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# Identifying Factors Contributing to Under-Five Mortality in Nigeria

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**Abstract**

The under-5 mortality rate (U5MR) is the probability that a child born in a specified year will die before turning 5 years of age. U5MR is still high in Nigeria. Therefore, this study aimed to identify factors contributing to under-5 mortality in Nigeria. The data used in this study were from the 2018 NDHS, encompassing 2013–2018. The methods of analysis used for this study were frequency, percentage, and Zero Inflated Negative Binomial (ZINB) regression. Data were analyzed using R programming v.4.1.2 and $p < 0.05$ was considered to be statistically significant. The result showed 35.4% under-5 mortality out of the 33,924 infant mortality sample data that were collected. The findings revealed maternal age, regions (North East and North West), maternal education (no education), wealth index (poorest households), and size of child at birth (very small birth size) as significant factors associated with under-5 mortality in Nigeria. The results also showed that the odds of under-5 mortality increase as the age of the mother increases. Therefore, the Nigerian government should understand that poverty is not just an economic problem but also a significant factor in health; as a result, the battle against poverty needs to receive the necessary attention.

**Keywords:** Under-5 mortality; World Health Organization; Zero inflated distribution; Risk factors; Nigeria.

## Introduction

The under-5 mortality rate (U5MR) is the probability that a child born in a specified year will die before turning 5 years of age, given current age-specific mortality rates. The usual measurement unit is deaths per 1,000 live births (Azuike et al. 2019). According to reports from Nigeria, sub-Saharan Africa, and the rest of the world, U5MR is still high (Adeboye et al. 2010, Okonofua et al. 2016, Yaya et al. 2016). There are significant regional variations in Nigeria's childhood mortality rate, which was 128 deaths per 1000 live births in 2013 (Yaya et al. 2017) and 132 deaths per 1000 live births in 2018 (NPC 2013).

According to a recent estimate of child mortality worldwide, Nigeria had the most significant absolute number (0.858 million) of deaths among children under the age of 5 in 2019 (Ezeh et al. 2022). Despite national and international implementation efforts on the reduction of mortality, Nigeria has yet to reach the Sustainable Development Goals (SDGs) targets of 25 U5MR per 1,000 live births by 2030. The Nigerian healthcare systems have been weakened, especially in rural regions, by inadequate medical facilities, a lack of trained medical personnel, and outdated medical equipment (Welcome 2011). As a result, the Nigerian government established and put into action a National Health Policy (NHP) and Ward Health System (WHS), both of which have as their primary objectives lowering the mortality rate for children under 5 (NPC 2013). Despite all these efforts, Nigeria continues to have a high rate of under-5 child deaths.

Since U5MR is a persistent public health issue in Nigeria and other developing nations, researchers have worked extremely hard to identify the causes of this threat (Buor 2003, Becher et al. 2004). To lessen the threat, it is crucial to identify the factors that increase the risks of under-5 mortality. According to statistics, Nigeria and most sub-Saharan African nations have significant challenges in reaching the SDG3.

To better guide the creation of policies and the execution of programs for effective health intervention, further study is required. Therefore, this study aimed to identify factors contributing to under-5 mortality in Nigeria.

## Materials and Methods

### Source of data

The data used in this study were from the 2018 Nigeria Demographic and Health Survey (NDHS). A total of 33,924 infant mortality sample data were collected in the 2018 survey. The 2018 survey, which covered 2013–2018, was the most recent at the time of this study. It was completed with the assistance of several foreign partners (Bamigbala et al. 2022a).

### Ethical considerations

The study was based on NDHS data that had been made publicly available. The ethical practices were the responsibility of the organizations (NDHS) that ordered, paid for, or managed the surveys. ICF International and an institutional review board in each country have both authorized all DHS surveys, ensuring that the protocols follow those set forth by the US Department of Health and Human Services for the protection of human subjects.

### Study variables

The outcome variable is the under-5 mortality, while the independent variables are sex (male and female), child's age (less than 12 months, 12–36 months, and 37–59 months) place of residence (rural and urban), maternal age group (15–19 years, 20–24 years, 25–29 years, 30–34 years, 35–39 years, 40–44 years and 45–49 years), regions (north-central, north-east, north-west, south-east, south-south and south-west), maternal education (no education, primary, secondary and tertiary), wealth index (poorest, poorer, middle class, richer, and richest), and size of child at birth (very large, average and very small).

### Methods of data analysis

### Poisson (P) regression model

The simplest distribution used for modelling count data is the Poisson distribution with probability density function given by:

$$f\left(y_i;\mu\right)=\frac{\exp\left(-\mu\right)\mu^{y_i}}{y_i!} \qquad (1)$$

### Negative binomial (NB) regression model

Another way of modelling over-dispersed count data is to assume a negative binomial (NB) distribution for $y_i \mid x_i$ which can arise as a gamma mixture of Poisson distributions. The probability density function for NB is given by:

$$f\left(y_i;\mu,\theta\right)=\frac{\Gamma\left(y_i+\theta\right)}{y_i!\Gamma\left(\theta\right)}.\left(\frac{\theta}{\mu+\theta}\right)^{\theta}\left(\frac{\mu}{\mu+\theta}\right)^{y_i} \quad (2)$$

with mean $\mu$ and shape parameter $\theta$; $\Gamma\left(.\right)$ is the gamma function.

### Zero inflated models

The problem with Poisson regression models having far more zeros than expected by the distributional assumptions of the Poisson and Negative Binomial models result in incorrect parameter estimates. Using Zero Inflated Poisson (Lambert 1992) or Zero Inflated Negative Binomial models are proposed as a solution for this problem (Loeys et al. 2012).

### Zero inflated Poisson (ZIP) regression

The Zero-Inflated Poisson (ZIP) regression is used for count data that exhibit over-dispersion and excess zeros. The data distribution combines the Poisson distribution and the logit distribution. The Zero Inflated Poisson can be modelled by mixed Poisson distribution, comprising the part with zero and the other part consist of the zeros that would normally be expected under a Poisson model

$$P(Y_i = y_i) = \pi_i + (1-\pi_i)\exp(-\mu_i) \qquad if\, y_i = 0$$

$$P(Y_i = y_i) = (1-\pi_i)\frac{\exp(-\mu_i)\,\mu_i^{y_i}}{y_i!} \quad if\, y_i > 0 \tag{3}$$

$0 \le \pi_i < 1$ is a proportion and $E(Y_i) = (1-\pi_i)\mu_i$ and $Var(Y_i) = (1-\pi_i)\mu_i(1-\pi_i\mu_i)$ as the conditional expected values and variance of $y_i$ respectively.

**Zero Inflated Negative Binomial (ZINB) regression**

Zero-inflated negative binomial regression is for modelling count variables with excessive zeros and it is usually for over-dispersed count outcome variables. Furthermore, theory suggests that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modelled independently. The ZINB model can be written as:

$Y_i = 0,$ with probability $\pi_i$

$Y_i \sim NB(\mu_i, k)$ with probability $(1-\pi_i)$

So that,

$$\Pr(Y_i = 0) = \pi_i + (1-\pi_i)(1+k\mu_i)^{-1/k}$$

$$\Pr(Y_i = y_i) = (1-\pi_i)\frac{\Gamma\left(y_i + 1/k\right)(k\mu_i)^{y_i}}{\Gamma(y_i+1)\Gamma\left(1/k\right)(1+k\mu_i)^{y_i+1/k}}, \quad y_i = 1,2,\ldots \tag{4}$$

Where the mean and variance of the $Y_i$ are:

$$E(Y_i) = (1-\pi_i)\mu_i$$

$$Var(Y_i) = (1-\pi_i)\mu_i\left(1-\mu(\pi_i + k)\right)$$

Where $\mu_i$ is the mean of the underlying negative binomial distribution and $k$ is the over-dispersion parameter.

$Y_i$ = the number of under5 mortality

$X_1, X_2, \ldots, X_n$ = selected independent variables.

**Hurdle model**

Hurdle regression is also known as two-part model which is originally developed by Mullahy (1986). Mullahy explained that, “The idea behind the hurdle formulations is that a model of binomial probability controls the binary outcome of whether a variable count has a zero or a positive outcome. If the realization is non-zero (positive), the “hurdle is crossed”, and the conditional distribution of the positives is governed by a truncated at-zero count data model.” The attraction of Hurdle regression is that it reflects a two stage decision-making process in most human behaviours and therefore has an appealing interpretation (Cameron and Trivedi 1998).

**Hurdle Poisson (HP) regression model**

We consider a Hurdle Poisson regression model in which the response variable $Y$ has the distribution

$$P(Y_i = y_i \mid \mu, \pi_0) = \pi_0 \qquad if\, y_i = 0$$

$$P\left(Y_i = y_i \middle| \mu, \pi_0\right) = \left(1-\pi_0\right) \frac{\exp\left(-\mu_i\right) \mu_i^{y_i}}{\left(1-\exp\left(-\mu\right)\right) y_i!} \quad if\, y_i > 0 \tag{5}$$

Zero inflated Poisson distribution is parameterized as given by Equation (3) with
$\pi_0 = \pi + \left(1-\pi\right)\exp\left(-\mu\right)$

**Hurdle Negative Binomial (HNB) regression model**

Hurdle Negative Binomial regression model in which the response variable $Y$ has the distribution

$$P\left(Y_i = y_i \middle| \mu, \alpha, \pi_0\right) = \pi_0 \qquad if\, y_i = 0$$

$$P\left(Y_i = y_i \middle| \mu, \alpha, \pi_0\right) = \left(1-\pi_0\right) \frac{q}{1-\left(1-\alpha\mu\right)^{-1/\alpha}} \quad if\, y_i > 0 \tag{6}$$

Where $q = q\left(y;\mu,\alpha\right) = \dfrac{\Gamma\left(y + 1/\alpha\right)}{\Gamma\left(y+1\right)\Gamma\left(1/\alpha\right)} \left(1+\alpha\mu\right)^{-1/\alpha - y} \alpha^y \mu^y$

**Generalized Poisson (GP) regression**

The advantage of using Generalized Poisson regression model is that it can be fitted for both over-dispersion, $Var\left(Y_i\right) > E\left(Y_i\right)$ as well as under-dispersion, $Var\left(Y_i\right) < E\left(Y_i\right)$. The GP probability density is given as

$$f\left(y_i;\mu_i,\alpha\right) = \left(\frac{\mu_i}{1+\alpha\mu_i}\right) \frac{\left(1+\alpha y_i\right)^{y_i-1}}{y_i!} \exp\left(\frac{\mu_i\left(1+\alpha y_i\right)}{1+\alpha\mu_i}\right) \tag{7}$$

$y_i = 0,1,2,\ldots\ and\ \mu_i = \mu_i\left(x_i\right) = \exp\left(x_i\beta\right)$

**Model selection**

Akaike's information criterion (Akaike 1973) is used to compare models in order to select the best one. The AIC is as a result defined as;

$$AIC = -2L + 2k \tag{8}$$

where k indicates the number of parameters in the model and L indicates the log-likelihood. The lowest AIC value among the models is the best fitted model. AIC is used when comparing non-nested models fitted by maximum likelihood to the same data set. The statistic considers model parsimony and penalizing for the number of predictors used in the model, thus, AIC = 2 log L + 2 number of parameters.

**Statistical analysis**

The methods of analysis used for this study are frequency, percentage, and Zero Inflated Negative Binomial (ZINB) Regression. The statistical software used for the analysis was R program v.4.1.2 and $p < 0.05$ was considered to be statistically significant.

**Results and Discussion**

Table 1 shows the socio-demographic characteristics of the respondents. Out of all the 33,924 infant mortality sample data collected in the 2018 survey, 50.9% were male, while 49.1% were female. Regarding age, 27.9% of the respondents were within the age range of 25–29 years, while 22.5% were within 30–34 years.

Based on the place of delivery, 34.5% of the respondents reside in an urban area, while 65.5% reside in a rural area. 30.4% of the respondents were from the North West, 21.3% were from the North East, 17.3% were from the North Central, 11.2% were from the South East, and 10.4% were from the South

West, while 9.4% were from the south-south region of Nigeria.

Based on the mother's educational background, 45.4% had no formal education, 15.5% had primary education, 31.3% had secondary education and 7.8% had tertiary education. 23.8% of the respondents were the poorest, while 14.1% were the richest. Based on the size of a baby at birth, 9.1% were very large, 4.8% were very small while 86.1% were within average while 4.8% were very small.

**Table 1:** Socio-demographic characteristics of the respondents

| Factors | Categories | Frequency | Percentage (%) |
|---|---|---|---|
| Sex of child | Male | 17257 | 50.9 |
| | Female | 16667 | 49.1 |
| | **Total** | **33924** | **100%** |
| Age of child | Less than 12 months | 6759 | 19.9 |
| | 12–36 months | 13750 | 40.5 |
| | 37–59 months | 13415 | 39.5 |
| | **Total** | **33924** | **100%** |
| Maternal age | 15–19 | 1434 | 4.2 |
| | 20–24 | 6626 | 19.5 |
| | 25–29 | 9470 | 27.9 |
| | 30–34 | 7647 | 22.5 |
| | 35–39 | 5447 | 16.1 |
| | 40–44 | 2407 | 7.1 |
| | 45–49 | 893 | 2.6 |
| | **Total** | **33924** | **100%** |
| Place of residence | Urban | 11699 | 34.5 |
| | Rural | 22225 | 65.5 |
| | **Total** | **33924** | **100%** |
| Region | North Central | 5875 | 17.3 |
| | North East | 7211 | 21.3 |
| | North West | 10305 | 30.4 |
| | South East | 3798 | 11.2 |
| | South South | 3202 | 9.4 |
| | South West | 3533 | 10.4 |
| | **Total** | **33924** | **100%** |
| Mother’s Education | No education | 15391 | 45.4 |
| | Primary | 5274 | 15.5 |
| | Secondary | 10623 | 31.3 |
| | Tertiary | 2636 | 7.8 |
| | **Total** | **33924** | **100%** |
| Wealth index | Poorest | 8066 | 23.8 |
| | Poorer | 7743 | 22.8 |
| | Middle class | 7171 | 21.1 |
| | Richer | 6166 | 18.2 |
| | Richest | 4778 | 14.1 |
| | **Total** | **33924** | **100%** |
| Size of child at birth | Very large | 3085 | 9.1 |
| | Average | 29214 | 86.1 |
| | Very small | 1625 | 4.8 |
| | **Total** | **33924** | **100%** |

The distribution of under-5 mortality (U5M) calculated in Table 2 showed that the observed zero counts in the data was 64.6% indicating excess zeros and the observed U5M calculated has non-negative integer values. Further screening of the U5M calculated showed that the variance (1.20121) is much greater than the mean (0.62849), indicating over-dispersion. The use of Poisson model with the mean estimated from the data is a good starting point of count data modelling. Due to the restrictive assumption of equidispersion regarding the Poisson model, other competing models were fitted to the data. This implies that count data models that take into account excess zero, such as Zero-Inflated Poisson Models, Zero-Inflated Negative Binomial Models, Hurdle Poisson, Hurdle Negative Binomial might deliver a better fit.

According to the data in Table 3, Poisson regression and Negative binomial regression are not the best-performing models for the data set with the largest AIC values. Since the Zero-Inflated Negative Binomial regression model has the smallest AIC value of 65097.96, one can say the ZINB regression model is the best model for the dataset. Therefore, the interpretation of the results on under-5 mortality in Nigeria was based on the ZINB model (Bamigbala et al. 2016).

**Table 2:** Number of under-5 mortality

| Number of deaths | Frequency | Percentages |
|---|---|---|
| 0 | 21917 | 64.6 |
| 1 | 6690 | 19.7 |
| 2 | 3092 | 9.1 |
| 3 | 1240 | 3.7 |
| 4 | 542 | 1.6 |
| 5 | 231 | 0.7 |
| 6 | 129 | 0.4 |
| 7 | 48 | 0.1 |
| 8 | 26 | 0.1 |
| 9 | 4 | 0.0 |
| 10 | 5 | 0.0 |
| **Total** | **33924** | **100.0** |
| **Mean** | **0.62849** | |
| **Variance** | **1.20121** | |

**Table 3:** Model selection

| Models | AIC |
|---|---|
| Poisson (P) regression | 66952.94 |
| Negative Binomial (NB) regression | 65422.71 |
| Zero Inflated Poisson (ZIP) regression | 65232.21 |
| Zero Inflated Negative Binomial (ZINB) regression | **65097.96*** |
| Hurdle Poisson (HP) regression | 65278.96 |
| Hurdle Negative Binomial (HNB) regression | 65147.31 |
| Generalized Poisson (GP) regression | 65404.53 |

* Best fit model.

The results for the non-zero group (Table 4) indicated that maternal age, regions, maternal education, wealth index, and size of child at birth had significant effects ($p < 0.05$) on the number of under-5 mortality in Nigeria.

The expected number of under-5 mortality from the North East region increases by 27% the expected number of under-5 mortality in North Central. Similarly, the expected number of under-5 mortality increased by 53.7% for those living in North West compared to those in the North Central. In addition, the expected number of under-5 mortality in South West decreased by 37.8% to the expected number of under-5 mortality in North Central. In regard to this finding, according to a newly reported subnational child mortality estimate, there are significant disparities in U5MR among the six geopolitical zones, with the North West having the highest U5MR at 187 deaths per 1000 live births and the South West having the lowest at 62 deaths (NPC 2018). Uneven U5MR has been linked to socioeconomic and cultural gaps, poor access to healthcare, and variations in public health intervention coverage, according to Kazembe and Mpeketula (2010) and Becher et al. (2004). However, insecurity may limit access to high-quality maternal healthcare services in the Northern region of the country, which is replete with poverty, poor antenatal care access, and other problems.

**Table 4:** Estimated coefficients of ZINB regression model for non-zero and zero groups of under-5 mortality in Nigeria

| | Non-zero group | | | Zero group | | |
|---|---|---|---|---|---|---|
| **Variables** | **Estimate** | **P-value** | **Odd ratio** | **Estimate** | **P-value** | **Odd ratio** |
| Intercept | -1.99265 | 0.0000 | 0.1363 | -14.5969 | 0.9726 | 0.00000 |
| **Sex of child** | | | | | | |
| Male (Ref) | | | 1.0000 | | | 1.0000 |
| Female | -0.0019 | 0.9211 | 0.9981 | 0.04278 | 0.5421 | 1.0437 |
| **Age of child** | | | | | | |
| Less than 12 months (Ref) | | | 1.0000 | | | 1.0000 |
| 12–36 months | 0.05491 | 0.0624 | 1.0564 | 0.06997 | 0.4986 | 1.0725 |
| 37–59 months | 0.05044 | 0.0841 | 1.0517 | -0.05571 | 0.5924 | 0.9458 |
| **Maternal age** | | | | | | |
| 15–19 years (Ref) | | | 1.0000 | | | 1.0000 |
| 20–24 years | 0.78254 | 0.0000** | 2.1870 | 13.29779 | 0.9750 | 595877.3 |
| 25–29 years | 1.42890 | 0.0000** | 4.1741 | 13.78542 | 0.9741 | 970357.6 |
| 30–34 years | 1.87024 | 0.0000** | 6.4899 | 13.74626 | 0.9742 | 933092.9 |
| 35–39 years | 2.11664 | 0.0000** | 8.3032 | 13.54241 | 0.9746 | 761016.3 |
| 40–44 years | 2.35341 | 0.0000** | 10.5214 | 13.48260 | 0.9747 | 716834.3 |
| 45–49 years | 2.56697 | 0.0000** | 13.0263 | 13.59508 | 0.9745 | 802173.3 |
| **Place of residence** | | | | | | |
| Urban (Ref) | | | 1.0000 | | | 1.0000 |
| Rural | 0.06014 | 0.05044 | 1.0620 | -0.28521 | 0.0033* | 0.7519 |
| **Regions** | | | | | | |
| North Central (Ref) | | | 1.0000 | | | 1.0000 |
| North East | 0.24275 | 0.0000** | 1.2747 | -0.12800 | 0.3763 | 0.8799 |
| North West | 0.42968 | 0.0000** | 1.5368 | -1.02731 | 0.0000** | 0.3580 |
| South East | -0.01857 | 0.7699 | 0.9816 | 0.31711 | 0.0400* | 1.3732 |
| South South | -0.03376 | 0.6187 | 0.9668 | 0.53447 | 0.0006** | 1.7065 |
| South West | -0.47420 | 0.0000** | 0.6224 | -0.64736 | 0.0737 | 0.5234 |
| **Maternal education** | | | | | | |
| No Education (Ref) | | | 1.0000 | | | 1.0000 |
| Primary | -0.11086 | 0.0005** | 0.8951 | -0.27537 | 0.0293* | 0.7593 |
| Secondary | -0.40555 | 0.0000** | 0.6666 | -0.29173 | 0.1023 | 0.7470 |
| Tertiary | -0.53210 | 0.0000** | 0.5874 | 0.45403 | 0.1037 | 1.5746 |
| **Wealth index** | | | | | | |
| Poorest (Ref) | | | 1.0000 | | | 1.0000 |
| Poorer | 0.01199 | 0.6345 | 1.0121 | 0.25147 | 0.0278* | 1.2859 |
| Middle class | 0.00425 | 0.8939 | 1.0043 | 0.51839 | 0.0000** | 1.6793 |
| Richer | -0.1586 | 0.0003** | 0.8533 | 0.68236 | 0.0000** | 1.9785 |
| Richest | -0.3457 | 0.0000** | 0.7077 | 0.97713 | 0.0000** | 2.6568 |
| **Size of child at birth** | | | | | | |
| Very large (Ref) | | | 1.0000 | | | 1.0000 |
| Average | 0.01843 | 0.6223 | 1.0186 | 0.03981 | 0.7598 | 1.0406 |
| Very small | 0.23306 | 0.0000** | 1.2625 | -0.12612 | 0.5322 | 0.8815 |
| **Log (Theta)** | 1.80608 | 0.0000** | 6.0865 | | | |

Ref = Reference category of the variable; * $p < 0.05$; ** $p < 0.001$.

Based on maternal education, the expected number of under-5 mortality for mothers with primary education decreased by 10.5% as compared to those with no education. In addition, the expected number of under-5 mortality for mothers with a secondary and higher level of education decreased by 33.3% and 41.3% as compared to those with no education, respectively. This is consistent with a national representative study from Nigeria (Adeolu et al. 2016) and a study in Bangladesh (Maniruzzaman et al. 2018). It should be noted that education has a positive impacts on people's behaviour and health knowledge (Bamigbala et al. 2022b, Okoro et al. 2022). It has been asserted repeatedly that a significant contributing factor to the risks of childhood mortality is the education of the mother. Studies have claimed that mothers' education aids in promoting good health practices and enhancing healthy behaviours, such as infant care and feeding practices. A mother's education changes her role in the family and empowers her to use cutting-edge medical services and take immediate action to improve her children's health (Ruiz-López et al. 2010). This finding may also be because educated mothers are more likely to seek medical assistance throughout their pregnancies and after giving birth. An educated mother is also more likely to recognize the value of immunizations and make sure her child has the proper vaccinations. Additionally, educated mothers are more likely to live in locations that are socially and economically developed, have decent water and sanitation infrastructure, and have well-equipped medical facilities.

Furthermore, the probability of under-5 mortality decreased with an increase in the class of wealth index (richer and richest) of the mother. The estimated odds that the number of under-5 mortality is from a richer and richest family decreased by 14.7% and 29.2%, respectively compared to those from the poorest households. This is consistent with earlier research (Argeseanu 2004, Azuike et al. 2019). This might be explained by the richer families' higher capacity to pay for both curative and preventive healthcare. More than two-thirds of Nigerians live below the $1.25 per day international poverty level (Ezeh et al. 2015). There is a high probability of U5MR as a result of the majority of mothers' limited ability to get suitable healthcare services for their children due to such poverty.

The expected number of under-5 mortality for women whose children birth sizes were very small increases by 26.2% more than the number of under-5 deaths in women whose children birth size were very large. This observation is consistent with prior research (Ezeh et al. 2021, Pal et al. 2021). This observation may be explained by the influence of biologically linked risk factors such as poor nutritional status, low birth weight, and premature birth (Lau et al. 2013).

Finally, the results show that the odds of under-5 mortality in the non-zero group increase as the age of the mother increases. This is similar to the findings of Adetoro and Amoo (2014) and a study in Burkina Faso (Becher et al. 2004). It has been reported that gestational diabetes, congenital anomalies, antepartum haemorrhage, hypertension, and surgical births occur more among older mothers (Stothard et al. 2009, Ribeiro et al. 2014). The increased risk of under-5 mortality among children of older mothers may be explained by these.

## Conclusion and Recommendations

This study applied the nationally representative data from the Nigeria Demographic and Health Survey 2018 to explore factors associated with under-5 mortality in Nigeria. The findings suggest that maternal age, regions, maternal education, wealth index, and size of child at birth had significant effects on the number of under-5 mortality in Nigeria.

Therefore, the Nigerian government should understand that poverty is not just an economic problem but also a significant factor in health; as a result, the battle against poverty needs to receive the necessary attention. Additionally, it is urgently needed to conduct more research on the Northern geopolitical populations to identify any other reasons that might be causing U5MR despite government intervention initiatives.

Furthermore, supporting women's education and skill development will not only lower U5M but also provide women with greater economic and social power to support their families, boost their self-esteem, and have control over health resources. Lastly, public health initiatives that encourage older mothers to seek prompt, appropriate medical care and checkups throughout pregnancy are still essential, which could lead to a reduction in U5MR.

**Conflict of Interest**

The authors declare that no conflicts exist.

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