR) is defined as the probability that a child born in a specific year or period will die during the first 28 completed days of life, expressed per 1,000 live births (Data for Impact Project [D4I], United States Agency for International Development [USAID], n.d.). Data from the United Nations Interagency Group for Child Mortality Estimation (UN-IGME) indicated that the global NMR in 2020 was 17 deaths per 1,000 live births, with about 6,500 neonatal deaths every day. In sub-Saharan Africa (SSA), the NMR was 27 per 1,000 live births in 2019, and a child born in SSA was ten times more likely to die in its first month than a child born in a high-income country. In Kenya, the NMR was 20 per 1,000 live births (UN-IGME, 2019).

Evidence has shown that at least 50 percent of all under-five deaths occur during the neonatal period. Understanding what occurs during this period can therefore help improve targeted interventions to avert under-five mortality. Close to 75 percent of countries at risk of missing the Sustainable Development Goal (SDG) target on under-five mortality are in SSA, and children in low-income and lower-middle-income countries continue to face far higher mortality rates than those in high-income countries (Sharrow, et al., 2022). One-third of the countries in SSA reported annual NMRs of more than 30 deaths per 1,000 live births in 2017, and two-thirds of countries at risk of missing the SDG neonatal mortality target were in SSA (Hug, Alexander, You, Alkema, & UN Interagency Group for Child Mortality Estimation, 2019).

Providing accurate estimates is an essential component of evaluating and tracking progress toward achieving the SDG targeting the reduction of neonatal mortality to 12 per 1,000 live births (or lower) by 2030. Most countries in SSA are at risk of missing the SDG's NMR target, so there is a need for an intensified understanding of the risk factors so that appropriate interventions can be implemented to reduce neonatal deaths.

Gaps and challenges exist in obtaining reliable neonatal mortality estimates due to a lack of high-quality data on mortality and poor vital registration systems. In Kenya, no recent survey data are available on neonatal mortality because the last Kenya Demographic and Health Survey (KDHS) was conducted in 2014. Kenya is implementing the 2022 KDHS and the report is expected to be available in late 2022 or early 2023. The results will provide an opportunity for further analysis and comparison with the 2014 KDHS. In the absence of the availability of specific estimates, the understanding of NMR trends has been inferred by under-five mortality trends.

Both direct and indirect methods are used to estimate neonatal mortality. The direct methods use data on children from vital registration systems or specially designed surveys, such as Demographic and Health Surveys (DHS), including date of birth, survival status, and date of death or age at death of the deceased. Indirect methods use less detailed data commonly collected from women in less specialized surveys and censuses, including the number of children ever born, the number of children still living, and the time since first birth. Indirect methods rely on assumptions about fertility and mortality patterns that may not hold, especially in countries with high HIV-related mortality (DHS Program, n.d.). Statistical methods may also be employed for NMR projection using modeling and estimation of change in rates over time.

USAID in Kenya recently awarded funding for a range of new program activities focused on maternal and child health (MCH) in nine counties (Homa Bay, Kakamega, Kisumu, Kwale, Nairobi, Nakuru, Turkana, Trans-Nzoia, and Vihiga). The overall goal of this project was to conduct secondary analysis to provide quality and easily accessible estimates of neonatal mortality in these nine Kenyan counties to aid in decision making for improved programs and policies.

Research Questions:

1. What are the sources of neonatal mortality data in the nine counties?
2. a. What are the NMR estimates using the data sources identified in Question 1 and how do they compare with the Kenya Health Information System (KHIS)?

   b. What are the trends and projections of NMR in the nine counties using KHIS data?
3. What are the factors associated with neonatal mortality rates in the nine counties?

Methods

This study involved a desk review and secondary analysis of available data on neonatal mortality in nine counties in Kenya: Homa Bay, Kakamega, Kisumu, Kwale, Nairobi, Nakuru, Turkana, Trans-Nzoia, and Vihiga.

Research question 1: What are the sources of neonatal mortality data (beyond KHIS, KPHC, and KDHS)?

This involved a desk review. We reviewed the literature for potentially relevant data sources using the following key terms: “neonatal mortality,” “neonatal death,” “live birth,” “Kenya,” and “data sources.” Once data sources were identified, we assessed the extent of data available online and through downloadable reports and files/spreadsheets. We further developed an inventory to summarize the available data sources and indicators, their relevance, and their potential for secondary analysis.

Research question 2a: What are the NMR estimates using the data sources identified in question 1 and how do they compare with the KHIS?

This analysis used routinely collected administrative data from the KHIS and KDHS for 2014 identified in question 1.

KHIS, which was initially known as District Health Information Software 2, was introduced in Kenya in 2011 to establish a central database, with health facility level reporting to address both local and national needs (Manya, Braa, Titlestad, Øverland, & Mumo, 2012). The District Health Information Software 2 is an open-source, web-based platform most used as a health management information system across the world. The software was developed as a global collaboration managed by the Health Information Systems Programme Center at the University of Oslo (dhis2, n.d.).

KHIS data on neonatal deaths and live births are available in aggregated format from January 2011 to date in all counties. All health facilities in the Republic of Kenya are obligated by law to report the health services they offer to citizens through the KHIS platform. The data are reported monthly per health facility and aggregated into administrative units, starting from the ward, subcounty, county, and national levels.

Before initiating analysis using KHIS data, permission was sought via email from the custodian (Ministry of Health). Aggregated data at the facility level were downloaded in Microsoft Excel format for the nine counties. The variables of interest were the number of live births, number of neonatal deaths, county, and period.

The initial plan was to also compare the NMR from the Kenya Population and Housing Census (KPHC) data; however, on reviewing all volumes of the KPHC reports, we noted that the data on deaths were reported up to one year and were not disaggregated into months or days, and we therefore could not calculate NMR data from the KPHC data. No further analysis was performed using KPHC data.

To estimate the NMR using routinely collected administrative data (KHIS), we used a direct method of calculating NMR per county for 2014. We used the number of newborns who died during the first 28 days in a health facility and the total live births in the facility.

We constructed the data from KHIS to include year to start from April 2013 to May 2014 to reflect the same time period for both KDHS and KHIS data; these are the months that would constitute the one-year KDHS survey. KDHS-based NMRs were calculated using the KEBR70FL file data using the *chmort* function of the *DHS.rates package* in R (R Foundation, 2021). KHIS-based NMRs were calculated using the direct method in R and 95 percent confidence intervals (CIs) were constructed. We compared NMR rates obtained from the KDHS and KHIS for the nine counties.

Research question 2b: What are the trends and projections of NMR in the nine counties using KHIS data?

We used the 2011–2021 KHIS data to describe the trends and project NMR in the nine counties for the years between 2022 and 2025.

Before data analysis, we aggregated data in quarterly intervals for each county. As an initial analysis, we described the NMR time trend by plotting the data at quarterly intervals to identify any trend, seasonality, or anomaly. To estimate the trend component of our time series, we applied a smoothing approach by calculating the simple moving average.

We used time series forecasting techniques to build projection models. We considered three approaches: (1) error, trend, and seasonality (ETS); (2) Bagged ETS; and (3) autoregressive integrated moving average (ARIMA) models.

ETS models are a family of time series models with an underlying state-space model consisting of an error term (E), a trend component (T) and a seasonal component (S). They have been shown in the literature to be relevant and have a solid theoretical foundation (Hyndman & Athanasopoulos, 2018). The error that is often relevant for prediction rather than point forecast can be additive or multiplicative. Trend provides the long-term direction of a series, and it could be nonexistent (N), additive (A), multiplicative (M), damped additive (Ad), or multiplicative damped (Md). Seasonality describes the repeating components of a series with known periodicity and could be nonexistent, additive, or multiplicative.

We fitted the model using the *ets* R function; before doing the forecast, we divided the data into train and test data sets to allow us to assess the performance of our model (Hyndman & Athanasopoulos, 2018).

The Bagged ETS model improves forecast accuracy. The model applies a Box-Cox transformation to the data to address instabilities that might be due to uncertainties brought about by data, parameters, and model selection (Bergmeir, Hyndman, & Benítez, 2016). The model involves decomposing the series into the trend, seasonal, and remainder components, and then bootstrapping the remainder component using a moving block bootstrap. The trend and seasonal components are then added back in to achieve an inverted Box-Cox transformation. This then generates a random pool of similar bootstrapped time series (Bergmeir, et al., 2016). The best model is chosen from several exponential smoothing models using bias corrected Akaike information criterion (AIC). The point forecast is then calculated for each of the models and the resulting forecasts are combined using the median. We fitted the Bagged ETS model using *baggedETS function,* also in the forecast package in R.

ARIMA is a statistical analysis model that uses time-series data to predict future trends. It measures the linear relationship between an observation at a given time and at a given distance over time series while removing the effects of other intermediate observations in between (Agarwal, Tripathi, & Pareek, 2021). In this method, a statistical model is said to be autoregressive if it predicts future values based on past values. The ARIMA model adopts techniques of the autocorrelation function and partial autocorrelation function plots, which are tests that indicate the statistical significance of autocorrelation and the limits of the CIs (Silva, Araújo, Frias, Vilela, & Bonfim, 2021). In the analysis of the ARIMA models, the presence of autocorrelation is only useful when the time series is classified as a stationary pattern whereby the values develop in time around constant average and variance, enabling the forecast technique (Silva, et al., 2021). The function *Arima* in R was used.

In selecting the most appropriate model for forecasting, we applied the following steps:

i. Fit the three models: ETS models, with and without Box-Cox transformation; Bagged ETS; and ARIMA

ii. Evaluate root mean square error (RMSE)

iii. Undergo an iterative process in all nine counties

iv. Obtain point forecasts and plots using the model with the lowest RMSE

Research question 3: What are the factors associated with neonatal mortality rates in the nine counties?

This was a secondary data analysis of the 2014 KDHS, which is the latest reported DHS in Kenya. The KDHS provides a nationally representative sample to estimate demographic and health indicators for the whole country.

Permission to use the data was granted by the DHS Program. The Births Recode file was used to extract data on maternal and neonatal characteristics for the neonates born in the last five years. We restricted the data to the nine counties. Our final data included 4,379 neonates in unweighted numbers or 6,395 in weighted numbers.

Outcome Variable

The dependent variable was neonatal death, defined as the death of a child within the first 28 days of life. It was treated as a binary variable, where death was coded 1 (1 = if a death occurred within the first month after birth) or alive was coded 0 (0 = if the baby was alive in the first month of life). Because we confined our analysis to children born in the last five years in the nine counties, "neonatal death" in our study was defined as neonatal death among children born in the last five years in the nine counties.

Independent Variables

Our independent variables included individual-level and community-level variables. The individual-level variables were categorized into two areas: "demographic and household characteristics" and "obstetric and health service-related characteristics." Community-level variables were categorized into two areas: "direct factors" variables used without aggregation and "aggregated variables," which were generated by aggregating individual-level variables at the cluster level. Missing values in all variables were coded as 99 and labeled as “other” or “don’t know.”

Demographic and Household Variables

Maternal age was based on the mother’s age at the time of the birth and was categorized into less than 19 years, 20–29 years, and 30 years and above. Marital status was grouped as never married, married, and divorced/widowed/separated. Religion was categorized as Christian, Muslim, or no religion/other. Maternal and paternal education was categorized as no education, primary, secondary, and above. The wealth index was grouped into three categories: poor (poorer and poorest), medium, and rich (richer and richest). Maternal occupation was grouped into working for pay and not working for pay. Media exposure was measured by three variables: reading newspapers, watching television, and listening to the radio. These were then combined and categorized as exposed or not exposed. The source of drinking water was categorized as improved, not improved, or other/not a dejure resident. Improved water sources include piped water into the dwelling, yard, or plot; a public tap/standpipe or borehole; a protected well or protected spring water; rainwater; and bottled water. The type of toilet was grouped into improved, not improved, and other/not a dejure resident. Improved toilets were those that flushed into a septic tank, piped sewer system, or pit latrine; ventilated improved pit latrine; pit latrine with slab; and composting toilet. Maternal Body Mass Index was calculated from the mother’s height and weight and was categorized as <18.5 kg/m², 18.5–24.9 kg/m² and ≥ 25 kg/m². A mother’s smoking status was based on whether the mother smoked cigarettes and was grouped as yes or no. Alcohol drinking status was also grouped as yes or no.

Obstetric and Health Service-Related Variables

The place of delivery was grouped into those women who delivered at home and in a health facility. The mode of delivery was categorized as caesarean and vaginal deliveries. Preceding birth interval was grouped as less than 2 years, 2–4 years, and above 4 years. Birthweight was classified as not weighed/don’t know (missing), low, normal, and above normal, per existing literature (Imbo, Mbuthia, & Ngotho, 2021). The type of birth was single or multiple. Birth order was the order in which the neonate was born and was categorized as first, 2–4, and 5 and above. The age at first birth was grouped into less than 20, 20–29, and 30 and above. Initiation of breastfeeding was classified as immediately, 1–24 hours, and above 24 hours. The sex of the neonate was either male or female. Birth attendants and postnatal care attendants were grouped as skilled and unskilled attendants. Doctors and nurses/midwives were the individuals classified as skilled attendants. The number of antenatal care (ANC) visits was classified as no ANC, 1–3, and 4 visits or more. The timing of the first ANC visit was classified into the first trimester, second trimester, and third trimester. Women’s healthcare decision making autonomy was measured as whether the mother reported that she was able to make health decisions on her own.

Community-Level Characteristics

The direct community-level characteristics were the place of residence, region, or county; and distance to the health facility. Residence was categorized as either urban or rural. Distance to the health facility to get medical help was based on whether it was a big problem. The aggregated community-level variables included community health facility delivery, which was a dichotomy of the proportion of deliveries in a community that occurred in any health facility. It was divided into two quantiles based on existing literature for aggregating individual variables and categorized using median cutoffs because data were not normally distributed and categorized as low and high (Tesema & Worku, 2021). Community poverty level was measured as the proportion of women from the poor and poorest wealth quintiles, and the measure was divided into two quantiles and categorized as low and high. Community education level was defined as the proportion of women's education (secondary and higher) in the primary sampling unit and classified as low and high. Community mass media exposure was the proportion of women exposed to mass media in the primary sampling unit. The proportion was divided into two quantiles and categorized as low or high.

Statistical Analysis

Background characteristics of the respondents were summarized, and frequencies were reported. Bivariate analysis was performed to examine the relationship between the independent variables and neonatal death. Odds ratios and 95 percent CIs were used to measure the association between each independent variable and neonatal mortality.

Variables that were significant at $p<0.2$ in the bivariate analysis were included in the multilevel models. The methods applied in our multilevel modelling analysis using DHS data have been cited elsewhere (Elkasabi, Ren, & Pullum, 2020; Tesema & Worku, 2021; Zaw, Mon, & MacQuarrie, 2019; Ononokpono & Odimegwu, 2014; Imbo, et al., 2021). Four models were fitted in the multilevel logistic regression. The first model was the null model with no explanatory variable. The second model was a model with individual-level variables. The third model was a model with community-level variables, and the fourth model included both the community- and individual-level variables. The null model was used to measure the extent of cluster variability in neonatal mortality. Cluster variability was measured based on the intra-class correlation coefficient, median odds ratio, and proportional change in variance.

Model fit statistics were performed based on the log-likelihood, AIC, and Bayesian information criterion. The model with the lowest AIC and highest log-likelihood was taken as the final model. Multi-collinearity of the independent variables was also checked using the variance inflation factor, with a value of less than 10 considered to be substantial.

All analysis was done using Stata version 16. The weighted data were used for analysis to adjust for unequal probability of selection and non-response. The commands "*svyset,*" "*svy: tab,*" and "*svy:melogit*" were used to account for the complex survey design. However, the model fit statistics and cluster variability measures were estimated without the "*svy*" command due to the limitations of the *"svy."*

Results

Sources of Neonatal Mortality Data in the Nine Counties (Beyond KHIS, KPHC and KDHS)

A total of 15 data sources (Appendix A) were identified from the desk review, of which nine had data on neonatal mortality indicators. Three sources (KDHS, KHIS, and KPHC) were suitable for secondary analysis but only two sources were used since the KPHC data was not disaggregated.

Comparing NMR Estimates Using the Data Sources Identified in Question 1 with the KHIS

Table 1 summarizes the KHIS and KDHS estimates for NMR. When compared with the KDHS estimates, the KHIS estimates were lower in all counties except Kisumu and Nairobi. In these two counties, the KHIS confidence limits did not include the KDHS point estimate.

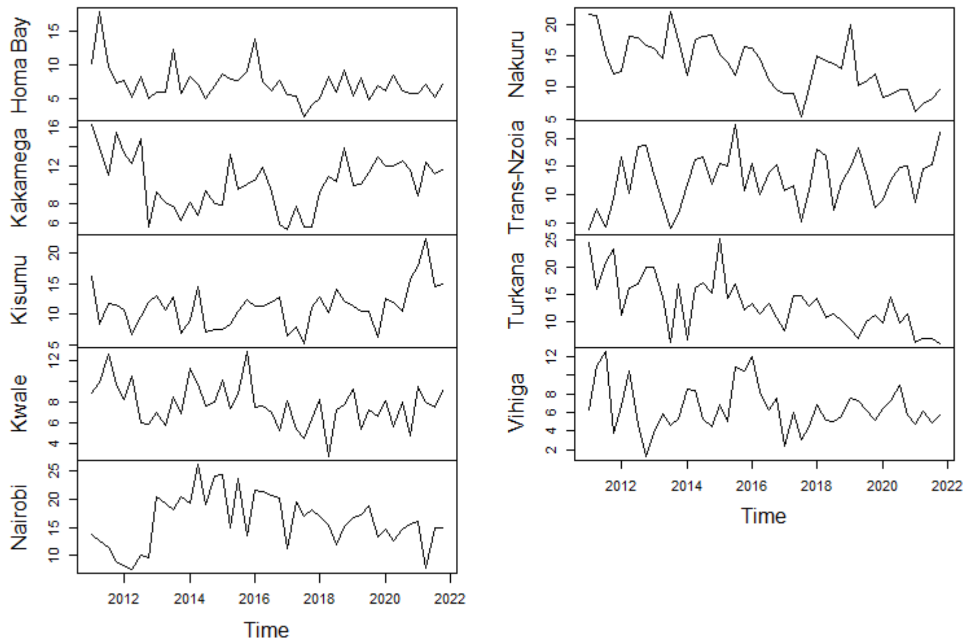
Table 1. Estimated NMR per 1000 live births

	KHIS		KDHS
County	**NMR**	**95% CI**	**NMR**
Homa Bay	8.15	6.99–9.44	14.92
Kakamega	7.78	6.88–8.77	27.08
Kisumu	10.09	8.91–11.38	8.66
Kwale	8.77	7.32–10.43	12.3
Nairobi	20.52	19.63–21.44	17.29
Nakuru	16.85	15.59–18.18	27.05
Trans-Nzoia	8.09	6.49–9.96	19.24
Turkana	10.69	8.47–13.30	47.85
Vihiga	6.48	5.05–8.18	25.45

Trends and Projections of NMR in the Nine Counties Using KHIS Data

Figure 1 shows the findings comparing trends in NMRs from 2011–2022 using the KHIS data. We observed a striking decline in 2017 in almost all counties. It was also evident that some counties, such as Kakamega and Vihiga, showed moderately constant rates over the years. The figure shows that some counties exhibited obvious trends (Homa Bay, Nakuru, and Turkana) whereas others showed nonuniformity. The various counties observed different ETS models as follows: {A, N, N} = Kakamega, Nairobi, Nakuru, {M, Ad, N} = Turkana, {M, N, N} = Kisumu, Trans-Nzoia, Vihiga, Homa Bay, and Kwale, Where N- Non-existent, A- additive, M- multiplicative, Ad-damped additive and Md- multiplicative damped.

Figure 1. Quarterly neonatal mortality time series plot for the nine counties



Projected Forecast Results

Various models were applied to project estimates. Table 2 summarizes the performance of each model. From the results, the Bagged ETS model was superior to the other methods and was therefore employed in forecasting using the KHIS data.

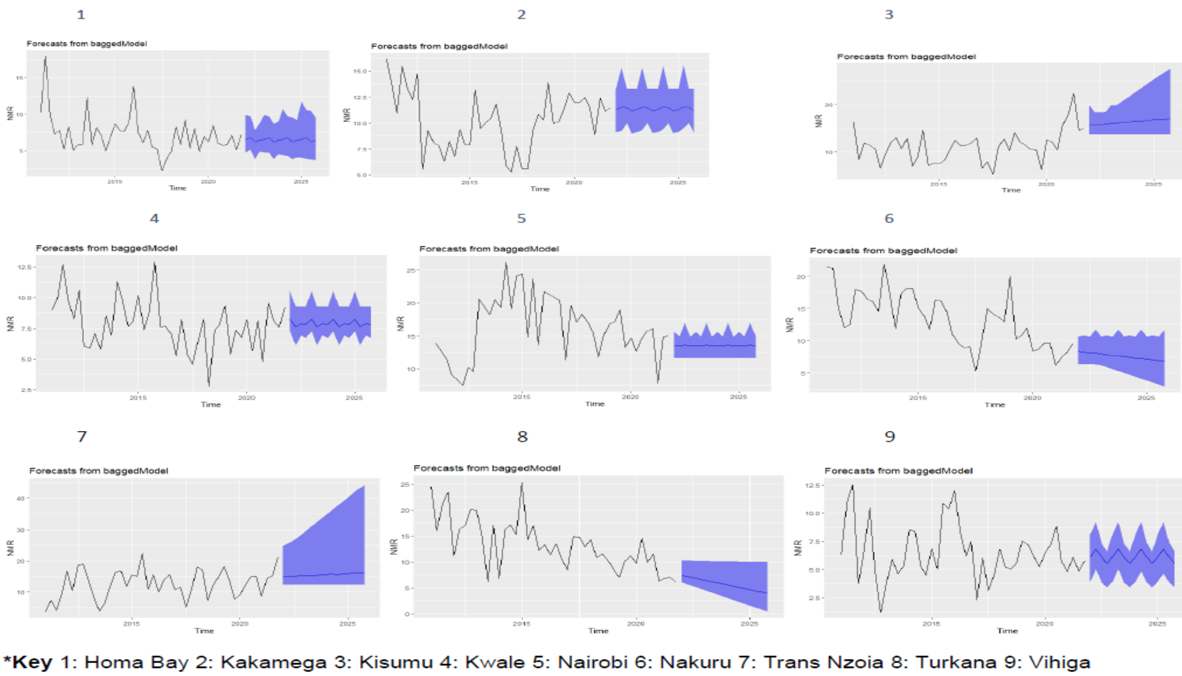
Table 2. RMSE comparison on a test set

County	ETS	ETS (Box-Cox)	Bagged ETS	ARIMA
Homa Bay	0.991	1.002	0.832	0.969
Kakamega	1.211	1.156	1.075	1.958
Kisumu	5.896	5.981	5.905	5.924
Kwale	2.367	1.707	1.744	1.705
Nairobi	3.012	2.729	3.277	2.962
Nakuru	3.981	3.545	3.255	4.256
Trans-Nzoia	3.986	4.157	3.813	4.007
Turkana	2.513	2.679	2.473	3.633
Vihiga	1.278	1.274	1.245	1.398

Figure 2 shows projected forecasts using the Bagged ETS model. All counties demonstrated virtually constant rates in the projected period except Nakuru and Turkana, which showed a decline. Turkana county has had new MCH programming initiatives in recent years that could have led to the decline. The key observations were heavy tails due to uncertainty and asymmetrical prediction intervals.

The point forecast estimates for the nine counties are shown in Appendix B. For point forecasts, Kisumu and Trans-Nzoia led with about 15; Kakamega and Nairobi closely followed with slightly less than 10; and the rest ranged between 6 to 8.

Figure 2. Projected forecasts for the nine counties 2022–2025



Factors Associated with Neonatal Mortality in the Nine Counties

There were 177 deaths among the 6,218 live births across the nine counties, giving a total proportion of neonatal deaths at 2.8% as per the KDHS 2014.

Demographic Characteristics

Table 3 summarizes the demographic and household characteristics of the women surveyed. The findings showed a high proportion of married women (84%), with slightly more than half ages 20–29 years (59.5%). The majority of the women were Christian (92.8%). In terms of education, most of the women (91.9%) had attained primary education and above. Slightly more than 3 percent of the women worked for pay and 17 percent did not, with 52.8% of women having missing data. Far more women reported not smoking (47.5%), than did (0.1%). Similarly, more women reported not drinking alcohol (45.9%) than did (1.7%). For smoking and alcohol status slightly more than half of the data was missing. Far more women (28.5%) had normal body mass index (18.5–24.9 kg/m^2), whereas 3.2% were underweight, 15.6% were overweight/obese and 52.7% had missing data.

Table 3. Demographic characteristics of women in the nine counties in Kenya

Characteristics	Frequency (N= 6,395)	Percentage (%)
	Mean=29, Median=28, SD=6.51, Range 15–49 years	
Maternal age		
15–19 years	173	2.7
20–29 years	3,806	59.5
30+ years	2,416	37.8
Marital Status		
Never married	429	6.7
Married	5,373	84.0
Divorced/separated/widowed	593	9.3
Religion		
Christian	5,935	92.8
Muslim	383	6.0
No religion/other	77	1.2
Maternal education status		
No education	520	8.1
Primary	3,441	53.8
Secondary and above	2,434	38.1
Maternal occupation		
Not working for pay	1,089	17.0
Working for pay	1,928	30.2
Other(missing)	3,378	52.8
Maternal body mass index		
<18.5 kg/m^2	202	3.2
18.5–24.9 kg/m^2	1,824	28.5
≥25 kg/m^2	996	15.6
Not measured	3,373	52.7
Mother's smoking status		
No	3,036	47.5

Characteristics	Frequency (N= 6,395)	Percentage (%)
Yes	7	0.1
Other (missing)	3,352	52.4
Mother's alcohol drinking status		
No	2,932	45.9
Yes	111	1.7
Other (missing)	3,352	52.4

Household Characteristics

As presented in Table 4, the proportion of women in the rich wealth quintile was 49.4%. More women lived in households that had an improved source of water (74.2%) and an improved toilet (52%). A large percentage of women (78.6%) were exposed to at least one form of media (television, newspaper, and radio).

Table 4. Household characteristics of women in the nine counties in Kenya

Characteristics	Frequency (N= 6,395)	Percentage (%)
Paternal education		
No education	180	2.8
Primary	1,339	20.9
Secondary and above	1,273	19.9
Don’t know (not in union/other)	3,603	56.4
Wealth Index		
Poor (poorer & poorest)	2,120	33.2
Medium	1,117	17.5
Rich (richer & richest)	3,158	49.4
Source of drinking water		
Improved	4,742	74.2
Non-improved	1,380	21.6
Other/not a dejure resident	273	4.2
Type of toilet		
Improved	3,322	52.0
Non-improved	2.882	45.0
Other/not a dejure resident	191	3.0

Characteristics	Frequency (N= 6,395)	Percentage (%)
Media exposure		
Not exposed	1,299	20.3
Exposed	5,027	78.6
Missing/not a de jure resident	69	1.0

Obstetric Characteristics

The obstetric characteristics are shown in Table 5. The majority of the women had vaginal deliveries (90.1%). More women reported their preceding birth interval to be more than two years (55.5%). For half of the women in our sample, the most recent birth was their second to fourth child (50.6%). A substantial proportion of women had singleton births (96.5%) and were younger than 19 years old when they had their first birth (55%). Women gave birth to male and female babies in equal proportions. The majority of the women (67.9%) reported that they did not know their baby's birthweight and therefore had missing data, whereas 24.8% of the babies had normal birthweight. More women initiated breastfeeding immediately (26.5%) whereas 53 percent did not know or had missing data.

Table 5. Obstetric characteristics of women in the nine counties in Kenya

Characteristics	Frequency (N= 6,395)	Percentage (%)
Mode of delivery		
Vaginal	5,762	90.1
Caesarean section	632	9.9
Preceding birth interval		
<2 years	955	15.0
2–4 years	2,085	32.6
>4 years	1,464	22.9
Don't know (missing)	1,891	29.5
Type of birth		
Single	6,173	96.5
Multiple	222	3.5
Birth order		
First	1,858	29.0
2 to 4	3,234	50.6
≥5	1,302	20.4

Characteristics	Frequency (N= 6,395)	Percentage (%)
Age at first birth		
≤19	3,510	55.0
20–29	2,773	43.3
30+	112	1.7
Initiation of breastfeeding		
Immediately	1,693	26.5
1–24 hrs	1,046	16.4
>24 hours	260	4.1
Don't know/missing	3,396	53.0
Birth weight		
Low	153	2.4
Normal	1,589	24.8
Above normal	313	4.9
Not weighed/don't know/missing	4,340	67.9
Sex of the child		
Male	3,224	50.4
Female	3,171	49.6

Health Service-Related Characteristics

Table 6 shows the health service-related characteristics. More than half of the women delivered at health facilities (57.2%). Skilled birth attendants conducted more than half (65.4%) of the deliveries. Forty-six percent of the women had attended the recommended four or more ANC visits, with more women having their first ANC visit during the second trimester (45.9%) instead of the first or third. More women indicated that they were the main decision makers regarding their healthcare (44.9%) than not (2.7%), while 52.5% did not know or had missing data. About 21 percent of the women also reported that they received postnatal care from a skilled attendant and 63 percent had missing data.

Table 6. Health service-related characteristics of women in the nine counties in Kenya

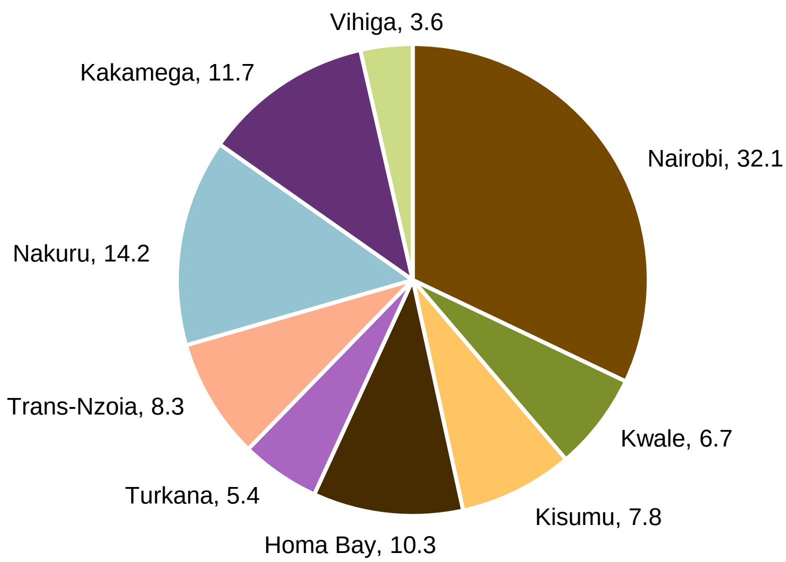
Characteristics	Frequency (N= 6,395)	Percentage (%)
Place of delivery		
Home	2,114	33.0
Health facility	3,656	57.2
Other	624	9.8

Characteristics	Frequency (N= 6,395)	Percentage (%)
Birth attendant		
Skilled	4,182	65.4
Unskilled	2,189	34.2
Number of ANC visits		
None	158	2.5
1 to 3	1,636	25.6
≥4	2,940	46.0
Don’t know/missing	1,661	25.9
Timing of first ANC visit		
First trimester	1,130	17.7
Second trimester	2,936	45.9
Third trimester	520	8.1
Don’t know/missing	1,808	28.3
Postnatal care attendant (n=6395)		
Skilled attendant	1,321	20.7
Non-skilled attendant	80	1.3
Did not attend postnatal care	626	9.8
Other (missing)	4,367	63.0
Women's healthcare decision-making autonomy		
No	171	2.7
Yes	2,868	44.9
Don’t know (missing)	3,356	52.5

Community-Level Characteristics

As shown in Figure 3, the highest proportion of women who had neonatal deaths was from Nairobi (n=2,051/6,395 live births, 32%) and the lowest was from Vihiga County (n=229/6,395 live births, 3.6%).

Figure 3. Neonatal deaths by county of residence



The community-level characteristics are shown in Table 7. There were equal proportions of women who resided in rural and urban areas. More women reported that the distance to the health facility was not a big problem (36.1%) than was (11.4%). More than half of the women in the nine counties lived in communities with a low community education level (62.6%) and high community poverty (53.3%). A high proportion of the women also lived in communities with high media exposure (87.8%) and high community health facility delivery (95%).

Table 7. Community-level characteristics of women in the nine counties in Kenya

Characteristics	Frequency (N= 6,395)	Percentage (%)
Residence		
Urban	3,287	51.0
Rural	3,108	49.0
Distance to a health facility		
Big problem	727	11.4
Not a big problem	2,311	36.1
Other	3,356	52.5

Characteristics	Frequency (N= 6,395)	Percentage (%)
Community education level		
Low	4,004	62.6
High	2,391	37.4
Community poverty		
Low	2,986	46.7
High	3,409	53.3
Community media exposure		
Low	778	12.2
High	5,617	87.8
Community health facility delivery		
Low	317	5.0
High	6,078	95.0

Bivariate Analysis of Factors Associated with Neonatal Mortality

Appendix C presents the findings from the bivariate analysis of factors statistically significantly associated with neonatal mortality in the nine counties at p-value<0.2. The following demographic and household factors were associated with lower odds of neonatal mortality: neonates born to women who were never married, women in the medium wealth quintile, women's smoking status, a preceding birth interval of more than two to four years, a singleton birth, birth order of two to four, and immediate initiation of breastfeeding or within 24 hours and having more than four ANC visits. There were also lower odds of neonatal mortality among neonates born to women from Kakamega county. County of residence was statistically significantly associated with neonatal mortality, with Nakuru having higher odds compared with Nairobi.

Multilevel Logistic Regression Analysis of Factors Associated with Neonatal Mortality

Appendix D shows the model fit statistics and random effect parameters for the four multilevel logistic regression models. Model 4 was taken as the best model because it had the lowest deviance value (913.68) and the lowest AIC value (973.68).

Table 8 shows the results from the various multilevel logistic regression models that were considered. Based on Model 4, upon controlling for individual and community-level factors, neonates born to women who had never married had lower odds of neonatal mortality (adjusted odds ratio [AOR]=0.07; 95% CI 0.01–0.42) compared with married women. Neonates born to women from the medium wealth quintile were 69 percent less likely (95% CI 0.11–0.91) to have had a neonatal death compared with those from the poorest wealth quintile. Neonates born to women who had singleton births had lower odds (AOR=0.13; 95% CI 0.04–0.49) of neonatal mortality compared with multiple births. Women whose most recent birth was the second to fourth child (95% CI 0.13–0.56) and the fifth child and above (95% CI 0.11–0.78) had 70 percent lower odds of neonatal mortality compared with those whose most recent birth was the first child. The findings also documented that babies born to women who initiated breastfeeding immediately after delivery (AOR=0.13; 95% CI 0.03–0.54) or within 24 hours (AOR=0.14; 95% CI 0.03–0.57) had lower odds of neonatal mortality compared with those who breastfed after 24 hours. Compared with children born to women who did not attend ANC, those who attended more than four visits were 88 percent less likely (95%CI 0.02–0.82) to have had neonatal deaths. Neonates born by women residing in Nakuru county (AOR=5.06; 95% CI 1.61–15.84) had higher odds of neonatal mortality compared with those residing in Nairobi County.

Table 8. Multilevel logistic regression analysis of factors associated with neonatal mortality in the nine counties in Kenya

Variable	Model 2 (Individual-level variables)	Model 3 (Community-level variables)	Model 4 (Individual- and community-level variables)
Marital status			
Married	1		1
Never married	0.07 (0.01–0.42)		0.07 (0.01–0.42)
Divorced/separated/ Widowed	1.68 (0.59–4.80)		1.68 (0.59–4.80)
Maternal education			
No education	1		1
Primary	0.44 (0.14–1.40)		0.44 (0.14–1.39)
Secondary and above	0.72 (0.18–2.95)		0.72 (0.17–2.92)
Wealth Index			
Poor (poorer & poorest)	1		1
Medium	0.32 (0.11–0.91)		0.31 (0.11–0.91)
Rich (richer & richest)	0.73 (0.17–3.19)		0.73 (0.17–3.18)
Type of birth			
Multiple	1		1
Single	0.13 (0.04–0.49)		0.13 (0.04–0.49)
Birth order			
First	1		1
2 to 4	0.27 (0.13–0.56)		0.27 (0.13–0.56)
≥5	0.3 (0.11–0.79)		0.30 (0.11–0.78)

Variable	Model 2 (Individual-level variables)	Model 3 (Community-level variables)	Model 4 (Individual- and community-level variables)
Mode of delivery			
Cesarean section	1		1
Vaginal	0.26 (0.06–1.19)		0.26 (0.06–1.20)
Breast Initiation			
>24 hours	1		1
Immediately	0.13 (0.03–0.54)		0.13 (0.03–0.54)
1–24 hrs.	0.14 (0.03–0.57)		0.14 (0.03–0.57)
Don't know	0.32 (0.09–1.14)		0.32 (0.09–1.14)
ANC visits			
No ANC	1		1
1 - 3	0.51 (0.09–2.92)		0.51 (0.09–2.92)
≥4	0.12 (0.02–0.82)		0.12 (0.02–0.82)
Don't know	0.83 (0.16–4.37)		0.83 (0.16–4.38)
Birth attendant			
Unskilled	1		1
Skilled	0.69 (0.08–5.81)		0.69 (0.08–5.79)
Place of delivery			
Home	1		1
Health facility	0.95 (0.11–8.06)		0.94 (0.11–8.01)
Other	3.82 (0.39–37.09)		3.81(0.39–36.91)
Community health facility delivery			
Low		1	
High		2.77 (0.71–10.79)	4.97 (0.99–24.79)
County			
Nairobi	1	1	1
Kwale	0.80 (0.19–3.37)	2.12 (0.68–6.58)	0.86 (0.20–3.59)
Kisumu	0.71 (0.20–2.50)	0.40 (0.12–1.34)	0.71 (0.20–2.50)
Homa Bay	1.11 (0.24–5.18)	0.71 (0.24–2.05)	1.10 (0.23–5.17)
Turkana	0.40 (0.07–2.29)	1.12 (0.37–3.44)	0.64 (0.11–3.62)
Trans-Nzoia	0.90 (0.22–3.76)	0.10 (0.33–2.87)	1.26 (0.31–5.08)
Nakuru	5.09 (1.63–15.90)	2.76 (1.07–7.11)	5.06 (1.61–15.84)
Kakamega	0.16 (0.02–1.18)	0.10 (0.01–0 .87)	0.16 (0.02–1.27)
Vihiga	1.51 (0.36–6.35)	1.05 (0.36–3.07)	1.50 (0.36–6.34)

Discussion

Neonatal mortality reduction requires quality data to guide investments in building stronger health systems and services; improve coverage, quality, and equity of care in the antenatal period and during birth; and expand coverage of high-quality care in the first week of life (Sharrow, et al., 2022). Moreover, improvements in neonatal survival require that a higher proportion of deliveries occur in well-equipped facilities with high-quality ANC care and targeted interventions provided during delivery and the first week of life (Hug, et al., 2019; Afulani, et al., 2019).

Compared to KDHS estimates, KHIS estimates were lower in all counties except Kisumu and Nairobi. The lower estimates could be due to greater underreporting by health facilities. We also noted that for the two counties whose estimates were higher, the KDHS estimates for NMR were outside the CI limits for the KHIS estimates, which highlights the importance of the KHIS data in providing aggregated NMR estimates per county with enhanced reporting.

We observed a striking decline in rates in 2017 in almost all counties, which was followed by a return to normal estimates. It was noted that during that year, the healthcare system was paralyzed due to doctor and nurse strikes. Nurses are crucial to the provision of MCH services at health centers and dispensaries. The year 2017 was also an election year in the country and because the election results were annulled, prolonged disruption occurred in healthcare services that could have led to low reporting rates by healthcare facilities (Waithaka, et al., 2020).

Kakamega and Vihiga counties showed moderately constant rates over the years. This could be attributed to initiatives and programs to address high maternal and child mortality rates by the Kakamega county government and development partners (County Government of Kakamega, 2022).

It was initially difficult to identify unique time series properties in the data set. We therefore used the ETS model best suited to identify any unobserved states (level, trend, or seasonality). The various counties observed different ETS models (Hyndman & Athanasopoulos, 2018).

All counties except Nakuru and Turkana demonstrated virtually constant rates within the projected period. This could be attributed to high impact interventions during the continuum of care in MCH by the county government and other partners to support MCH which occurred in these counties. For example, Turkana County, through the Afya Timiza program that was launched in 2016 by USAID, has significantly improved MCH (USAID, 2019).

For point forecasts, Kisumu and Trans-Nzoia led with about 15, Kakamega and Nairobi closely followed with slightly more than 10, and the rest ranged between 6 and 8. Two key observations were made regarding the projections: heavy tails likely because of uncertainty arising from the various sources of error related to time-series forecasting (Spiliotis, Nikolopoulos & Assimakopoulos, 2019) and asymmetrical prediction intervals, as has been shown in the literature (Chatfield, 2001).

From the findings addressing factors associated with neonatal mortality, variations occurred in the proportion of neonatal deaths (the outcome variable) in the counties, with Nairobi being the highest and Vihiga the lowest. This could be attributed to factors such as accessibility to MCH services, socioeconomic status, and cultural factors.

Upon controlling for individual- and community-level factors, neonates born to women who had never been married had lower odds of neonatal mortality (AOR=0.07; 95% CI 0.01–0.42) compared with those born to married women. This finding could be attributed to the fact that being single is more prevalent among young mothers who are more likely to be under the care of their parents and therefore better prepared for pregnancy (Ramaiya, et al., 2014). Kenya has also recorded high prevalence of teenage pregnancy (54.6%) in the East African region, with more than 50 percent being unmarried (Worku, Tessema, Teshale, Tesema, & Yeshaw, 2021).

Neonates born to women from the medium wealth quintile were 69 percent less likely (95% CI 0.11–0.89) to experience death compared with those born to women from the poorest wealth quintile. This could be attributed to the fact that financially stable women can access quality healthcare during pregnancy compared with those who are not (Ashish, et al., 2020). Other, unmeasured risk factors, that are correlated with poverty could also be a contributing reason.

Neonates born to women who had singleton pregnancies had lower odds (AOR=0.13; 95% CI 0.04–0.49) of neonatal mortality compared with those born to women who had multifetal gestation (twins or more). Studies have found that multifetal gestations put a neonate at high risk of mortality compared with a singleton birth (Tesema & Worku, 2021).

Neonates born to women whose most recent birth was the second to fourth child (95% CI 0.13–0.56) had lower odds of neonatal mortality compared with those whose mothers most recent birth was the first child. Women who have had more than one birth have more experience in terms of recognizing danger signs and being more prepared for pregnancy compared with primigravida women. Similarly, women who have had poor pregnancy outcomes before may be less likely to conceive again. Studies from Ethiopia had similar findings (Tesema & Worku, 2021).

From our findings, neonates whose mothers reported having initiated breastfeeding immediately after delivery (AOR=0.13; 95% CI 0.03–0.54) or within 24 hours (AOR=0.14; 95% CI 0.03–0.57) had lower odds of neonatal mortality compared with those whose mothers reported initiating breastfeeding after 24 hours, which has been reported in other studies in Kenya (Imbo, Kamau-Mbuthia & Ngotho, 2019). It is also worth noting that children born with complications are not able to start breastfeeding right away, thus increasing their risk of morbidity and mortality.

Compared with neonates whose mothers did not attend ANC, those who attended more than four visits were 90 percent less likely (95% CI 0.02–0.82) to have had a neonatal death. ANC is an important determinant of mortality. The more ANC visits a woman has reduces their risk of mortality (Zaw, et al., 2019; Imbo, et al., 2021; Tesema & Worku, 2021; Machio, 2018; Imbo, et al., 2019).

The bivariate analysis showed lower odds of neonatal mortality among babies born to women who delivered at health facilities, which underscores the importance of skilled deliveries and facility births (Zaw, et al., 2019; Imbo, et al., 2019; Machio, 2018). Neonates born to women residing in Nakuru (AOR=5.06; 95% CI (1.61–15.84) had higher odds of neonatal mortality compared with those born to women residing in Nairobi county.

Conclusion and Recommendations

This secondary analysis revealed the limited amount of data on neonatal mortality at the county level. Of the 15 sources available, only two were used for analysis as the others did not provide birth outcomes data disaggregated by month. The KHIS data were unique because they provided disaggregated estimates and projections of neonatal mortality in the nine counties—estimates that were county-specific and could be used in project implementation. This analysis also provided a comparison of KHIS and KDHS estimates, thereby indicating the potential for improvement in reporting KHIS data and possibly creating avenues for using KDHS data to inform KHIS data and support programming activities. KDHS data were deemed more accurate as they used a robust methodology for estimating NMR and, in most cases, provided higher estimates of neonatal mortality. KDHS data were also less likely to have errors because they employed enumerators who were trained at one point in time, whereas KHIS data entry is done at the facility level with different people at different times. If it were reliable, KHIS has the advantage of providing real-time data that can be aggregated and collected monthly from all 47 counties in Kenya. There is a need to triangulate these data with Civil Registration and Vital Statistics (CRVS) data to support case-based management for maternal health.

The analysis of factors associated with neonatal mortality across the counties also provides opportunities for tailored interventions and scaling up of program activities to improve neonatal mortality indicators in the counties to reduce the NMR. The methods of analysis applied in this project can be replicated by other counties in Kenya and countries in contexts with similar sources of data, which is a key strength. A key limitation was the existence of missing data in some observations that were included as a category in the analysis, which has an impact on the interpretation.

NMRs remain high and projections show trends that remain constant over time. There is a need to enhance reporting mechanisms to improve the KHIS data and ensure more accurate estimates of NMR. There is also the need to put measures in place to support data availability in the KHIS even when there are shocks in the health system, for example, in the event of healthcare worker strikes and election uncertainties. Because KHIS data are reported monthly, there is a need to explore ways of using the data being collected to support decision making and program activities at the county level.

For the projected estimates with targeted initiatives, the trends improve or remain constant over time. Evidence from counties that have collaborated with development partners has shown improved NMR rates over time, which should be strengthened and replicated in other counties.

Factors associated with neonatal mortality showed similarity with known risk factors from studies in similar settings, even at the county level. Initiatives to support women to attend ANC and skilled birth attendance are key to reducing neonatal mortality. There is a need to improve services provided during ANC visits because more women are attending clinics. It is also important to address poverty as a risk factor to ensure that women have enough support for their pregnancy and delivery. Initiatives should be tailored to primigravida women to ensure that they have safe and successful deliveries. Continued efforts for exclusive breastfeeding and postnatal care initiatives need to be enhanced in all counties. There is a need to provide support for counties to ensure enough facilities and a skilled workforce to manage high-risk births, complications, and high-volume deliveries.

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Appendix A. Data Sources

Civil registration and vital statistics
Global Network's Maternal Newborn Health Registry
Kenya Demographic and Health Survey 2014
Kenya Harmonized Health Facility Assessment 2018/19
Kenya Integrated Household Budget Survey
Kenya Malaria Indicator Survey 2020
Kenya Ministry of Health DHIS2 (KHIS)
Kenya Population and Housing Census 2019
Kenya Population-Based HIV Impact Assessment 2018
Performance Monitoring for Action (International Centre for Reproductive Health Kenya)
UNICEF data warehouse
UNICEF: Multiple Indicator Survey (Kakamega) 2013/14
UNICEF: Multiple Indicator Survey (Turkana) 2013/14
World Bank (United Nations Interagency Group for Child Mortality Estimation)
World Health Organization Global Health Observatory

Appendix B. Point Forecast Estimates for the Nine Counties

Homa Bay County

Period	Point Forecast	Low 100	High 100
2022 Q1	6.506	4.905	8.994
2022 Q2	6.851	5.161	12.222
2022 Q3	6.125	4.510	7.984
2022 Q4	6.634	4.849	11.951
2023 Q1	6.511	4.902	8.994
2023 Q2	6.860	4.815	12.594
2023 Q3	6.129	4.510	7.984
2023 Q4	6.641	4.643	11.951
2024 Q1	6.516	4.556	8.994
2024 Q2	6.869	4.470	12.977
2024 Q3	6.134	4.383	7.984
2024 Q4	6.648	4.297	11.951
2025 Q1	6.522	4.211	8.994
2025 Q2	6.878	4.124	13.372
2025 Q3	6.138	4.038	7.984
2025 Q4	6.656	3.951	11.951

Kisumu County

Period	**Point Forecast**	**Low 100**	**High 100**
2022 Q1	15.886	14.221	19.019
2022 Q2	15.884	12.844	19.019
2022 Q3	15.904	11.637	19.019
2022 Q4	16.005	12.829	19.019
2023 Q1	16.159	14.221	19.789
2023 Q2	16.157	12.844	20.720
2023 Q3	16.178	11.637	21.650
2023 Q4	16.278	12.829	22.581
2024 Q1	16.432	14.221	23.512
2024 Q2	16.431	12.844	24.442
2024 Q3	16.451	11.637	25.373
2024 Q4	16.551	12.829	26.304
2025 Q1	16.705	14.221	27.234
2025 Q2	16.704	12.844	28.165
2025 Q3	16.724	11.637	29.095
2025 Q4	16.824	12.829	30.026

Kakamega County

Period	**Point Forecast**	**Low 100**	**High 100**
2022 Q1	11.407	7.712	13.427
2022 Q2	11.596	10.089	13.946
2022 Q3	11.482	8.637	13.782
2022 Q4	11.390	9.261	13.427
2023 Q1	11.407	7.712	13.427
2023 Q2	11.596	10.089	13.946
2023 Q3	11.482	8.637	13.782
2023 Q4	11.390	9.261	13.427
2024 Q1	11.407	7.712	13.427
2024 Q2	11.596	10.089	13.946
2024 Q3	11.482	8.637	13.782
2024 Q4	11.390	9.261	13.427
2025 Q1	11.407	7.712	13.427
2025 Q2	11.596	10.089	13.946
2025 Q3	11.482	8.637	13.782
2025 Q4	11.390	9.261	13.427

Kwale County

Period	**Point Forecast**	**Low 100**	**High 100**
2022 Q1	*8.361*	7.302	12.405
2022 Q2	*7.632*	5.850	10.325
2022 Q3	*7.945*	6.360	10.325
2022 Q4	*7.886*	6.465	10.489
2023 Q1	*8.361*	7.302	12.405
2023 Q2	*7.632*	5.850	10.325
2023 Q3	*7.945*	6.360	10.325
2023 Q4	*7.886*	6.465	10.489
2024 Q1	*8.361*	7.302	12.405
2024 Q2	*7.632*	5.850	10.325
2024 Q3	*7.945*	6.360	10.325
2024 Q4	*7.886*	6.465	10.489
2025 Q1	*8.361*	7.302	12.405
2025 Q2	*7.632*	5.850	10.325
2025 Q3	*7.945*	6.360	10.325
2025 Q4	*7.886*	6.465	10.489

Nakuru County

Period	Point Forecast	Low 100	High 100
2022 Q1	8.425	6.870	10.795
2022 Q2	8.273	6.870	10.008
2022 Q3	8.177	6.870	10.008
2022 Q4	8.156	6.644	11.871
2023 Q1	8.001	6.359	10.795
2023 Q2	7.850	6.075	10.008
2023 Q3	7.754	5.790	10.008
2023 Q4	7.734	5.506	11.871
2024 Q1	7.579	5.222	10.795
2024 Q2	7.429	4.937	10.008
2024 Q3	7.333	4.653	10.008
2024 Q4	7.314	4.368	11.871
2025 Q1	7.159	4.084	10.795
2025 Q2	7.009	3.799	10.008
2025 Q3	6.914	3.515	10.008
2025 Q4	6.895	3.230	11.871

Nairobi County

Period	Point Forecast	Low 100	High 100
2022 Q1	13.580	11.607	15.648
2022 Q2	13.487	11.607	14.933
2022 Q3	13.626	11.607	16.955
2022 Q4	13.511	11.607	14.933
2023 Q1	13.580	11.607	15.648
2023 Q2	13.487	11.607	14.933
2023 Q3	13.626	11.607	16.955
2023 Q4	13.511	11.607	14.933
2024 Q1	13.580	11.607	15.648
2024 Q2	13.487	11.607	14.933
2024 Q3	13.626	11.607	16.955
2024 Q4	13.511	11.607	14.933
2025 Q1	13.580	11.607	15.648
2025 Q2	13.487	11.607	14.933
2025 Q3	13.626	11.607	16.955
2025 Q4	13.5114	11.6071	14.9325

Turkana County

Period	Point Forecast	Low 100	High 100
2022 Q1	7.362	4.552	10.237
2022 Q2	7.190	5.555	10.212
2022 Q3	6.917	5.192	10.190
2022 Q4	6.756	4.829	10.169
2023 Q1	6.434	4.466	10.150
2023 Q2	6.264	4.103	10.133
2023 Q3	5.994	3.741	10.117
2023 Q4	5.836	3.378	10.102
2024 Q1	5.515	3.015	10.089
2024 Q2	5.348	2.652	10.077
2024 Q3	5.079	2.289	10.066
2024 Q4	4.923	1.926	10.056
2025 Q1	4.604	1.563	10.047
2025 Q2	4.438	1.189	10.038
2025 Q3	4.172	0.803	10.031
2025 Q4	4.017	0.418	10.024

Trans-Nzoia County

Period	Point Forecast	Low 100	High 100
2022 Q1	14.925	12.374	24.747
2022 Q2	15.053	12.374	25.608
2022 Q3	15.036	12.374	26.544
2022 Q4	15.152	12.374	27.911
2023 Q1	15.259	12.374	29.278
2023 Q2	15.385	12.374	30.646
2023 Q3	15.367	12.374	32.013
2023 Q4	15.481	12.374	33.380
2024 Q1	15.587	12.374	34.747
2024 Q2	15.712	12.374	36.114
2024 Q3	15.693	12.374	37.482
2024 Q4	15.806	12.374	38.849
2025 Q1	15.912	12.374	40.216
2025 Q2	16.037	12.374	41.583
2025 Q3	16.017	12.374	42.950
2025 Q4	16.130	12.374	44.318

Vihiga County

Period	Point Forecast	Low 100	High 100
2022 Q1	6.154	3.953	8.163
2022 Q2	6.816	5.039	9.202
2022 Q3	6.119	3.855	7.345
2022 Q4	5.529	3.434	6.606
2023 Q1	6.153	3.953	8.163
2023 Q2	6.815	5.039	9.204
2023 Q3	6.118	3.855	7.347
2023 Q4	5.528	3.434	6.606
2024 Q1	6.152	3.953	8.163
2024 Q2	6.814	4.855	9.207
2024 Q3	6.117	3.855	7.349
2024 Q4	5.527	3.435	6.606
2025 Q1	5.152	3.953	8.163
2025 Q2	6.813	4.660	9.210
2025 Q3	6.116	3.855	7.352
2025 Q4	5.5255	3.4356	6.6058

Appendix C. Bivariate Analysis of Factors Associated with Neonatal Mortality in the Nine Counties in Kenya

Characteristic	Odds Ratio	95% Confidence Interval	P-value
Marital Status			
Married	1		
Never married	0.16	0.04–0.63	0.009
Maternal education status			
No education	1		
Primary	0.53	0.22–1.28	0.158
Secondary and above	0.84	0.30–2.37	0.745
Wealth Index			
Poor (poorer & poorest)	1		
Medium	0.44	0.20–0.97	0.041
Rich (richer & richest)	0.75	0.32–1.77	0.505
Mother's smoking status			
Yes	1		
No	0.01	0.00–0.49	0.021
Other	0.0	0.00–0.52	0.022
Mode of delivery			
Caesarean section	1		
Vaginal	0.27	0.07–1.10	0.068
Preceding birth interval			
<2 years	1		
2–4 years	1.14	0.53–2.47	0.733
>4 years	0.91	0.40–2.06	0.811
Don’t know	3.96	1.92–8.15	0.000
Type of birth			
Multiple	1		
Single	0.09	0.02–0.35	0.000
Birth order			
First	1		
2 to 4	0.39	0.23–0.66	0.001
≥5	0.49	0.22–1.07	0.072

Characteristic	Odds Ratio	95% Confidence Interval	P-value
Initiation of breastfeeding			
>24 hours	1		
Immediately	0.09	0.02–0.52	0.007
1–24 hrs	0.16	0.03–0.87	0.034
Birth attendant			
Unskilled	1		
Skilled	0.57	0.24–1.32	0.185
Number of ANC visits			
No ANC visit	1		
1–3	0.46	0.09–2.41	0.356
≥4	0.13	0.02–0.82	0.030
Don’t know	1.36	0.29–6.51	0.697
ANC timing			
Third trimester	1		
First trimester	0.3	0.06–1.80	0.2
Second trimester	0.9	0.24–3.63	0.911
Don’t know	4.8	1.09–20.95	0.038
Birth weight			
Low birth weight	1		
Normal	0.52	0.08–3.63	0.511
Above normal	1.31	0.09–18.48	0.842
Not weighed/other	1.72	0.25–11.80	0.58
PNC attendant			
Unskilled	1		
Skilled	0.18	0.01–2.77	0.216
Other	1.74	0.16–19.36	0.652
Place of delivery			
Home	1		
Health facility	0.59	0.25–1.37	0.220
Other	2.28	0.48–10.88	0.300
County			
Nairobi	1		
Kwale	2.02	0.65–6.24	0.221

Characteristic	Odds Ratio	95% Confidence Interval	P-value
Kisumu	0.40	0.12–1.33	0.135
Homa Bay	0.71	0.24–2.04	0.519
Turkana	0.84	0.29–2.42	0.748
Trans-Nzoia	0.81	0.28–2.30	0.686
Nakuru	2.77	1.08–7.11	0.035
Kakamega	0.10	0.01–0.82	0.032
Vihiga	1.05	0.36–3.07	0.932
Community hospital delivery			
Low	1		
High	2.90	0.92–9.12	0.069

Appendix D. Multilevel Model Fit Parameters

Random effect parameters	Null model	Model 2 (Individual-level variables)	Model 3 (Community-level variables)	Model 4 (Individual- and community-level variables)
Cluster level variance (Standard Error)	0.338 (0.25)	0.224 (0.25)	0.218 (0.23)	0.195 (0.25)
Intra-class correlation coefficient	9.32%	6.38%	6.22%	5.53%
Median odds ratio	1.737	1.568	1.558	1.5163
Proportional change in variance	ref	33.73%	35.50%	42.31%
Model fit statistics				
Log-likelihood	-527.22	-457.99	-520.14	-456.84
Deviance	1054.44	915.98	1040.28	913.68
Akaike Information Criterion	1058.443	973.99	1062.28	973.68
Bayesian information criterion	1071.212	1159.01	1132.518	1165.08
Mean Variance Inflation Factor				7.87

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