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MODELLING CHILDHOOD MORTALITY PATTERNS IN NIGERIA: INSIGHTS FROM 2024 NATIONAL SURVEY DATA

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ABSTRACT

Childhood mortality remains a major public health concern in Nigeria, with persistent regional disparities and uneven progress in child survival outcomes. This study examines the determinants and spatial distribution of childhood mortality using data from the 2024 national demographic survey. A Negative-Binomial Zero-inflated geo-additive regression modelling approach was applied to account for overdispersion, excess zero counts, nonlinear relationships, and spatial dependence in child death outcomes. Vital socioeconomic, demographic, and healthcare-related predictors were included in the analysis. The results show significantly higher childhood mortality risk in the North-West and North-East, as well as in selected southern states, compared with the North-Central region. Also, higher maternal education, richer household, health insurance enrolment, modern transportation to health facilities, and urban place of residence are associated with increased child survival at the 5% significance level. Moreover, the age of the mother, age at first birth, and parity show nonlinear effects, suggesting complex reproductive health patterns. Spatial clustering of mortality is evident, especially in northern states. These findings suggest that reducing childhood mortality in Nigeria requires coordinated efforts that address socioeconomic inequalities, improve access to quality healthcare, and target high-risk regions. Policies promoting female education, expanded health insurance coverage, and improved healthcare infrastructure are recommended.

Keywords: Zero-inflation, Overdispersion, NDHS 2024, Childhood Mortality, Nigeria

INTRODUCTION

High levels of under-five mortality remain a persistent global public health challenge, with a disproportionate burden borne by developing countries, including Nigeria. Globally, an estimated 4.8 million children under the age of five died in 2023, with the majority of these deaths occurring in countries such as Nigeria, the Democratic Republic of the Congo, and India, as reported by the World Health Organization (2023). This pattern underscores the continued vulnerability of children in low- and middle-income countries and highlights the urgency of addressing the structural and systemic drivers of child mortality.

A comparison of childhood mortality indicators from the 2018 and 2024 Nigeria Demographic and Health Surveys (NDHS) reveals mixed progress, particularly in the context of disruptions associated with the COVID-19 pandemic. While neonatal mortality declined marginally from 41 to 39 deaths per 1,000 live births, infant mortality increased from 63 to 67, and under-five mortality rose substantially from 110 to 132 deaths per 1,000 live births. Despite modest improvements in neonatal outcomes, all three indicators remain significantly above the benchmarks recommended by the World Health Organization, i.e. 12, 20, and 25 deaths per 1,000 live births for neonatal, infant, and under-five mortality, respectively. These trends suggest that recent gains have been uneven and insufficient to meet global targets, thereby necessitating renewed policy attention and more robust analytical approaches.

Childhood mortality is inherently multidimensional, shaped by a complex interplay of socioeconomic, demographic, and environmental factors. In Nigeria, persistent inequalities in income distribution, maternal education, and access to quality healthcare services continue to influence child survival outcomes. Children from socioeconomically disadvantaged households are more likely to face malnutrition, poor access to safe water and sanitation, and limited utilization of healthcare services, all of which elevate mortality risks (Ezeh et al., 2022; UNICEF, 2024). In addition, maternal characteristics like age, education, and health-seeking behaviour play a critical role, as more educated mothers are better positioned to adopt appropriate childcare practices and effectively utilize available health services.

Beyond individual and household-level determinants, geographic and spatial disparities constitute a defining feature of childhood mortality patterns in Nigeria. Marked differences persist between rural and urban areas, as well as across regions, particularly between the northern and southern parts of the country. These disparities are often driven by variations in healthcare infrastructure, availability of skilled health personnel, cultural norms, and levels of socioeconomic development. The presence of spatial clustering in mortality outcomes suggests that children in certain locations are systematically disadvantaged, thereby underscoring the importance of incorporating spatial analytical frameworks to better capture and address these inequalities.

Furthermore, recent developments in healthcare financing and service delivery, including the expansion of health insurance schemes and improvements in transportation systems have introduced new dimensions to the study of child survival. Access to health insurance can reduce financial barriers to healthcare utilization, while the mode of transportation to healthcare facilities can significantly influence the timeliness and quality of care received, particularly in emergency situations. Despite their potential importance, these factors remain underexplored in the context of childhood mortality in Nigeria, representing a critical gap in the empirical literature.

Existing studies on childhood mortality in Nigeria have largely relied on data from the 2013 and 2018 NDHS. However, recent healthcare reforms, economic fluctuations, and the aftermath of the COVID-19 pandemic underscore the need for more up-to-date evidence to capture current dynamics. Moreover, most prior research has applied either spatial models or zero-inflated models independently, depending on the structure of the data. There remains a notable gap in the literature regarding the integration of zero-inflated geo-additive models within a Bayesian framework capable of simultaneously addressing excess zeros, overdispersion, nonlinear relationships, and spatial heterogeneity.

Against this backdrop, this study contributes to the existing body of knowledge by identifying spatial hotspots of childhood mortality in Nigeria using a Bayesian inferential framework that accounts for excess zeros and overdispersion, based on the most recent NDHS data. In addition, the study extends prior research by examining the influence of health insurance coverage and mode of transportation to healthcare facilities as emerging determinants of child survival. By adopting a comprehensive and methodologically robust approach, this study provides deeper insights into the drivers of childhood mortality and offers evidence to inform targeted, data-driven policy interventions aimed at reducing mortality and improving child health outcomes in Nigeria.

MATERIALS AND METHODS

Study Population

The study population comprises 104,557 women aged 15-49 years who were interviewed by the staff of the National Population Commission of Nigeria in the 2024 Nigeria Demographic and Health Survey (See Table 1). The Commission typically collects nationally representative data on the health and demographic characteristics of Nigerians, encompassing all 36 states and the Federal Capital Territory of Nigeria.

Inclusion and Exclusion Criteria

The analysis in this study is restricted to women of reproductive age (15-49 years), irrespective of whether they had lost a child or not. However, observations with missing or inconsistent information on key variables were excluded from the analysis.

Sampling Technique

A random sample of 26,000 women (approximately one-quarter of the study population) was selected without replacement for analysis (See Table 1). The subsampling was necessary to balance the computational demands of Bayesian Markov Chain Monte Carlo estimation with model efficiency.

Ethical Considerations

This study is based on secondary data and does not involve direct participation of human subjects by the author. The dataset was obtained upon registration from the DHS Program (https://www.dhsprogram.com). All data are anonymized and publicly available; therefore, no additional ethical approval was required.

Data Analysis

Dependent Variable

The dependent variable is the total number of children aged 0 – 59 months (under five years) reported by each mother to have died before the survey, regardless of age at death. This measure serves as a robust proxy for childhood mortality in the Nigerian context, where mortality is heavily concentrated among children under five. Both the population and sample data exhibit overdispersion, as the variance exceeds the mean, and contain a high proportion of zero child deaths (approximately 64%), indicating excess zeros (see Table 1).

Table 1: Description of Dependent Variable (y_i)

Population data (N = 104,557); mean = 0.72, variance = 1.58												
y_i	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Freq.	66732	18652	9643	4697	2561	1275	515	290	85	71	24	12
%	63.82	17.84	9.22	4.49	2.45	1.22	0.49	0.28	0.08	0.07	0.02	0.01
Sample data (n = 26,000); mean = 0.73, variance = 1.60												
y_i	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Freq.	16598	4579	2434	1152	657	327	128	76	25	16	8	0
%	63.84	17.61	9.36	4.43	2.53	1.26	0.49	0.29	0.10	0.06	0.03	0.00

Source: Author's Computation, 2026

Predictors

The covariates of childhood mortality derived from the 2024 NDHS capture key dimensions, including biological and social risk factors, socioeconomic status and living conditions, access to healthcare, geographic location, and fertility behaviour (Table 2).

Table 2: Description of Predictors

Predictor of childhood mortality	Factor	Factor Levels
Maternal Characteristics	Mother's age	Nil
	Mother's age at first birth	Nil
	Mother's highest educational level	None, Primary, Secondary, Higher (Ref.)
Household economic status	Wealth index	Poorest, Poorer, Richer, Richest, Middle (Ref.)
	Type of place of residence	Urban, Rural (Ref.)
Health access	Covered by health insurance	Yes, No (Ref.)
	Distance to health facility	
	Mode of transport to the nearest health facility	
Location	De-jure region of residence	North-West, North-East, North-Central (Ref.), South-East, South-South, South-West
Fertility behaviour	Total children ever born	Nil

Source: NDHS Report, 2025

Model Formulation

Let Y_i denote a non-negative count variable representing the number of child deaths reported by the i-th woman in the 2024 NDHS, for *i* = 1, 2,..., n. The response variable is modelled as a function of continuous, categorical, and spatial covariates within the framework of structured additive regression models (Fahrmeir & Lang, 2001; Brezger & Lang, 2006). The conditional distribution of Y_i is specified as follows:

$Y_i|\mu_i \sim Poisson\ (\mu_i)$

with canonical log-link:

$$\log(\mu_i) = \eta_i \quad (1)$$

To simultaneously estimate linear, nonlinear, and spatial effects within a Bayesian framework, the structured additive predictor is defined as proposed by Fahrmeir et al. (2013):

$$\eta_i = \beta_0 + \sum_{k=1}^{p} \beta_k Z_{ik} + \sum_{j=1}^{3} f_j(X_{ij}) + f_{spatial}(s_i) \quad (2)$$

where:

Z_{ik}= categorical covariates with regression coefficients

$f_j(\cdot)$ = smooth nonlinear functions of continuous covariates

$f_{spatial}(s_i)$ = spatial effects for State s_i

The three metrical predictors, namely respondent's current age, age at first birth, and total children ever born, were modelled using penalized splines (P-splines), with each smooth function expressed as:

$$f_j(x) = \sum_{m=1}^{k} \gamma_{jm}\, B_m(x) \quad (3)$$

where:

$B_m(x)$ = B-splines basis functions

γ_{jm} = spline coefficients

k = number of knots

First-order random walk priors were assumed for the metrical predictors to ensure smoothness as follows:

$$\gamma_{jm} = \gamma_{jm-1} + u_{jm}, \quad u_{jm} \sim N\left(0, \tau_j^{-1}\right) \quad (4)$$

where $\tau_j$is the smoothing parameter that controls the degree of penalization

The application of P-splines on metrical predictors allows flexible modelling (Lang & Brezger, 2004).

The spatial modelling was achieved by incorporating a Gaussian Markov Random Field (GMRF) prior with geo-spline basis into equation (2) to account for spatial mortality autocorrelation, which reflects shared socio-economic contexts, while also reducing bias from unmeasured spatially structured confounders (Besag, York & Mollie, 1991). A conditional autoregressive (CAR) prior was specified as:

$$f_{spatial}(s)/f_{spatial}(-s) \sim N\left(\frac{1}{N_s}\sum_{r\sim s} f_{spatial}(r), \frac{1}{N_s\tau_s}\right)$$

$r \sim s$ = neighbouring states

N_s = number of neighbours of state s

τ_s = precision parameter

To address issues of overdispersion and excess zeros in the child mortality data, the following alternative distributions were modelled:

(a) Negative-Binomial Model

$Y_i \sim NB(\mu_i, k)$

where k = overdispersion parameter (Hilbe, 2011)

(b) Zero-inflated Negative-Binomial (ZINB) Model

The PMF of the ZINB model is:

$$P(Y_i) = \begin{cases} \pi_i + (1-\pi_i);\ Y_i = 0 \\ \\ (1-\pi_i); \qquad Y_i > 0 \end{cases}$$

where $\pi_i = probability\ of\ zero\ child\ loss$

The ZINB model assumes a combination of a structural zero process and a count-generating negative-binomial process.

Lastly, estimation of model parameters was achieved through the Markov Chain Monte Carlo (MCMC) of 12,000 iterations. Given that θ denotes a vector of all parameters, the posterior inference is estimated as:

$p(\theta/y) \propto L(y/\theta)p(\theta)$

where:

$L(y/\theta)$ = likelihood

$p(\theta)$ = prior distribution

The estimated posterior means represent parameter point estimates, while 95% credible intervals were used to determine the significance or otherwise of model parameters. The "R2BayesX" package (version 0.3-1), developed by Umlauf et al. (2015), was employed to perform geo-additive regression modelling and to generate plots of spatial effects and nonlinear relationships of continuous predictors.

RESULTS AND DISCUSSION

Results

The effects of categorical predictors, metrical covariates, and spatial variables on childhood mortality are presented as follows:

Table 3: Effects of categorical predictors on childhood mortality

Predictor	Category	Posterior Mean (β)	Incidence Rate (e^{β})	95% Credible Interval for β Lower	Upper	Significant (5%)
	Intercept	-0.0837	0.9197	-0.4684	0.2151	No
Region of residence (Ref.: North-Central)	North-East	0.2470	1.2802	0.1969	0.3027	Yes
	North-West	0.3087	1.3617	0.2612	0.3598	Yes
	South-East	0.1233	1.1312	0.0525	0.1954	Yes
	South-South	0.1131	1.1197	0.0326	0.1938	Yes
	South-West	-0.0178	0.9824	-0.1139	0.0806	No
	Not a de jure resident	0.0507	1.0520	-0.2524	0.3372	No
Type of residence (Ref.: Rural)	Urban	-0.0749	0.9278	-0.1160	-0.0369	Yes
Wealth index (Ref.: Middle)	Poorer	0.2440	1.2763	0.1995	0.2879	Yes
	Poorest	0.2274	1.2553	0.1830	0.2762	Yes
	Richer	-0.0617	0.9402	-0.1212	-0.0053	Yes
	Richest	0.1068	1.1127	0.0350	0.1817	Yes
Mother's highest education level (Ref.: Higher)	No education	0.1387	1.1488	0.0333	0.2479	Yes
	Primary	0.2066	1.2295	0.1080	0.3169	Yes
	Secondary	0.1801	1.1973	0.0807	0.2780	Yes
Covered by health insurance (Ref.: No)	Yes	-0.3488	0.7055	-0.4793	-0.2190	Yes

Predictor	**Category**	**Posterior Mean (β)**	**Incidence Rate (e^{β})**	**95% Credible Interval for β Lower**	**Upper**	**Significant (5%)**
Distance to health facility (Ref.: Big problem)	Not a big problem	0.0337	1.0343	0.0033	0.0640	Yes
Mode of transportation to the nearest healthcare (Ref.: Animal-drawn cart)	Bicycle	-0.0056	0.9944	-0.2747	0.3588	No
	Boat with motor	-0.9960	0.3693	-1.5973	-0.3776	Yes
	Boat without a motor	0.0755	1.0784	-0.2900	0.5111	No
	Car/Truck	-0.4139	0.6610	-0.6798	-0.0608	Yes
	Tricycle	0.2123	1.2365	-0.1846	0.6407	No
	Motorcycle	-0.1377	0.8714	-0.3855	0.1971	No
	Public Bus	-0.1698	0.8438	-0.4257	0.1596	No
	Walking	-0.1155	0.8909	-0.3597	0.2234	No
	Others	0.7339	2.0832	-0.3960	1.6769	No

As shown in Table 3, the number of child deaths is significantly higher in several regions compared to the *North-Central* zone. Specifically, the *North-West* (36.17%), *North-East* (28.02%), *South-East* (13.12%), and *South-South* (11.97%) regions exhibit significantly higher child mortality. In contrast, the *South-West* records a 1.76% lower rate relative to *North-Central*, although this difference is not statistically significant.

Place of residence also has a significant effect, with *urban* areas exhibiting a 7.22% lower level of child mortality compared to *rural* areas. Household wealth status is also an important determinant of child mortality. Compared with women in the middle wealth category, child mortality is higher among those in the *poorer*, *poorest*, and *richest* households (27.63%, 25.53%, and 11.27%, respectively). In contrast, women in the *richer* category experience a 5.98% reduction.

Maternal education is strongly associated with child mortality outcomes. Women with *no education*, *primary education*, and *secondary education* have 14.88%, 22.95%, and 19.73% higher child mortality, respectively, compared to women with *higher education*. Access to healthcare also plays a critical role, as women covered by health insurance experience a significant 29.45% reduction in child mortality.

Unexpectedly, women who reported that distance to a health facility is not a major problem show a 3.43% higher level of child mortality compared to those who perceive it as a barrier. Reliance on boats and tricycles is associated with higher child mortality compared to more efficient transportation modes. Conversely, the use of motorized and more accessible transport options, including *motorized boats*, *cars/trucks*, *motorcycles*, *walking*, *public buses*, and *bicycles*, is associated with reductions in child mortality relative to *animal-drawn carts*.

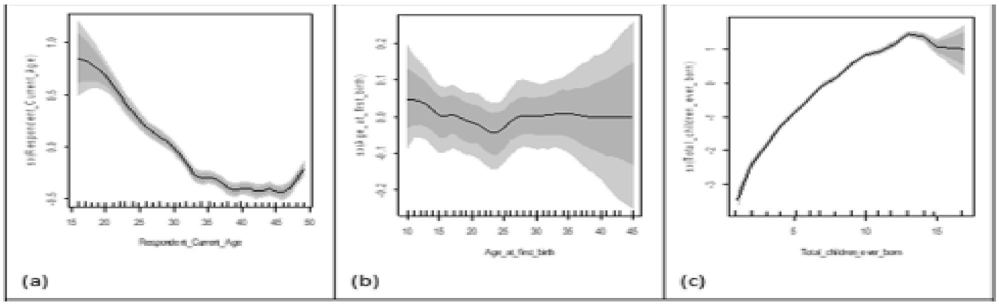

Figure 1: Effects of (a) Women's Current Age; (b) Women's Age at First Birth; and (c) Total Children ever Born, on Childhood Mortality in Nigeria

Figures 1a-1c illustrate the nonlinear effects of key continuous variables. Child mortality generally decreases with maternal age but increases slightly after age 45. Age at first birth shows a declining effect on child mortality up to approximately 25 years, after which the risk begins to rise. Additionally, higher parity is associated with increased child mortality, although this trend declines slightly beyond 12 children.

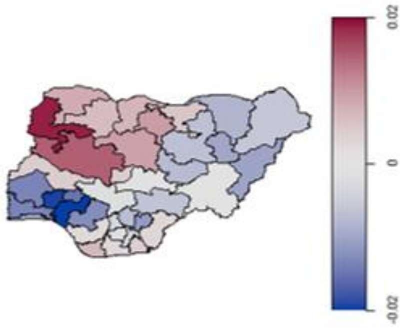

Figure 2: Spatial Distribution of Childhood Mortality in Nigeria

In Figure 2, higher child mortality is observed in Kebbi State, Niger State, Kaduna State, Kano State, Katsina State, Jigawa State, Sokoto State, and Bayelsa State, with the highest burden recorded in Kebbi State. In contrast, relatively lower mortality levels are observed across most states in the South-West and parts of the South-East.

Discussion

The findings reaffirm that childhood mortality remains a critical public health concern, driven by a complex interplay of socioeconomic, demographic, healthcare, and spatial factors. This multidimensional nature aligns with broader evidence from low- and middle-income countries, where child survival outcomes are shaped by both individual and contextual determinants (World Health Organization, 2023; United Nations Children's Fund, 2024).

One of the most striking findings is the persistence of pronounced regional disparities in childhood mortality. The significantly elevated risks observed in the North-West and North-East regions are consistent with previous national and sub-national studies, indicating that northern Nigeria continues to experience a disproportionate burden of child deaths (Adewuyi et al., 2023; National Population Commission Nigeria & ICF, 2019). These disparities are often linked to entrenched poverty, limited access to healthcare services, and sociocultural constraints affecting maternal and child health utilization. Furthermore, ongoing insecurity and fragile health systems in these regions exacerbate vulnerabilities and restrict service delivery (World Bank, 2024). This pattern is consistent with global evidence that geographic inequalities in healthcare access and living conditions continue to be major determinants of child mortality (WHO, 2023).

Socioeconomic status emerges as a fundamental determinant of childhood mortality. The higher risks observed among children from poorer households underscore the persistent role of economic deprivation in shaping survival outcomes. This result is consistent with recent evidence showing that children from low-income households are more likely to experience malnutrition, poor access to safe water and sanitation, and limited availability of quality healthcare services (Ezeh et al., 2022; UNICEF, 2024). The observed wealth gradient reinforces the argument that poverty reduction is central to improving child health outcomes. However, the non-linear relationship across wealth categories suggests that income alone does not fully explain disparities, as factors such as urban crowding and inequities in service quality may also contribute (Fotso & Kuate-Defo, 2005).

Maternal education is identified as a strong protective factor against childhood mortality. Children of mothers with lower educational attainment experience significantly higher mortality risks compared to those whose mothers have higher levels of education. This is consistent with a growing body of empirical evidence showing that maternal education enhances health literacy, promotes appropriate childcare practices, and increases the utilization of healthcare services (Babalola & Fatusi, 2009; WHO, 2023). Educated women are more likely to access antenatal and postnatal care, adhere to immunization schedules, and adopt improved nutritional practices, thereby reducing the likelihood of child mortality. This reinforces the critical role of female education as a long-term strategy for improving population health outcomes.

Access to healthcare services also plays a crucial role in determining childhood survival. The observed reduction in mortality among women covered by health insurance highlights the importance of financial risk protection in facilitating healthcare utilization. This finding supports existing evidence that health insurance reduces out-of-pocket expenditure and improves access to essential maternal and child health services (Aregbeshola & Khan, 2022; World Bank, 2024). Given that Nigeria's healthcare system remains heavily dependent on out-of-pocket payments, expanding health insurance coverage, particularly among vulnerable populations, could significantly reduce preventable child deaths.

Interestingly, the finding that perceived distance to healthcare facilities does not consistently translate into lower mortality suggests that physical proximity alone is insufficient to ensure improved health outcomes. This indicates that other dimensions of healthcare access, such as service quality, availability of skilled personnel, affordability, and cultural acceptability, may be more critical determinants of healthcare utilization. Similar conclusions have been reported in recent literature, emphasizing that improving healthcare outcomes requires a comprehensive, multi-dimensional approach rather than a sole focus on geographic accessibility (Peters et al., 2023).

Transportation to healthcare facilities further highlights structural inequalities in access to care. The association between improved transport options and reduced mortality underscores the importance of timely access to healthcare, particularly during emergencies. Delays in reaching health facilities, often conceptualized within the "three delays model," remain a significant contributor to preventable child deaths in developing countries (WHO, 2023). These findings suggest that strengthening transport infrastructure and emergency referral systems could play a critical role in improving child survival outcomes.

The decline in mortality risk with increasing maternal age up to a certain threshold suggests that maternal experience and improved socioeconomic stability are associated with higher child survival. However, increased risks at older ages point to biological complications associated with advanced maternal age. Similarly, early childbearing is linked to higher mortality risk due to biological immaturity and socioeconomic disadvantage. High parity is also associated with increased risks due to resource dilution and maternal depletion. These findings are consistent with recent demographic and epidemiological studies emphasizing the importance of optimal birth timing and spacing (Cleland et al., 2023; United Nations Population Fund, 2024).

The spatial analysis further reveals clustering of childhood mortality in specific states, particularly in northern Nigeria. This spatial dependence suggests that unobserved contextual factors such as environmental conditions, regional policies, and health system performance play a significant role in shaping mortality outcomes. The presence of spatial autocorrelation highlights the need for geographically targeted interventions rather than uniform national strategies. By incorporating spatial effects within a Bayesian framework, this study provides a more nuanced understanding of how location-specific factors influence child survival.

These findings indicate that childhood mortality in Nigeria is influenced by the interplay of socioeconomic factors, maternal characteristics, and healthcare accessibility, as well as geographic disparities. Addressing these challenges requires integrated, multisectoral interventions that simultaneously tackle poverty, expand educational opportunities, strengthen healthcare systems, and reduce regional disparities. Such an approach is essential for achieving sustainable reductions in child mortality and meeting global development targets.

CONCLUSION

The findings reveal that child mortality remains a significant public health concern, characterized by substantial regional disparities and strong associations with socioeconomic conditions, maternal characteristics, and healthcare access, while also showing that improvements in maternal education, household economic status, and access to healthcare services can substantially enhance child survival outcomes; moreover, the identification of spatial clusters of high mortality highlight the need for geographically targeted interventions, and by incorporating nonlinear and spatial effects within a Bayesian framework, this study offers a more nuanced understanding of mortality patterns and contributes to the existing literature, ultimately emphasizing the importance of evidence-based policies aimed at reducing inequalities and strengthening healthcare systems to achieve meaningful reductions in childhood mortality in Nigeria, including targeted regional interventions in high-burden areas, particularly in northern Nigeria, expansion of health insurance coverage, increased investment in maternal education, improvement of rural healthcare infrastructure, enhancement of transport and emergency referral systems, promotion of family planning and reproductive health services, and the adoption of data-driven, spatially informed policy design.

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