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Research Article

Analysis of Spatial Pattern of the Level and Spread of Anaemia among Young Children in Southwestern Nigeria

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Abstract

Challenges posed by anaemia among young children in sub-Saharan Africa are immense considering its attendant consequences on their quality of life. Using data from the National Demographic Health Surveys (2018 and 2021 combined), the level and spread of anaemia in six states that constitute the southwestern region of Nigeria are assessed among young children under five years in this study. From the haemoglobin level of 1582 children examined, 914 (57.8%) are anaemic (Hb level below 11.0 g/dl), indicating a relatively higher anaemia level among the respondents. Using binary logistic regression, mothers' education, wealth status, residence (urban/rural), and states are significant contributors to the anaemia status of the children. A higher percentage of poor respondents and rural dwellers are found to have low haemoglobin levels. Also, male children are found to be more anaemic compared to female children. Using BayesX, a software for structured additive regression, both Gaussian and binomial distributions are used to assess anaemia status. Results show that the Gaussian distribution is better overall. The non-linear effect of age of children reveals that the haemoglobin level increases as age increases to about 50 months old before it starts declining, while the frequency of household numbers is not a significant determinant. Spatial analysis of the effect of the subnational reveals that there is no significant difference in the haemoglobin level of children from Oyo, Ogun, Lagos, and Ogun states. Children from Osun state have significantly higher haemoglobin levels, while those from Ondo state have the least.

1. Introduction

Anaemia occurs when the number of red blood cells and their oxygen-carrying capacity in the body is insufficient to the physiological required level in the body. Such levels vary among different ages, genders, pregnancy levels, smoking habits, and so on [1, 2]. Although anaemia is a complex condition that has a number of causes. Some very common determinants that can interact with each other in complex ways to make it a challenging condition are: iron and protein deficiency; chronic diseases (like cancer and rheumatoid arthritis); chronic infections (like HIV/AIDS, and malaria); genetic disorders (like sickle cell); and pregnancy [3–6]. Among children below five years, the negative effects of anaemia are numerous; among significant ones are motor and growth developments; poor immune system; vulnerability to different infections; poor learning ability; delayed responsiveness; altered cognition; and in extreme cases, death [7–9]. Deficiency in iron among children, which is the major cause of anaemia, can lead to permanently impaired motor and cognitive functions, especially in situations where adequate corrective measures are not taken [3, 10], leading to a population where a higher proportion would be below their mental and physical potentials.

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From the global prevalence of about 25% of anaemia, children under the age of five have the highest proportion of about half of the total cases, while pregnant women have about 42% [1]. This proportion is significantly higher among children in sub-Saharan Africa, with about two-thirds of the total reported cases being children [1]. With the resulting consequential effects of anaemia on the general populace, attempts have been made to reduce the burden amongst the most vulnerable set of people. The scourge remains one of the most pronounced health challenges in many African countries, affecting a significant percentage of the children population [11]. Anaemia has a negative effect on the cognitive development and physical growth of children, and it also damages different immune mechanisms, resulting in increased morbidity rates [4, 12].

Anaemia develops when blood lacks enough healthy red blood cells or haemoglobin. Haemoglobin is a main part of red blood cells and binds oxygen [13] which is often used to determine the anaemia status of children. According to the World Health Organisation [14], a child is considered anaemic if his haemoglobin (Hb) level is below 11.0 grams per decilitre (g/dl). Different models have been used to analyse anaemia. Using a Bayesian semi-parametric approach [3] assessed the spatial prevalence of anaemia in Nigeria and its possible determinants. Also, [15] used the spatial structured additive quantile regression model to examine prevalence of childhood anaemia. The Bayesian random effect model was utilised [5] used a Bayesian random effect to model the geographical distribution of child anaemia by fitting a binary logistic model, while [16] applied multilevel generalised linear models for the binary and ordinal classifications of anaemia prevalence. The variance components model was used by [17], while [18] utilised a bivariate probit model. This study incorporates spatial data to other covariates to assess spatial pattern of anaemia level among six states (subnational) that make up the southwest region of Nigeria. Spatial analysis helps in understanding geographic patterns, trends, and relationships among covariates. The technique involves identification of significant factors of interest which assist in implementing target interventions to improve situation [3, 19].

In some research [3, 7, 11], anaemia is categorised into four levels according to its severity (severe, moderate, mild, and non-anaemic). However, a major advantage of modelling data in continuous form is to avoid loss of information that could be incurred if such data were categorized. Depending on the motivation for a study, some form of analysis may however necessitates re-categorisation of data from its natural form to a categorical variable. In this study, haemoglobin levels of children under five years are collected along with other covariates from both the 2018 and 2021 National Demographic Health Surveys (NDHS) for the six states (subnational) of the southwestern region of Nigeria. The Hb level is used to assess the anaemia status of the children examined across different covariates and states.

2. Area of the Study

The southwestern region of Nigeria comprises six states: Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo. The 2018 NDHS put the estimated population of the region at close to 40 million [20]. Among the six regions in Nigeria, the southwest has the highest wealth quantile of about 50% of the entire country compared to the Northeast region with a mere 2% [21].

Figure 1: Map of Nigeria showing States in South-west Region

2.1. Data

Data on haemoglobin level and other covariates are combined for the six states of southwest Nigeria (Ekiti, Lagos, Ogun, Ondo, Osun, and Oyo) from both the 2018 and 2021 NDHS [20, 22]. After all data cleaning and deletion of missing values, 1582 children are examined in all. The haemoglobin levels are categorised into anaemic (Hb level below 11.0 g/dl) and non-anaemic (Hb 11.0 g/dl and above) for binary analysis. From the original data, the wealth index has five levels (Richest, Richer, Middle, Poorer, and Poorest), but to ease result interpretation, the variable is re-categorised into three levels (Rich, Middle, and Poor). Other assessed covariates are mothers' education, gender of the child, number of household members, age of the children in months, residence (urban and rural), and having malaria two weeks preceding the survey. The study is therefore limited to the variables on the anaemia level of the children as collected during the survey.

2.2. Data Analysis

The binary logistic regression is used to assess the odds ratio of the covariates when the Hb level of the examined children is categorised into anaemic and non-anaemic. The logistic regression model has been used to analyze binary response variables [23, 24] when the relationship between a response variable and several covariates are to be assessed with the response variable being denoted by 1 and 0, indicating Presence/Absence or Yes/No. The efficiency of logistic regression has been proven in analysing categorical data [25, 26].

The spatial pattern of the anaemia status is examined using the software for Bayesian Inference and its R language interface [19, 27]. The response variable is assumed to have come from (i) a Gaussian distribution – when the Hb level is used, and (ii) a binomial distribution – when the variable is categorised into anaemic and non-anaemic. Both the non-linear effect of the age of examined children in months and the

non-linear effect of number of household members are assessed with the random walk prior of the second order with three spline degrees and 20 equidistant knots.

3. Spatial Model

In semi-parametric regression, different forms of covariates can be modelled using geo-additive predictors [3, 28], hence:

$$\eta_{ij} = \alpha + f(x_{ij}) + f_{hhmem} + f_{age} + f_{state} \tag{1}$$

where: $f(x_{ij})$ represents different fixed effect variables.
f_{hhmem} represents different fixed effect variables.
f_{age} represents the non-linear effect of the average age of a child in each household.
f_{state} is the spatial effect of states.

4. Results

Table 1 shows the distribution of different covariates among the respondents across the six states (subnational). Out of 1582 examined, 914 (57.8%) of the examined children are anaemic (Hb level below 11.0 g/dl). 1035 (65.42%) of them reside in urban areas, while 34.6% reside in rural areas. From these, 68.2% of rural dwellers are anaemic while 52.3% of those residing in urban areas are anaemic.

Also, over 70% of children whose mothers are without formal education are anaemic, while only 41% of those with higher education are anaemic. The table also shows that anaemia prevalence is highest among the poor, indicating the significant effect of the wealth index on the anaemia status of the children. Male children (60.5%) are found to be more anaemic in comparison to female children (54.4%).

Children with malaria two weeks before the survey are also found to be more anaemic than those without. Among the six states in the geopolitical zones, children from Ondo state are the most anaemic, with almost three-quarters of the examined children in the state being anaemic, while those from Osun state are the least anaemic, with 48%.

The chi-square test of dependency reveals that all the covariates have significant dependency on the anaemia status of examined children at 5% level of significance ($p < 0.05$).

Table 1: Socio-Demographic characteristics of respondents and Anaemic Status.

Characteristics	**Frequency**	**Anaemia Status**		**Chi-Square P-value**
		Non-Anaemic 668 (42.2%)	**Anaemic 914 (57.8%)**	
Place of residence	***Total (%)***			
Rural	547 (34.6%)	174 (31.8%)	373 (68.2%)	0.000*
Urban	1035(65.4%)	494 (47.7%)	541 (52.3%)	
Mother's level of education	***Total (%)***			
No formal education	212 (13.4%)	63 (29.7%)	149 (70.3%)	
Primary	237 (15.0%)	76 (32.1%)	161 (67.9%)	0.000*
Secondary	796 (50.3%)	331 (41.6%)	465 (58.4%)	
Higher Education	337 (21.3%)	198 (58.8%)	139 (41.2%)	
Wealth Index	***Total (%)***			
Poor	115 (7.3%)	32 (27.8%)	83 (72.2%)	
Middle	214 (13.5%)	61 (28.5%)	153 (71.5%)	0.000*
Rich	1253(79.2%)	575 (45.9%)	678 (54.1%)	
Gender of the child	***Total (%)***			
Male	825 (52.1%)	326 (39.5%)	499 (60.5%)	0.023*
Female	757 (47.9%)	342 (45.2%)	415 (54.8%)	
Child has malaria in last 2 weeks	***Total (%)***			
Yes	394 (24.9%)	139 (35.3%)	255 (64.7%)	0.001*
No	1188(75.1%)	529 (44.5%)	659 (55.5%)	
State	***Total (%)***			
Oyo	298 (18.8%)	129 (43.3%)	169 (56.7%)	
Osun	226 (14.3%)	117 (51.8%)	109 (48.2%)	
Ekiti	205 (13.0%)	86 (42.0%)	119 (58.0%)	0.000*
Ondo	252 (15.9%)	65 (25.8%)	187 (74.2%)	
Lagos	335 (21.2%)	159 (47.5%)	176 (52.5%)	
Ogun	266 (16.8%)	112 (42.1%)	154 (57.9%)	

*Significant factors at $\alpha = 0.05$

4.1. Binary Logistic Regression

Examining the covariates on anaemia status (anaemic and non-anaemic), Table 2 shows the results of the binary logistic regression. From the table, the odds of a child under five years being anaemic are higher among rural dwellers compared to those residing in urban areas. The

table also reveals that the odds are highest among mothers with no formal education. Also, respondents from poor backgrounds have the highest odds of being anaemic in comparison with the other two categories, although the difference is not significant.

Children who had malaria two weeks before the survey were found to have significantly higher odds of being anaemic than those without malaria. Among the six states in the region, the odds of being anaemic are highest among those from Ondo state, followed by those from Oyo state, while those from Osun state have the lowest odds.

Table 2: Logistic Regression of Anaemia Status on some factors.

Factor	P-Value	Odds Ratio	95% C.I. for Odds Ratio
Place of residence			
Urban (Ref. Category)		1.000	
Rural	0.000	1.623	[1.258, 2.093]
Mother's level of education	0.000		
No formal education (Ref. Category)		1.000	
Primary	0.000	0.366	[0.234, 0.574]
Secondary	0.081	0.700	[0.469, 1.045]
Higher Education	0.642	0.600	[0.365, 0.949]
Wealth Index	0.484		
Poor (Ref. Category)		1.000	
Middle	0.777	0.925	[0.541, 1.584]
Rich	0.596	0.765	[0.462, 1.050]
Gender of the child			
Female (Ref. Category)		1.000	
Male	0.031	1.266	[1.022, 1.568]
The child has had malaria in the last 2 weeks			
Yes (Ref. Category)		1.000	
No	0.005	0.700	[0.545, 0.900]
Household member	0.309	1.027	[0.975, 1.082]
Age	0.000	0.971	[0.964, 0.977]
State	0.000		
Ogun (Ref. Category)		1.000	
Oyo	0.143	1.318	[0.911, 1.906]
Osun	0.580	0.897	[0.610, 1.319]
Ekiti	0.048	1.497	[1.003, 2.234]
Ondo	0.000	2.704	[1.814, 4.031]
Lagos	0.198	1.267	[0.883, 1.818]
Constant	0.000	3.608	

*Significant factors at $\alpha = 0.05$

4.2. Model Diagnostic for the Spatial Analysis

Using Bayes X [27], software for Bayesian inference under the Structured Additive Regression models [21], two distributions are assumed for the status of the anaemia of the children examined. The Gaussian distribution is assumed when the haemoglobin level of the children is on the continuous scale, while the binomial distribution is assumed by categorising the variable into anaemic (haemoglobin level below 11.0 g/dl) and non-anaemic (haemoglobin level more than 0 g/dl). The nonlinear effects of the age of the children and frequency of household members are examined by assuming the second-order random walk prior with three spine degrees and 20 equidistant knots. 25000 iterations with a 5000 burn-in period and a 30-thinning parameter were also assumed for the analysis.

The Deviance Information Criterion (DIC) which summarizes model fits is used for model comparison [29]. Table 3 shows the DIC, the posterior mean of the deviance ($\overline{D}$) , and the effective number of parameters that measure the model complexity (ρD) .

Table 3: Models diagnostic

	Gaussian distribution	Binomial distribution
Run time (seconds)	20	115
DIC	1606.8411	1975.7664
$\overline{D}$	1557.9425	1934.7164
ρD	24.4493	20.5250

From the above table, assuming the Gaussian distribution has the smaller DIC and $\overline{D}$, indicating a better model and fit, respectively, while the binomial distribution is more parsimonious with lesser ρD [21, 30, 31]. The Gaussian model also has a significantly lower simulation runtime.

4.3. Fixed Effects Model assuming the Gaussian distribution

Table 4 shows the result of the fixed effect model for the spatial analysis when the Gaussian distribution is assumed. The table presents the posterior mean along with the 97.5% credible intervals. The table shows a significantly higher Hb level for children residing in urban areas when compared to those from rural settings.

There was also evidence of a higher significant difference in mean Hb of the children whose mothers have both secondary and higher education, while those whose mothers have no formal education have the lowest Hb level. For the wealth index, the mean Hb level was significantly higher for the rich household, while it was not significant for those of the middle-class households. The result also reveals that children from poor levels of wealth index are the most anaemic with the lowest Hb level.

It is also observed from the table that female children have significantly higher Hb levels in comparison to the male children. Finally, there was evidence of a significant difference in mean Hb for children who had malaria two weeks preceding the survey. Children who had malaria before the survey have significantly lower Hb levels.

Respondents from the *middle* class of Wealth Index have non-significant higher Hb level when compared to those from *poor* background while those from *rich* category have significantly higher Hb level.

Table 4: Fixed Effects model for the Gaussian distribution

Factor	***Posterior Mean***	**Std. Devi**	**97.5% C.I.**
Place of residence			
Rural (Ref. Category)	0		
Urban	0.2695	0.0853	[0.0998, 0.4257]
Mother's level of education			
No formal education (Ref. Category)	0		
Primary	0.1384	0.1419	[-0.1322, 0.4160]
Secondary	0.3681	0.1279	[0.1134, 0.6175]
Higher education	0.7764	0.1389	[0.5095, 1.0642]
Wealth Index			
Poor (Ref. Category)	0		
Middle	0.1866	0.1769	[-0.1591, 0.5279]
Rich	0.4955	0.1693	[0.1813, 0.8663]
Gender of the child			
Male (Ref. Category)	0		
Female	0.1503	0.0706	[0.0038, 0.2912]
Child has malaria in last 2 weeks	0	0.0863	[-0.6061, -0.2747]
No (Ref. Category)	-0.4383		
Yes			
Constant	9.6729	0.2291	[9.2486, 10.0880]

4.4. Nonlinear Effect of Age

Figure 2 below shows the nonlinear effect of the age of the children on their haemoglobin level. The figure shows that the haemoglobin level of the children increases as age increases till about 50 months, when it starts declining. Both 90% (green colour) and 97.5% (red colour) credible intervals for the posterior mean are also presented.

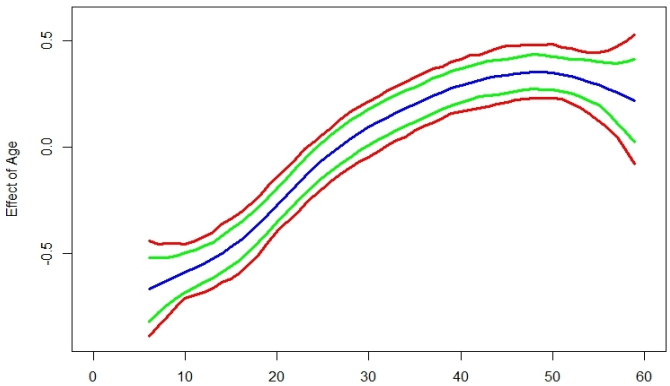

Figure 2: Nonlinear effect of age of children

4.5. Nonlinear Effect of Number of Household Members

The nonlinear effect of the number of households on the haemoglobin level of the examined children is presented in Figure 3 below. The figure reveals that haemoglobin level is minimal when members of a household are less than 10, after which it continues to rise.

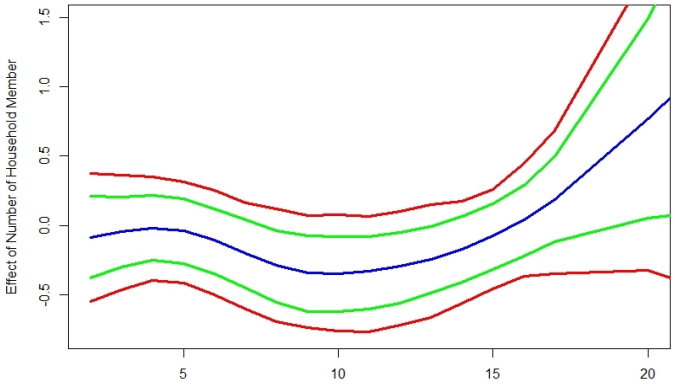

Figure 3: Nonlinear effect of number of household member

4.6. Spatial Effects of States

Figures 4 and 5 present the posterior mean and the 95% credible intervals of spatial effects of states on the haemoglobin level. Figure 4 shows that children from Osun state have the highest haemoglobin level, while those from Ondo state have the least. There are not many disparities among the children from Oyo, Ogun, and Lagos states. The figure for 95% posterior credible intervals reveals that there is no significant difference in the haemoglobin level of children from Oyo, Ogun, Lagos, and Ogun states. Children from Ogun state have significantly lower haemoglobin levels, while those from Osun state have significantly higher levels.

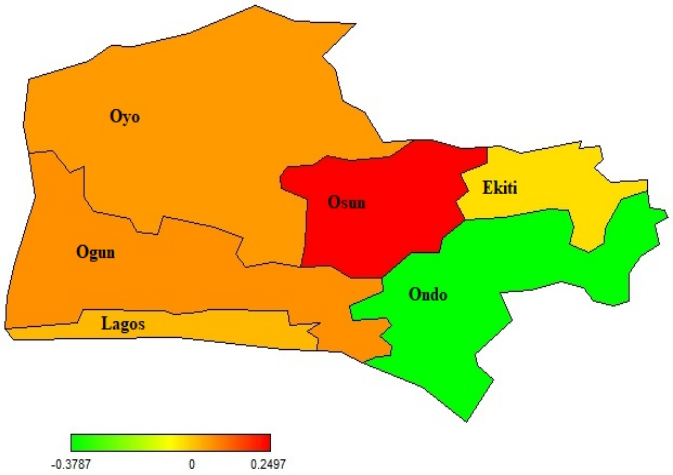

Figure 4: Posterior mean of spatial effects

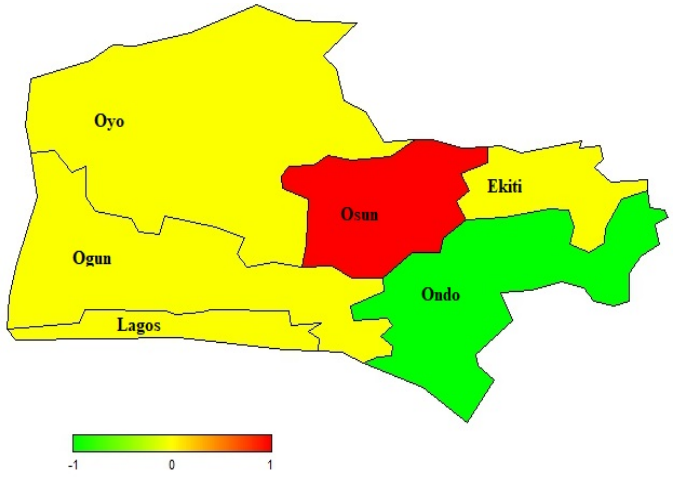

Figure 5: Spatial Effect for 95% Posterior Credible intervals

5. Discussion

In this study, the level and spread of anaemia in six states that constitute southwestern Nigeria are assessed among young children under five years using data from the National Demographic Health Surveys [8]. Although some studies [3, 25] had reported findings in anaemia status across Nigeria, our study focuses on only the South-west region alone.

Of 1582 children examined, 57.8% are anaemic (Hb level below 11.0 g/dl), indicating a relatively higher anaemia level among the respondents. Although this prevalence is lower than 67% in a similar study across the entire Nigeria [11], it is higher than the 40% acceptable limit set by the World Health Organisation [6]. A higher proportion of anaemic children obtained in this study is similar to earlier studies among children across other sub-Saharan African countries [32–35].

Results from this study reveal that a mother's educational status has a significant effect on the anaemia status of the children. Children whose mothers have no formal education are mostly anaemic. This result supports findings from similar studies [11, 25, 34, 36, 37]. This may be due to the lack of adequate health and dietary practices necessary to improve the diet of the children. Also, increasing access to education for mothers will in turn reduce the likelihood of the children being anaemic [25]. More educated mothers are more likely to provide healthier and more hygienic diets to their children [38].

Among the three examined wealth indices, children from poor families are found to be more anaemic. This supports results from similar studies [11, 25, 39–41]. It is essential to mention that the level of socioeconomic status of a household is crucial. Children from poor families are more exposed to imbalanced diets, largely because of affordability factors.

Children from rural settings are found to have lower haemoglobin levels when compared to those from urban areas. Other studies [7, 25] also reported higher rates of anaemic children in rural areas. Findings from the African Health Report of the World Health Organisation [42] revealed that rural settings in Africa have worse health indicators. Also, with the presence of more efficient health facilities in urban areas, residing children have access to better treatments and other services necessary for an improved quality of life.

In this study, male children are found to be more anaemic when compared to female children. This may be largely because female children are usually breastfed longer than male children in Nigeria [11, 43]. Also, male children are more involved in stressful and hazardous activities, leading to a higher likelihood of wounds and blood loss [3, 15, 44–46]. Although studies from Ethiopia [2] and Equatorial Guinea [7] reported no association between gender and the anaemia status of children.

Children with malaria two weeks from the survey are found to be more anaemic than those without. Malaria destroys red blood cells and in turn, reduces haemoglobin levels and causes loss of appetite [3, 35]. Similar studies [11, 34, 47, 48] have reported related findings.

Among the six states in the region, binary regression analysis reveals that children from Osun state have significantly higher haemoglobin levels while those from Ondo state have the least. Children from Ondo state are three times more anaemic when compared to those from Osun state, while they are almost twice as anaemic compared to those from Oyo and Ekiti states. Observed variations in the anaemia status of children among states could result from variations in health policies being implemented.

The non-linear effect of age of children reveals that the haemoglobin level increases as age increases to about 50 months old before it starts declining. These findings are similar to those of [7, 49, 50] where a higher anaemia proportion was found among children over five years old. This may be largely due to an increase in the need for iron at this stage of development for children [51].

6. Conclusion and Recommendations

The challenges posed by anaemia among young children in sub-Saharan Africa are immense, with its attending consequences on their lives [3, 6, 52]. The level and spread of anaemia in six states that constitute Southwestern Nigeria are found to be higher than the acceptable limit. States governments and policymakers in this region are therefore encouraged to focus on the identified significant factors in this study towards preparing adequate and effective intervention programmes. Iron-fortified foods and other micronutrients are to be promoted and, where possible, subsidized for children in the region. More efforts are also encouraged to be geared towards reduction of malaria and general reduction of poverty in the region. Current efforts to increase access to quality health should be sustained and more special interventions are encouraged to be made on improving accessibility.

Ondo state, with significantly higher anaemic children, is encouraged to imitate policies and action plans of states with fewer reported cases of anaemic children. Generally, governmental and non-governmental intervening policies should be geared towards improving women's education. This could play a pertinent role in the overall health status of children.

DECLARATIONS

Ethics approval and consent to participate: Not Applicable.
Consent for publication: Not applicable
Availability of data and materials: The research instrument and datasets used and analysed during the current study are available from the corresponding author on request.
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