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An Application of Hierarchical Logistic Modelling to Maternal Health Care Utilization in Nigeria.

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Abstract

Background: With a maternal mortality rate of 576 deaths per 100,000 live births, Nigeria accounts for about 10% of all maternal deaths, globally, and has the second highest mortality rate in the world. This high mortality rate makes maternal health a huge public health problem in the country. This paper, therefore, aimed at investigating socio-demographic factors affecting the utilization of Maternal Health Care (MHC) in the context of hierarchical modelling.

Methods: Data were extracted from the Nigerian Demographic and Health Survey, 2013. The data have a hierarchical structure, with the 20,116 Ever-Married Women nested within their respective states of residence. Three different hierarchical logistic regression models were formulated to allow for comparison of outcomes between clusters.

Findings: A proportion of opposed odds ratio of 0.45 indicate that in 45% of pair-wise comparisons between the urban and rural residence, the odds of MHC utilization was higher at an urban residence than at a rural residence by 1.388 times. The Median Odds Ratio (MOR) for Model 2 indicated the odds of MHC utilization was less than 2.41 for a woman in a state at higher risk compared to a different woman in a state at lower risk. The intra-class correlation coefficient revealed a 40% (Model 1), 21% (Model 2) and 16% (Model 3) chances of utilizing MHC, explained by between-states differences, respectively.

Conclusion: In order to close the variation in healthcare delivery in Nigeria, there is a need for government to execute state-specific interventions that would allow fair distribution and utilization of MHC.

Keywords: Maternal Mortality, Maternal Health Care Services, Hierarchical Modelling, Socio-Demographic Factors, Healthcare Utilization

Introduction

With a maternal mortality rate of 576 deaths per 100,000 live births [1], Nigeria explains about 10% of all maternal deaths, globally, and has the second highest mortality rate in the world, after India. The 2013 Nigerian Demographic and Health Survey (NDHS) ratio is not significantly different from the 2008 NDHS ratio of 545 deaths per 100,000 live births. It is also reported that, for every woman that dies from pregnancy-related causes, 20 – 30 more will develop short- and long-term damages to their reproductive organs resulting in some disabilities/diseases [2]. These high morbidity and mortality rates make maternal health a huge public health problem in the developing countries in the world, including Nigeria.

Maternal outcomes such as maternal deaths, child death, and other birth-related diseases could be linked to lack of access and poor utilization of good health facilities by the women. Despite the introduction of modern facilities, available statistics show that the majority of children born are by Traditional Birth Attendants (TBAs) in rural areas, most especially Nigeria. Access and utilization of health facilities by the public are determined largely by availability of health facilities, location, and perception of the significance of health. The choice of health facility is also dictated by economic factors. This situation is still prevalent despite several programmes introduced as interventions to check this trend and improve maternal health. One of such programmes is the 'Safe Motherhood Initiative' which was introduced to suggest strategic interventions in reducing maternal morbidity and mortality in Nigeria.

A number of examples in various regions of the world have found that socio-economic and demographic characteristics influence the likelihood of using professional health care at birth [3-5]. According to Shrestha and Shrestha [3], most of these studies are based on population located in both rural and urban areas. A positive relationship was observed for economic and educational status. Age pattern was inconsistent. Adewara, Ogunniran, and Onyeka-Ubaka [4] developed a multinomial logistic regression model for utilizing maternal healthcare services in Nigeria. Statistical models were developed to establish a link between utilization of Maternal Health Care Services (MHCS) and other factors such as Place of delivery and some socio-economic and demographic factors. And the most consistent factors influencing utilization of maternal healthcare services were found to be education, antenatal care, wealth index, and place of residence.

Hierarchical data with binary outcomes frequently occur in health services, population, demography, public health, and epidemiological research. Hierarchical logistic regression models allow one to account for the clustering of subjects within clusters of higher-level units when estimating the effect of subject and cluster characteristics on subject outcomes. The suitable approach to analyzing such survey data is therefore based on nested sources of variability which come from different levels of the hierarchy [6]. When the variance of the residual errors is correlated between individual observations as a result of these nested structures, traditional logistic regression is unsuitable. 2013 NDHS dataset, which is used to exemplify all aspects of working with multilevel logistic regression models, including model conceptualization, model description, and understanding of the structure of required multilevel data, was used.

This paper highlights the importance of hierarchical logistic regression analysis for studying maternal healthcare utilization in Nigeria from the 2013 NDHS data. The paper aims to investigate the factors affecting the utilization of maternal healthcare in the context of hierarchical modeling. It also aims to measure the influence of some selected factors on the utilization of healthcare facility by women in Nigeria, and emphasis is given to exploring the true effect of the factors on utilization of maternal healthcare taking into consideration the cluster effect of a higher level. In this article, the marginal or population-average effect of covariates measured at the subject and cluster level was estimated, and the interval odds ratio and the proportion of opposed odds ratios, a summary measures of effect for cluster-level covariates were described. Similarly, variance partition coefficient and the median odds ratio, a measure of components of variance and heterogeneity in outcomes were described.

Material and Methods

Modeling Hierarchical Data with Binary Outcomes

One common approach when analyzing hierarchical data is to use multilevel modeling approaches while incorporating the nested sources of variability at each level. For a multilevel analysis, the basic random intercept logistic regression model provides interesting information. The model allows the intercept to vary randomly across clusters through the introduction of cluster-specific random effects. However, the conventional multilevel logistic regression model incorporates cluster-specific random effects to account for the within-cluster correlation of subject outcomes. The cluster-specific random effect is given as:

$$Logit\{Pr(Y_{ij} = 1)\} = \alpha_0 + \alpha_{0j} + \alpha_1 x_{1ij} + \dots + \alpha_k x_{kij} + \beta_1 Z_{1j} + \dots + \beta_q Z_{qj} \quad (1)$$

Y_{ij} denotes the binary response variable measured on the *i*th subject within the *j*th cluster (Y_{ij} = 1 denotes success or the occurrence of the event, while Y_{ij} = 0 denotes failure or lack of occurrence of the event). In the model (1), x_{1ij} through x_{kij} denote the *k* predictor or explanatory variables measured on the subject; Z_{1j} through Z_{qj} denote the *q* predictor variables measured on the *j*th cluster while $\alpha_{0j} \sim N(0, \tau^2)$. The assumption is made that the random effects are independent of the model covariates (*X*, *Z*). For data, several variations of this model were fitted to the data and conduct a sequence of further analyses to enrich our interpretation of the data.

Random Intercept/Null Model (Model 1)

The null model, also called the “unconditional model” or a “one-way ANOVA with random effects,” is a type of random intercept model that predicts the level 1 intercept of the dependent variable as a random effect of the level 2 grouping variable, with no other predictors at level 1 or 2 in a two-level model [7].

Firstly a simple model with no predictors, i.e., an intercept-only model that predicts variation in the proportion of women that utilizes Maternal Health Care (MHC) was fitted from one state to another. The functional form of the model is:

$$Logit(odds) = \left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_{00} + u_{0j};\, u_{0j} \sim (0, var\ (u_{0j})) \quad (2)$$

Where β_{00}= fixed intercept; average log-odds of utilizing MHC

u_{0j}= deviation of the state-specific intercept from the fixed intercept (i.e., the level-2 residual)

Var(u_{0j}) = random intercept variance (the variance between states in state-average log-odds of utilizing MHC) [8].

Intra-Class Correlation under Model 1

The null model is used to calculate the intra-class correlation coefficient (ICC), which is a test of the need for mixed modeling. For the null model, the formula is given as [9]

$$ICC = \frac{level-2\ variance(\tau^2)}{level-2\ variance(\tau^2) + level-1\ variance} = \frac{Var(u_{0j})}{Var(u_{0j}) + (\frac{\pi^2}{3})} \quad (3)$$

and $\frac{\pi^2}{3} \approx 3.29$ refers to the standard logistic distribution; the assumed level-1 variance component: this assumed value was taken, as the logistic regression model does not include level-1 residual.

Maternal Healthcare Utilization Data

For analyzing the variation in the utilization of maternal healthcare services across states in Nigeria, data was extracted from the 2013 NDHS dataset. NDHS is a comprehensive survey conducted in Nigeria as part of the worldwide Demographic Health Survey (DHS) project. The unit of analysis for this study was Ever-Married Women (EMW) - women who had at least one live birth in the five years preceding the survey. The data have a hierarchical structure, with the EMW nested within their respective states of residence. The study sample consisted of 20116 EMW residing in the 37 states (including the Federal Capital Territory) of the federation.

Based on some scientific literature review of socio-demographic variables influencing the utilization of maternal healthcare services, three EMW-level (level-1) variables were selected for the study. They include two categorical variables: Education (no education, primary education, secondary education, tertiary education), wealth index (poorest, poorer, middle, richer, richest) and a binary variable; prenatal (yes: Prenatal care. vs. no: Prenatal care). Two state-level (level-2) variables were included: Residence (urban vs. rural) and Household. The first variable is binary, while the second is nominal. The binary outcome for the study was the utilization of health facility as place of delivery, which occurred for 7742 (38.5%) of EMW in the sample.

The response variable in this study is "place of delivery," which is binary and hence multilevel logistic regression model is a natural choice for modeling. Traditional logistic regression (which, in multilevel analysis terms, is single-level) requires the assumptions: (i) independence of the observations conditional on the explanatory variables and (ii) uncorrelated residual errors. These assumptions are not always met in practical nested data. However, the multilevel logistic regression analysis considers the variations due to hierarchy structure in the data. It allows the simultaneous examination of a group level effect (state) and individual level variables on individual level outcomes while accounting for the non-independence of observations within groups. Also, this analysis allows the examination of both between group and within group variability as well as how group level and individual level variables are related to variability at both levels [10].

Results

We fit three hierarchical logistic regression models. The first was the null model which did not contain any EMW or state predictors. It incorporated only state-specific random effects to model between-state variation in the utilization of maternal healthcare (Model 1). The second model included the 3 EMW predictors described above in addition to state-specific random effects (Model 2). The third model included both EMW predictors and the two-state predictors described above in addition to the state-specific random effects (Model 3). Estimated regression coefficients and odds ratios are reported in Tables 1 and 2, respectively. The odds ratios were obtained by exponentiating the estimated regression coefficients. In Table 1, the estimates of the variance of the distribution of the random effects were reported.

Table 1: Estimated Regression Coefficients and Variance Components for the Hierarchical Logistic Regression Models

Variables	MODEL 1		MODEL 2		MODEL 3	
EMW-level Predictors	RC(95% CI)	P-value	RC(95% CI)	P-value	RC(95% CI)	P-value
Intercept	-0.171(-0.654,0.313)	<0.001	-3.414(0.020,0.053)	<0.001	-3.292(0.023,0.061)	<0.001
Education						
Tertiary			2.019(5.231,10.833)	<0.001	2.023(5.304,10.787)	<0.001
Secondary			0.767(1.870,2.478)	<0.001	0.776(1.892,2.498)	<0.001
Primary			0.319(1.222,1.547)	<0.001	0.324(1.230,1.555)	<0.001
Wealth Index						
Richest			1.957(5.418,9.254)	<0.001	1.795(4.579,7.920)	<0.001
Richer			1.230(2.730,4.286)	<0.001	1.135(2.473,3.915)	<0.001
Middle			0.846(1.874,2.899)	<0.001	0.802(1.793,2.774)	<0.001
Poorer			0.482(1.299,2.019)	<0.001	0.477(1.290,2.012)	<0.001
Prenatal						
Prenatal care			2.193(6.613,12.143)	<0.001	2.175(6.539,11.851)	<0.001
State-level Predictors						
Residence						
Urban					0.142(0.074,0.274)	0.003
Household					0.076(0.033,0.178)	0.020
τ^2	2.237		0.853		0.643	
PCV	Reference		61.87%		71.26%	
VPC/ICC	0.40		0.21		0.16	
M.O.R	4.16		2.41		2.15	
PCV: Proportional Change of the Variance, VPC: Variance Partition Coefficient, ICC: Intra Class Correlation, M.O.R: Median Odds Ratio						

Note: values in parentheses are the lower and upper confidence intervals (CI); Regression Coefficient (RC)

Results from Random Intercept Model with Level-1 Predictors (Model 2)

This is also known as one-way ANCOVA with random effects models. In the model consisting of EMW predictors (Model 2), all of the three predictors were significantly associated with the odds of utilizing MHC (Table I): The intercept for this model was -3.414. Thus, in any given state (i.e., a state whose random effect was equal to zero), the probability of utilizing MHC for a woman whose covariates were equal to zero was

$$\frac{\exp(-3.414)}{1+\exp(-3.414)} = 0.032.$$

The reference woman did not utilize MHC as a result of delivery at home (for outcome), no education, poorest, no prenatal care (for predictors). The multilevel model has also revealed that there exist variations in the mean effect of the predictors over the Multilevel Logistic Regression Analysis response variable; utilization of MHC in Nigeria (Table 1). The variation is significant ($p<0.001$) at all levels of education (primary, secondary, tertiary), wealth index (poorer, middle, richer, richest), and prenatal care. In addition to the fixed effect, the intercept has very strong significant random effect at the state level.

Random Intercept Model with Level-1&2 Predictors (Model 3)

This is also known as random intercept ANCOVA models or means-as-outcomes ANCOVA models. All of the 3 EMW predictors, at all levels, were significantly associated with the log-odds of MHC utilization. Similarly, one of the two state-predictors; residence (urban) was significantly associated with the outcome (odds ratio=1.388, 95%CI=1.180, 1.633). The intercept for this model was -3.292. Thus, in any given state where a woman was an urban resident, the probability of utilizing MHC for a woman whose covariates were equal to zero was $\frac{\exp(-3.292)}{1+\exp(-3.292)} = 0.036$. As above, the reference woman did not utilize MHC as a result of delivery at home (for outcome), no education, poorest, no prenatal care (for predictors).

Table 2: Estimated Odds Ratio for the Hierarchical Logistic Regression Models

Variables	Model 2	Model 3
EMW-level Predictors	Odds-ratio (95%CI)	Odds-ratio (95%CI)
Education		
Tertiary	7.538 (5.231, 10.833)	7.564 (5.304, 10.787)
Secondary	2.153 (1.870, 2.478)	2.174 (1.892, 2.498)
Primary	1.375 (1.222, 1.547)	1.383 (1.230, 1.556)
Wealth Index		
Richest	7.081 (5.418, 9.254)	6.022 (4.579, 7.920)
Richer	3.420(2.730, 4.286)	3.112(2.473, 3.915)
Middle	2.331(1.874, 2.899)	2.23091.7933, 2.774)
Poorer	1.619(1.299, 2.019)	1.611(1.290, 2.012)
Prenatal		
Prenatal Care	8.961(6.613, 12.143)	8.803(6.539, 11.851)
State-level Predictors		
Residence		
Urban		1.388(1.180, 1.633)
POOR (%)		45

Note: values in parentheses are the lower and upper confidence intervals (CI)

Cluster-Specific Effect of the Hierarchical Logistic Regression Model:

The odds ratios for the individual variables reported in Table 2 are cluster-specific or conditional measures of association or intra-cluster measures of association. It is important to note that the interpretation of the odds ratio is conditional on both the other covariates as well as the cluster-specific random effect [11]. Therefore, they may be interpreted as odds ratios for within-cluster comparisons, that is, state-adjusted associations between the socio-demographic variables of the women and MHC utilization. In examining Model 2, one would interpret the odds ratio for prenatal care as suggesting that, when comparing two subjects who received prenatal care and who do not receive prenatal care, but who share identical values on the remaining 2 covariates and who also share the same state average effect (i.e., the value of the random effect), then the odds of MHC utilization are 8.961 times higher for the woman who received prenatal care compared to the odds of MHC utilization for the woman that do not receive prenatal care. In other words, when comparing two subjects within the same cluster such that one received prenatal care, and the other did not, but shares identical values of the remaining 2 covariates, the likelihood of utilizing MHC for the woman that received prenatal care is 8.961 times higher than the likelihood of utilizing MHC for the woman that did not receive prenatal care. Similarly, the odds of utilizing MHC for a woman having tertiary education, secondary education or primary education are 7.081, 2,153 or 1.375 higher than a woman who has no education respectively, while controlling for individual/state-level variables.

The Effect of Cluster-Level Variables

For this study, we considered the use of Proportion of Opposed Odds Ratios (POOR) proposed by Merlo as a measure of the magnitude of the effect of cluster variables. The POOR is the proportion of such odds ratios with the opposite direction to the overall odds ratio [12]. It can be evaluated as

$$\text{POOR} = \Phi\left(-\left|\frac{\alpha}{\sqrt{2\tau^2}}\right|\right) \qquad (4)$$

In this case study data, the POOR for residence was 0.45. Thus, in 45% of comparison between an urban residence and a rural residence, the odds ratio for this comparison would be different in direction to that of the overall odds ratio for place of residence. The overall odds ratio was 1.388 (Table 2), denoting the odds of utilizing MHC at an urban residence to be 1.388 times higher than at a rural residence. However, in 45% of pair-wise comparisons, the odds of MHC utilization would be higher at an urban residence than at a rural residence.

Variance Partition Coefficient

In order to estimate the effect of the cluster itself on the subject outcomes, known as the general contextual effect, there is need for measures of heterogeneity and components of variance (e.g., clustering). The Variance Partition Coefficient (VPC), also known as ICC, specifically for hierarchical structures, represents the proportion of the total observed individual variation in the outcome that is attributable to between-cluster variation. Moreover, as this proportion increases, the general contextual effect also increases and vice-versa.

Given a continuous outcome, and if $\sigma^2$and τ^2 denote the between-subject and between-cluster variation (e.g., obtained from a variance components model); then it is given that

VPC=$\frac{\tau^2}{\tau^2+\sigma^2}$. For simple hierarchical structures like women nested within states, the VPC is equivalent to the ICC [13].

Different methods such as the normal response approximation, the simulation method, the Taylor series linearization, and the latent response formulation are being used in the calculation of the VPC. For this study, we employed the latent response formulation based on its popularity and wide acceptance. Under this procedure, it is assumed that the binary outcome variable arises as the dichotomization of an underlying continuous latent variable following a logistic or a probit distribution. That is, the regression uses a logit or a probit link function, respectively. The variance of logistic distribution with scale parameter equal to one is$\frac{\pi^2}{3}$ [14].

In this data, the estimate of the between-state variance was 2.237 for Model 1, 0.853 for Model 2, and 0.643 for Model 3. These correspond to VPCs of 0.40, 0.21, and 0.16, respectively. The first of these has an unconditional interpretation, while the latter two have a conditional or residual interpretation. The VPC derived from the null model was 0.40; which implies that 40% of the individual variation in the underlying propensity to utilize MHC is due to systematic differences between states healthcare infrastructure (without considering the possibility of a different woman mix composition when estimating the state variance), while the remaining 60% is due to systematic differences between the women.

The second and third VPCs have a conditional interpretation: of the residual variation in outcomes that remains after accounting for the variables in the model, it is the proportion that is attributable to systematic differences between clusters. Thus, when using Model 2, we would infer that of the residual variation in outcomes that persists after adjusting for 3 EMW demographic variables, 21% is due to systematic differences between states healthcare infrastructure, while the remaining 79% is due to unmeasured differences between the women. However, it should be noted that if the VPC were close to 0, the outcomes for women from the same state would be no more similar than outcomes for a random sample of women from the population. Conversely, if the VPC were close to 1, then all women in the same state would have the same outcome [12].

The Median Odds Ratio as a Measure for Quantifying Variation

Another good measure for quantifying variation or heterogeneity in outcomes between clusters is the

Median Odds Ratio (MOR). The MOR was popularized in the epidemiological literature by Larsen and Merlo [15]. If one were to repeatedly sample at random two subjects with the same covariates from different clusters, then the MOR is the median odds ratio between the subject at higher risk of the outcome and the subject at the lower risk of the outcome (the cluster-specific random effects entirely quantify differences in risk). The MOR can be evaluated as:

$$\text{MOR} = \exp\left(\sqrt{2\tau^2} X \Phi^{-1}(0.75)\right) \qquad (5)$$

where $\tau^2$is the estimated variance of the distribution of the random effects, Φ denotes the cumulative distribution function of the standard normal distribution, while $\Phi^{-1}(0.75)$ = 0.6745 is the 75th percentile of a standard normal distribution.

In our case study data, the MOR was equal to 4.16 (Model 1), 2.41 (Model 2), and 2.15 (Model 3). In interpreting the MOR from model 2, when comparing two identical women from randomly selected states, the MOR comparing a woman in a state with the higher risk of utilizing MHC to a different woman (but with the same covariate values) in a state with the lower risk of MHC utilization was 2.41. Thus, in half such comparisons, the odds of MHC utilization would be less than 2.41 for a woman in a state at higher risk compared to a different woman (but with the same covariate values) in a state at lower risk. Similarly, the MOR (Model 3) comparing a woman in a state with the higher risk of utilizing MHC to a different woman (but with the same covariate values) in a state with the lower risk of MHC utilization was 2.15. It is expected that states having better healthcare infrastructure will be at a lower risk of MHC utilization while states having poor healthcare infrastructure will be at a higher risk of MHC utilization.

However, the MOR considers only the between-cluster variance, and its value can range from one to infinity. Therefore, the result of this study indicated an MOR of 2.41 as low because it corresponds to a VPC of 0.21. That is, 21% of the total variation in utilizing MHC is due to between state differences in MHC utilization.

Discussion

Multilevel logistic regression models result in odds ratios that have a cluster-specific or within-cluster explanation. Very few multilevel analyses have been done in Nigeria using maternal healthcare utilization binary data, and these analyses have found significant multilevel effects either at the individual levels or higher levels. Findings from Ononokpono and Odimegwu [16] demonstrated a significant association between community-level factors and delivery in a separate healthcare facility. Moreover, it was found that there was a strong association between education, region of residence (community level), and delivery in a health facility. Similarly, for individual-level variables, it was also revealed that educational attainment, occupation, ethnic origin, a woman's autonomy, household wealth index, parity, and religion were significantly associated with delivery care. However, the POOR and MOR measures of utilizing MHC were not assessed.

In support of the findings by Ononokpono and Odimegwu [16], our analysis also reveals evidence ($p<0.001$) of effects at the states level and the individual level and it also assessed the POOR and MOR measures of utilizing MHC. At the individual level, factors such as education status, wealth index, and prenatal care were significantly associated with MHC utilization in Nigeria. While at the state level, factors such as place of residence and household were also significantly associated with utilization of MHC.

Due to the importance of hierarchical logistic regression in assessing healthcare utilization and interventions, many countries, including those in Africa have utilized this methodology to bridge variations in health utilization at both communities, district, state, and regional levels. Findings show similar observations in Ethiopia [17] where it was found that urban residents in communities with high proportion of educated women and high utilization of antenatal care (ANC) had a significant effect on institutional delivery. Also, the random effects showed that the disparity in institutional delivery service consumption between communities was statistically significant.

A study on two decades of maternity care-fee exemption policies in Ghana found that the rich benefited much more than the poor [18]. Findings from the multilevel analysis recommend that removal of user fees is essential in improving skilled birth care use; however, other obstacles such as distance to facilities, lack of transportation, poor quality of care and lack of information need to be tackled to enhance uptake for the poorest and marginalized women.

In another study that examined the individual and community-level factors associated with the utilization of antenatal care, following the adoption of the focused antenatal care (FANC) approach in Zambia [19], findings show that factors such as the woman's employment status, the actual quality of ANC received and the husband's educational attainment are positively associated with the use of ANC.

In this work, the methods to estimate the marginal or population-average effect of cluster characteristics were described. These result in the formation of 3 different types of models that allow for the formal comparison of outcomes between clusters whose characteristics differ from one another. The POOR, a summary measure of the effects of cluster-level variables, was also described. Findings show that in 45% of pair-wise comparisons between the urban and rural residence, the odds of MHC utilization would be higher at an urban residence than at a rural residence by 1.388 times. The implication of this at the state level is that women residing in urban areas stand a better chance of utilizing MHC than those in rural areas.

The MOR quantifies the magnitude of variation in the utilization of MHC between states. The MOR (Model 2) indicated the odds of MHC utilization was less than 2.41 for a woman in a state at higher risk compared to a different woman (but with the same covariate values) in a state at lower risk. Similarly, the MOR (Model 3) indicated the odds of MHC utilization was less than 2.15 for a woman in a state at higher risk compared to a different woman (but with the same covariate values) in a state at lower risk. The intra-class correlation coefficient (ICC), which is a test of the need for mixed modeling, revealed 40% (Model 1), 21% (Model 2) and 16% (Model 3) chances of utilizing MHC that is explained by between-states differences respectively. A situation where women in one state are at lower/higher risk of utilizing MHC when compared to women in another state is an indication of inequality in assessing MHC services across the Nigerian states. The implication of this is that a sizable proportion of women are automatically denied of MHC as a result of their state of residence.

However, measures such as distance to health facility, to measure accessibility, is not captured in the household survey. Cultural issues are also important factors that influence utilization of MHC, but these are not considered in this study. Although the study accounts for some state-level disparity, based on these women socio-economic and demographic factors, a significant proportion of the disparity remains inexplicable. Consequently, the importance of these women sociocultural barriers needs to be acknowledged for the effective implementation of healthcare interventions.

Conclusion

This paper demonstrates the significance of hierarchical logistic regression analysis for studying maternal healthcare utilization in Nigeria. The study found a remarkable disparity in the utilization of MHC across the Nigerian states and the need for robust interventions for funding health through the removal of socio-economic barriers to modern health facilities. Findings from the multilevel analysis in this study also show that interventions aimed at promoting the utilization of MHC for child delivery should not only be implemented at the individual level but also extended to the state level. Therefore, the government needs to pay serious attention to interventions geared towards fostering the use of maternal healthcare facilities at the states. In addition, Place of Residence and other state-level factors were found to be significantly associated with the utilization of MHC.

To close the disparity in healthcare delivery, state-specific interventions that would allow fair allocation and use of maternal healthcare should be implemented. Significantly, there is need for interventions that explore effective procedure for improving maternal healthcare utilization based on these women's socio-demographic status.

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Competing Interest

None declared.

Authors' Contributions

Ogunniran Ademola John conceived the study design, acquisition of data, data analysis, and interpretation. Akarawak Eno Emmanuella contributed to conception, design, and interpretation and critically revised the early version of the manuscript. All authors read and approved the final manuscript before submission to the journal.

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