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Modelling Nutritional Status of Adolescent in Nigeria: A Modified Binomial Logistic Approach

[1]Kromtit F. M., [2]K. E Lasisi., [3]A.M Kwami., [4]Pam D. J., [5]Mafolasire Sheyi., [6]Echebiri C. J.

[1,2,3,4,6]Department of Mathematical Sciences, Abubakar Tafawa Balewa University, Bauchi, Nigeria

[5]Federal College of Forestry, Jos

ABSTRACT.

Adolescence marks a crucial phase of physical, psychological, and social development, transitioning from childhood to adulthood. This study, using Binary Logistic Regression, explores factors influencing the nutritional status of Nigerian adolescents. The selected factors, including education level, age group, blood group, rapid diagnostic test (RDT), and gender, were analyzed to estimate coefficients, standard errors, Wald test values, degrees of freedom, p-values, and confidence intervals. SPSS version 22.0 was employed to fit a binary logistic model, assess the significance of explanatory variables, and compare models. The study also investigates key variables and their impact on categorical responses like stunting and wasting.

Keywords: Adolescence; Binary Logistic Regression; Nutritional Status.

1.0 Introduction

Adolescence, constituting around 20% of the world population, is a crucial phase of physical and psychological development, bridging childhood and adulthood (Danjuma and Rabiul, 2020). Nutritional needs during this period are paramount for maintaining good health (Imdadul and Alauddin, 2020). However, adolescents face significant challenges, with a lack of balanced nutrition leading to severe health issues (Rabiul and Sheik Mohammed, 2020).

Sub-Saharan Africa has the highest proportion of adolescents globally, comprising 23% of the population aged 10–19 (UNICEF, 2012). Adolescents undergo rapid growth, puberty, and intense physical, psychological, and economic changes (Hermanussen, 2016). Despite their unique needs, they often lack appropriate services, leading to high adolescent birth rates and unmet needs (UNICEF, 2012).

The nutritional challenges adolescents face impact their physical growth, cognitive development, and overall health. Malnutrition in adolescent girls can result in low birth weight children, perpetuating a cycle of malnutrition. Understanding the nutritional status of adolescents, who make up 60% of Nigerian society (Aina et al., 1992), is crucial. Neglecting adolescents in nutrition initiatives can have long-term consequences, contributing to the intergenerational transmission of poverty (WHO, 2006).

Adopting a life-cycle approach to adolescent development is essential, emphasizing care, empowerment, and protection, especially for girls (UNICEF SOWC, 2011). Anaemia is a prevalent issue during adolescence, with serious implications for various health outcomes (Premalatha et al., 2012). Addressing the causes of anaemia is crucial for improving adolescent nutrition and health (Cheesbrough, 2005). Statistical models, though typically used for non-deterministic processes, play a key role in summarizing and making inferences from data (Davison, 2003).

While many studies focus on the nutritional status of children aged 0-5, there's a gap in understanding the mineral intake and dietary practices of adolescents, contributing to malnutrition (Lasisi, K. E. et al, 2015). It is imperative to fill this gap to develop effective strategies for promoting adolescent health and nutrition.

2.0 Statement of the Problem

The rapid growth and changes experienced by adolescents intensify the need for both macro and micro nutrients. Addressing these nutritional demands, especially in females, is crucial to breaking the cycle of intergenerational malnutrition. However, there exists a knowledge gap and insufficient information regarding the nutritional status of adolescents, hindering the formulation of targeted programming priorities in Nigeria. Building upon the work of Rediet T. R and Jemal A.H (2019), who assessed anemia and its determinants in female adolescents in West Ethiopia using a Binomial Logistic Regression model, our study aims to fill this gap by examining and improving understanding of adolescent nutrition in the Nigerian context.

3.0 Aim and Objectives of the Study

The aim of this study is to model the Nutritional Status of Adolescent in Nigeria, using a modified Binomial Logistic Regression method through the following objectives:

- To determine the prevalence of anemia among the adolescent boys and girls
- To determine the anthropometric indices and nutritional status of the adolescent boys and girls
- To build a statistical model that could fit the data for future predictions / forecasting of adolescents' nutritional status in Nigeria
- Test the modified model for its appropriateness and precision.

4.0 Brief Literature Review

The literature review discusses two distinct phases of adolescence, as outlined by Patton et al. (2016): early adolescence (ages 10–14 years) and late adolescence (ages 15–19 years). During early adolescence, characterized by the onset of the growth spurt and the development of sex organs and secondary sexual characteristics, there is considerable variability in the timing and magnitude of the growth spurt between genders and among individuals (Tanner and Davis, 1985; Tanner, 1987). Girls typically experience their growth spurt around 10 years and peak velocity at about 12 years, while boys initiate theirs around 12 years, surpassing girls within a year or two (WHO, 2006).

Early adolescence is marked by physical changes, beginning with the growth spurt, followed by the development of sex organs and secondary sexual characteristics. This period sees significant brain development, impacting emotional, physical, and mental abilities. Early adolescents become more aware of their gender and adjust their behavior or appearance to fit perceived norms (UNICEF SOWC, 2011). Given the social taboos surrounding puberty, it is crucial to provide early adolescents with information to protect against HIV, sexually transmitted infections, early pregnancy, and sexual violence (UNICEF SOWC, 2011).

In late adolescence (15–19 years), the brain continues to develop, enhancing analytical and reflective thought. Peer-group opinions remain important initially but diminish as adolescents gain clarity and confidence in their own identity and opinions. Late adolescence is associated with risks for girls, including depression and eating disorders, exacerbated by gender-based discrimination and societal beauty standards (UNICEF SOWC, 2011). Despite these risks, late adolescence is viewed as a time of opportunity, idealism, and promise, marked by individuals shaping their identities, engaging in work or further education, and actively contributing to shaping the world around them (UNICEF SOWC, 2011).

Adolescent development is a complex phase marked by factors like puberty, neurocognitive maturity, and social role transitions, all impacting nutrition (Bhutta et al., 2017). This period involves rapid growth, presenting a chance to address early childhood growth failure, although substantial catch-up potential is limited (Gopalan, 1989; UNICEF SOWC, 2011).

Growth failure and micronutrient inadequacy during adolescence can lead to delayed growth and an increased risk of chronic diseases in adulthood (Bhutta et al., 2017).

Adolescence is nutritionally critical for several reasons (WHO, 2006): the surge in physical growth demands more nutrients; socio-cultural factors and lifestyle changes can affect nutrient intake and needs; increased nutrient requirements exist during pregnancy and illness; it provides a second chance for growth catch-up if environmental conditions favor nutrient intake; and psychological changes influence dietary habits. This phase establishes habits persisting into adulthood, with adolescents becoming more independent in food choices and influenced by peers (Seymour et al., 1997).

Factors influencing adolescent nutrition include home food availability, time for food preparation, knowledge of food content, ability to purchase snacks, socio-demographic, behavioral, and environmental factors (Venter and Winterbach, 2010; Li et al., 2008; Ahmed et al., 2006; Bhutta et al., 2017). Media, parents, and peers can either promote negative images or introduce healthier nutritional approaches (Spencer et al., 2015).

Nutritional needs diverge between males and females after the pubertal growth spurt, influenced by earlier maturation in females and variations in physiological needs (WHO, 2006).

Studies on anaemia and iron deficiencies in Nigeria among adolescents are limited, often conducted in schools and hospitals. Prevalence of anaemia among women of reproductive age in Nigeria is 49.8%, with variations in prevalence during pregnancy and among different states (WHO, 2016; NDHS, 2018).

5.0 METHODOLOGY

In this section, variations in malnutrition prevalence associated with household socio-economic factors, using Multiple Indicators Cluster Survey data will be collected at National Bureau of Statistics are to be examined in this study which will determine the amount of resources (dietary intake, education, and health care) that are available for the adolescent and effect of anthropometrics data of the target population on their nutritional status would be examined as well.

Logistic regression, like any other model building technique in statistics is aimed at finding the best fitting and most economical and yet sensible model to assess the relationship between a response **variables** and at least one independent variables. It differs from the linear regression in that, it can be applied when the dependent variable is categorical and that it does not require rigorous assumptions to be met (Al-Ghamdi, 2011).

5.1 Variables to be measured

The variables to be used in this research work are as follows; dependent variable Y (the nutrition status) and the independent variables are (i.e. X_1= gender, X_2= educational status, X_3= anaemia status, X_4= age-grp, X_5 = RDT status, X_6 = weight, and X_7 =height).

5.2 The Model

The model in the context of this research will have the form as;

y_i ~ Binomial (n_i,π_i) where i = 1 and 2 for wasting and stunting respectively

Logit (y_i) = (Odds) = Ln ($\frac{\pi_i}{1-\pi_i}$) = $\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$

$$E\{Y_i\} = \pi_i = \frac{exp(X_j \beta')}{1 + exp(X_j \beta')}$$

π_i ~ logit-1(X_j β′)

y_i = the number of malnourished adolescents.

π_i=denote the probability of malnourished adolescents.

n_i = denote the number of adolescents.

Where X_j = Matrix of predictors (variables considered). j = 1, . . ., k

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \cdots \\ \beta_{k-1} \end{bmatrix}_{k\times 1} \quad X_j = \begin{bmatrix} 1 \\ x_{j1} \\ \cdots \\ x_{j,k-1} \end{bmatrix}_{k\times 1}$$

If the parameter βi is significantly different from zero, then it means that X_j has a significant effect on the likelihood of malnutrition. We set the significance level at α = 0.05, which is a

common standard. Setting this as a cut off means that we only accepted conclusions where there is a 95 per cent or greater chance that the observed correlation is not spurious. We first used one explanatory variable at a time in the logistic regression model to examine whether each variable by itself helps explain the probability of malnutrition.

5.3 Method of Parameter Estimation

Logistic regression uses the Maximum Likelihood Estimation method to estimate the model coefficients.

The joint probability function for binary logistic regression is:

$$g(Y_1, \dots, Y_p) = \prod_{i=1}^{p} f_i(Y_i) = \prod_{i=1}^{p} \pi_i^{Y_i} (1 - \pi_i)^{1-Y_i}$$

$$log_e g(Y_1, \dots, Y_p) = log_e \prod_{i=1}^{p} f_i(Y_i) = log_e \prod_{i=1}^{p} \pi_i^{Y_i} (1 - \pi_i)^{1-Y_i}$$

$$= \sum_{i=1}^{n} [Y_i log_e \pi_i + (1 - Y_i) log_e (1 - \pi_i)]$$

$$= \sum_{i=1}^{n} \left[Y_i log_e \left(\frac{\pi_i}{1 - \pi_i}\right)\right] + \sum_{i=1}^{n} log_e (1 - \pi_i)$$

Since $1 - \pi_i = \frac{1}{1+exp(\beta_0 + \beta_1 x_i)}$ and $log_e \left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_i$

Therefore, $log_e L(\beta_0,\ \beta_j) = \sum_{j=1}^{k} Y_i(\beta_0 + \beta_j x_j) - \sum_{j=1}^{k} log_e [1 + exp(\beta_0 + \beta_j x_j)]$.

We are trying to find β_0 and β_j to maximize the log-likelihood function:

$ln = log_e L(\beta_0\ ,\ \beta_j) = \sum_{j=1}^{k} Y_i(\beta_0 + \beta_j X_j) - \sum_{j=1}^{k} log_e\ [1 + \exp(\beta_0 + \beta_j X_j)]$.

Define:

$$\underset{\sim}{y}U = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_P \end{bmatrix} X_U = \begin{bmatrix} X_1^T \\ X_2^T \\ \dots \\ X_N^T \end{bmatrix}$$

The model is $Y = X^T\beta$. The estimator of β is $\underline{\hat{\beta}} = (X_U^T \sum_U^{-1} X_U)^{-1} X_U^T \sum_U^{-1} y_U$, where $\sum_u is$ a diagonal matrix with ith diagonal element σ_j^2.

5.4 Method of Data Analysis

The data analysis will be carried out using logistic binomial model. The data will be analyzed using SPSS-Package version 22.0

The Logistic Binomial Model

To model the dependent variable, we classified;

$$y_i = \begin{cases} 1 \text{ if an adolescent is malnourished} \\ 0 \text{ if an adolescent is not malnourished} \end{cases}$$

According to Harrell (2001), the formula for a logistic regression model is given by;

$\pi(x_j) = p(y_i = 1/x_j)$

$= [1+\exp(-\mathbf{X}^T\boldsymbol{\beta})]^{-1}$

$\mathbf{X}^T\boldsymbol{\beta} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_{k-1} x_{k-1}$

$$\beta_{kx1} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{k-1} \end{bmatrix}, \quad X_{kx1} = \begin{bmatrix} 1 \\ X_1 \\ \vdots \\ X_{k-1} \end{bmatrix}, X_{i_p x1} = \begin{bmatrix} 1 \\ X_{j1} \\ \vdots \\ X_{j,k-1} \end{bmatrix}$$

$x_1, x_2, \cdots, x_k$ are the independent variables.

β_0 is the coefficient of the constant term

$\beta_1, \beta_2, \cdots, \beta_{k-1}$ are the coefficient of the k independent variables

$\pi(x_j)$ is the probability of an event that depends on k-independent variables

Since $\pi(x_i) = [1+\exp(-\mathbf{X}^T\boldsymbol{\beta})]^{-1}$

$= \frac{1}{[1+\exp(-\mathbf{X}^T\boldsymbol{\beta})]}$

$\Rightarrow 1-\pi(x_i) = 1- \frac{1}{1+\exp(-X\boldsymbol{\beta})}$

$= \frac{[1+\exp(-\mathbf{X}^T\boldsymbol{\beta})]^{-1}}{1+\exp(-\mathbf{X}^T\boldsymbol{\beta})}$

$= \frac{\exp(-\mathbf{X}^T\boldsymbol{\beta})}{1+\exp(-\mathbf{X}^T\boldsymbol{\beta})}$

$\Rightarrow \frac{\pi(x_j)}{1-\pi(x_j)} = [\exp(-\mathbf{X}^T\boldsymbol{\beta})]^{-1}$

Thus, $\ln(\frac{\pi(x_j)}{1-\pi(x_j)}) = \text{logit}[\pi(x_j)]$

$= \mathbf{X}^T\boldsymbol{\beta}$

5.5 Assumptions of Logistic Regression

Logistic regression is not dependent on stringent assumptions to be met as compared to linear regression. The fact that logistic regression analysis does not require a lot of assumptions renders it more preferable in some instances to other methods. The following details show it differs from other techniques:

i. The error terms are with a mean of zero and a variance of π(x)[1- π(x)] . (Hosmer and Lemeshow, 2000).

ii. Binary logistic regression assumes that the dependent or outcome variable is dichotomous.

iii. The outcomes are independent and mutually exclusive

iv. Logistic regression requires large samples to be accurate: a minimum of 60 total cases. These requirements need to be satisfied.

5.6 Method of Parameter Estimation of Logistic Regression

Logistic regression uses the Maximum Likelihood Estimation method to estimate the model coefficients. We classified

$$Y = \begin{cases} 1 \text{ malnourish} \\ 0 \text{ not malnourish} \end{cases}$$

$\mathrm{pr}(Y=1)=\pi \qquad \mathrm{pr}(Y=0)=1-\pi$

For n random variable $x_1 \cdots, x_n$ with $p(X_j)=\pi$, then their joint probability is

$\pi_{j=1}^{n} \pi_j^{x_j}(1-\pi_j)^{1-x_j} = \exp\left[\sum_j^n x_j \log\left(\frac{\pi_j}{1-\pi_j}\right)\right] + \sum_j^n \log(1-\pi_j)$

$Y=\sum_{j=1}^{n} X_j$ = number of successes n trails

$Y \sim \mathrm{binomial}(n, \pi)$

$p(Y=y)=\binom{n}{y}\pi^y(1-\pi)^{n-y}$ y= $0 \cdots, n$

If $y_i \sim b(n_i, \pi_i)$

$(\pi_1 \cdots \pi_n / y_1 \cdots y_n) = \sum_{i=1}^{n} y_i \log(\frac{\pi_i}{1-\pi_i}) + n_i \log(1-\pi_i) + \log\binom{n_i}{y_i}$

$p_i = \frac{y_i}{n_i}$ in each subgroup in terms of factor levels and other explanatory variables which characterized the subgroup. By modelling the probability π_i

$$g(\pi_i) = X_j^T \beta$$

Where X = vector of explanatory variables (dummy for factor levels and measured values of covariate), β in a vector of parameters and g is a link function.

Fitting the logistic model

$$\pi_i = \frac{exp(\beta_1+\beta_2 x_j)}{1+exp(\beta_1+\beta_2 x_j)}$$

So $log(\frac{\pi_i}{1-\pi_i}) = \beta_1+\beta_2 x_2$ assume a single variable

And $log(1-\pi_i) = -log[1+exp(\beta_1+\beta_2 x_2)]$

From the above, the log-likelihood function is

$$l = \sum_{i=1}^{n} y_i(\beta_1+\beta_2 x_2) - n_i\, log[1+exp(\beta_1+\beta_2 x_2)] + log\binom{n_i}{y_i}$$

Differentiating with respect to $\beta_1 and \beta_2$ is

$U_1 = \frac{\delta l}{\delta \beta_1} = \sum\{y_i - n_i[\frac{exp(\beta_1+\beta_2 x_2)}{1+exp(\beta_1+\beta_2 x_2)}]\} = \sum(y_i - n_i \pi_j)$

$U_2 = \frac{\delta l}{\delta \beta_2} = \sum\{y_i x_i - n_i x_i[\frac{exp(\beta_1+\beta_2 x_2)}{1+exp(\beta_1+\beta_2 x_2)}]\} = \sum x_i(y_i - n_i \pi_j)$

Similarly, the informative matrix is

$$l = \begin{bmatrix} \sum n_i \pi_i(1-\pi_i) & \sum n_i x_i \pi_i(1-\pi_i) \\ \sum n_i x_i \pi_i(1-\pi_i) & \sum n_i x_i^2 \pi_i(1-\pi_i) \end{bmatrix}$$

Maximum likelihood estimates are obtained by solving the matrix equation

$$l^{(m-1)} b^{(m)} = l^{(m-1)} b^{(m-1)} + u^{(m-1)}$$

5.7 Derivation Model for Classification

Let G_1 and G_2 be two sub-populations or groups, say. It may be helpful to think of G_1 in a malnourished adolescent, comprising $100\pi_i$% of the population, and G_2 as the not-malnourished adolescent. Measurements Z made on individuals have the following distributions in the two groups:

G_1: $Z \sim N_p(\mu_1, \Sigma)$

G_2: $Z \sim N_p(\mu_2, \Sigma)$

We want to develop a model for classifying and predicting the chance of overturning a verdict case. Let z^* be an observation made on an individual drawn at random from the combined population and let Y represent the individual's group membership. The prior odds that the individual belongs to G_1 are $\pi_1/(1-\pi_1)$.

The joint density of Y and Z is

$f(y,z) = \pi_1 I(y=1) f_1(z) + (1-\pi_1) I(y=2) f_2(z)$

$= \begin{cases} \pi_1 f_1(z), & for y=1 \\ (1-\pi_1) f_2(z), & for y=2 \end{cases}$

and the marginal density of Z is the mixture obtained by summing over y, $i.e$

$f_z(z) = f(1,z) + f(2,z)$

$\pi_1 f_1(z) + (1 - \pi_1) f_2(z)$

Where π_1= chance of malnourished adolescents

1- π_1= chance of not malnourished adolescent

$$\pi_1 f_1(z) = \pi_1[(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_1)^T\Sigma^{-1}(z-\mu_1)\}]$$

$$(1-\pi_1) f_2(z) = (1-\pi_1)[(1+(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_2)^T\Sigma^{-1}(z-\mu_2)\})]^{-1}$$

The equation becomes

$$\pi_1[(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_1)^T\Sigma^{-1}(z-\mu_1)\}] + (1-\pi_1)[(1+(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_2)^T\Sigma^{-1}(z-\mu_2)\})]^{-1}$$

Dividing the R.H.S with (1-π_1)

$$\frac{\pi_1}{(1-\pi_1)}[(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_1)^T\Sigma^{-1}(z-\mu_1)\} + [(1+(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_2)^T\Sigma^{-1}(z-\mu_2)\})]^{-1}$$

Taking the natural logarithm of both sides

$$= \log_e\left(\frac{\pi_1}{(1-\pi_1)}\right) + \log_e\left[(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_1)^T\Sigma^{-1}(z-\mu_1)\} + [(1+(2\pi\Sigma)^{-1}\exp\{-\frac{1}{2}(z-\mu_2)^T\Sigma^{-1}(z-\mu_2)\})]^{-1}\right]$$

$$= \log_e\left(\frac{\pi_1}{(1-\pi_1)}\right) - (2\pi\Sigma) - \frac{1}{2}(z-\mu_1)^T\Sigma^{-1}(z-\mu_1) - \log_e 1 + (2\pi\Sigma) + \frac{1}{2}(z-\mu_2)^T\Sigma^{-1}(z-\mu_2)$$

$$= \log_e\left(\frac{\pi_1}{(1-\pi_1)}\right) - \frac{1}{2}\Sigma^{-1}\left[(z-\mu_1)^T\Sigma^{-1}(z-\mu_1) - (z-\mu_2)^T\Sigma^{-1}(z-\mu_2)\right]$$

$$= \log_e\left(\frac{\pi_1}{(1-\pi_1)}\right) - \frac{1}{2}\Sigma^{-1}\left[\mu_1^T\mu_1 - \mu_2^T\mu_2 - 2Z(\mu_1-\mu_2)\right]$$

$$= \log_e\left(\frac{\pi_1}{(1-\pi_1)}\right) + \left[\frac{1}{2}\mu_2^T\Sigma^{-1}\mu_2 - \frac{1}{2}\mu_1^T\Sigma^{-1}\mu_1 + Z\Sigma^{-1}(\mu_1-\mu_2)\right]$$

But

α = $\frac{1}{2}\mu_2^T\Sigma^{-1}\mu_2 - \frac{1}{2}\mu_1^T\Sigma^{-1}\mu_1$

β = $\Sigma^{-1}(\mu_1 - \mu_2)$

Substituting this back in the above equation, we obtain

= $\log_e\left(\frac{\pi_1}{(1\text{-}\pi_1)}\right) +$ $(\alpha+\beta^T Z^*)$

Taking log_eagain

$=\left[\frac{\pi_1}{(1-\pi_1)}\right] exp(\propto +\beta^T Z^*)$

6.0 RESULTS AND DISCUSSION

6.1 RESULTS

Nigerian adolescent nutritional data was analyzed with the aim of assessing the influence of some covariates on the response variable (malnutrition). Since the Multiple Indicator Cluster Survey (MICS5) data set contains several variables, only those that are believed to be related to nutritional status were selected. All categorical covariates are effect coded. The adolescent's age is assumed to be nonlinear; the state is special effect while other variables are parametric in nature.

Height-For-Age: It expresses the height of a child in relation to his/her age.

i. It reflects skeletal growth (stature), and is the best indicator of Stunting.

ii. It reflects the past nutritional history of a child rather than his current nutritional status.

iii. It is a measure of chronic malnutrition (longer-term malnutrition).

iv. It is useful for evaluating the effects of socio-economic change or development programmes in a certain place.

v. It is more useful for long term planning and policy development rather than emergencies.

Weight-For-Height: it expresses the weight of a child in relation to his/her height.

- It is a widely used nutritional or anthropometric index, and is the best indicator of Wasting
- It is appropriate in emergency assessments because it reflects short-term growth failure or current situation of the population.
- It is does not involve age which is often difficult to determine, especially in emergency situations.

Weight-For-Age: Expresses the weight of a child in relation to his/her age.

- Is a composite index, which reflects either wasting or stunting or a combination of the two (Underweight).
- Because of this mix, it is not useful to specifically assess acute malnutrition or chronic malnutrition.
- It is useful for individual growth of children using the "road to health" chart.
- The **"road to health"** chart which is used by MOH is based on this index.

Body mass index (BMI) was calculated from the mean weight and height measurements using the formula [Weight in Kg / (Height in cm)^2]. Values of height and BMI were related to age and compared with WHO growth standard for children 5- 19 years height-for-age and BMI-for-age z-scores (WHO, 2007). Adolescents were classified as stunted and thin if z-scores of height-for-age and BMI-for-age were ≤ −2 SD (moderate and severe) below the WHO median. Mild (−1), moderate (−2) and severe (−3) was used to describe the degree of stunting and thinness. Overweight was taken as +2 and +3 was used for obesity.

Table 1: HB Cut-Off for Anaemia (WHO, 2011)

POPULATION GROUP	**NON ANAEMIA**	**ANAEMIA (Hb Conc in g/dl)**		
		MILD	**MODERATE**	**SEVERE**
10-11 years	≥ 11.5	11.0 - 11.4	8.0 - 10.9	< 8.0
12-14 years	≥ 12.0	11.0 - 11.9	8.0 - 10.9	< 8.0

15-19 years GIRLS (Non-pregnant)	≥ 12.0	11.0 - 11.9	8.0 - 10.9	< 8.0
15-19 years BOYS	≥ 13.0	11.0 - 12.9	8.0 - 10.9	< 8.0

Table 2: Age Grouping

		Frequency	Valid Percent	Cumulative Percent
Valid	early adolescent	898	50.0	50.0
	late adolescent	899	50.0	100.0
	Total	1797	100.0	

Table 3: Gender Distribution

		Frequency	Valid Percent	Cumulative Percent
Valid	Male	882	49.0	49.0
	Female	917	51.0	100.0
	Total	1799	100.0	

Table4a: Wasting (BMI) Grouping

		Frequency	Valid Percent	Cumulative Percent
Valid	severe wasting	741	42.1	42.1
	moderate wasting	279	15.9	58.0
	mild wasting	311	17.7	75.7
	Normal	422	24.0	99.7
	Overweight	6	.3	100.0
	Total	1759	100.0	

Table 4b: BMI categorical coding

		Frequency	Valid Percent	Cumulative Percent
Valid	Normal	739	42.0	42.0
	Wasting	1020	58.0	100.0
	Total	1759	100.0	

Table 5a: Stunting (HFA) Grouping

		Frequency	Valid Percent	Cumulative Percent
Valid	Normal	621	34.5	34.5
	severely stunted	1008	56.0	90.5
	Stunted	171	9.5	100.0
	Total	1800	100.0	

Table 5b: HFA categorical coding

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Normal	621	34.5	34.5	34.5
	Stunted	1179	65.5	65.5	100.0
	Total	1800	100.0	100.0	

Table 6a: Malaria (RDT) Grouping

		Frequency	Valid Percent	Cumulative Percent
Valid	Negative	1234	71.1	71.1
	Pf+	485	28.0	99.1
	Non-Pf+	9	.5	99.6
	Pf or Mixed+	5	.3	99.9
	Invalid	2	.1	100.0
	Total	1735	100.0	

Table 6b: RDT Categorical Coding

		Frequency	Valid Percent	Cumulative Percent
Valid	Negative	1234	71.1	71.1
	Pf+	501	28.9	100.0
	Total	1735	100.0	

Table 7a: Anaemic (HB) Grouping

		Frequency	Valid Percent	Cumulative Percent
Valid	low hemoglobin	535	30.9	30.9
	Normal	1181	68.2	99.1
	High	16	.9	100.0
	Total	1732	100.0	

Table 7b: HB Categorical Coding

		Frequency	Valid Percent	Cumulative Percent
Valid	Anaemic	535	30.9	30.9
	Normal	1197	69.1	100.0
	Total	1732	100.0	

6.2 Nutritional Status, Malaria and Anaemic Prevalence among Adolescents

Table 2 reveals an equal proportion of early (10-14 years) and late (15-19 years) adolescents, with males constituting 49% and females 51% of the sample, as detailed in Table 3. Regarding wasting prevalence (Table 4a), 42.1% of adolescents are severely wasted, 15.9% moderately wasted, and 17.7% mildly wasted, while 24.0% are normal (non-wasted). Categorical coding (Table 4b) shows that the majority (58%) of adolescents are wasted. Table 5a demonstrates that 56.5% of adolescents are severely stunted, 9.5% moderately stunted, and 34.5% normal (non-stunting).

In Table 4, the Pseudo R square statistics include Cox & Snell and Nagelkerke R Square, both equally valid. Cox & Snell accounts for 0.232, and Nagelkerke R Square represents 0.313 of the total variation in the outcome variable (adolescent wasting status) explained by the logistic regression. The categorical distribution of stunting (Table 5b) indicates that 34.5% of adolescents are non-stunting, signifying a normal height for their age.

Malaria prevalence in Table 6 shows that the majority (71.1%) of adolescents tested negative for malaria parasites, with only 28.9% testing positive. Regarding the anaemic status of adolescents (Table 7), 30.9% are anaemic, while 69.1% have an adequate blood quantity for their age.

6.3: Logistic Regression with all Variables (The Enter Method)

6.3.1. Omnibus Tests of Model Coefficients

The enter method of model fitting which involves the entering of all variables at the same step. The results in Table 8 show the model chi-square and the significance levels for test of the null hypothesis that all the coefficients are equal to zero.

Table 8: Omnibus Tests of Model Coefficients

		Chi-square	df	Sig
Step1	Step	380.804	5	0.000
	Block	380.804	5	0.000
	Model	380.804	5	0.000

Table 8 assesses whether the model incorporating our explanatory variables provides a better fit to the data compared to the baseline model. The analysis reveals a statistically significant probability for the model chi-square (380.804) with a p-value (0.000) < 0.05, indicating the existence of a relationship between gender, education level, anaemic status, age group, and malaria status as predictors on one hand, and wasting status as a response on the other hand. This suggests that our model, including the five predictors (gender, education level, anaemic status, age group, and malaria status at step 1), outperforms a model with no predictors.

6.3.2 Model Summary

Table 9 shows goodness of fit test of the model. The -2 Log likelihood (goodness of fit test) value for the model obtained is 1573.601. This implies that the addition of the variables fitted in the model improved the prediction power of the model.

Table 9: Model Summary

Step 1	-2 log-likelihood	Cox & Snell R Square	Nagelkerke R Square
	1573.601[a]	0.232	0.313

Table 10 Estimates of the Logistic Binomial Mode**l**

	B	S.E	Wald	df	sig	Exp(β)
Level of education	-0.012	0.015	0.644	1	0.422	0.988
Gender	-0.114	0.124	0.843	1	0.359	0.892
RDT	0.058	0.126	0.210	1	0.647	1.059
HB grouping	-0.485	0.135	12.932	1	0.000	0.615
Age grouping	-2.135	0.128	277.899	1	0.000	0.118
Constant	4.606	0.422	119.320	1	0.000	100.133

Table 10 showed the results of the logistic regression model parameters. The Wald Statistic for level of education, gender and malaria status are 0.644, 0.843 and 0.210. These show that the three are important factors to determine the wasting status of an adolescent. The effect of Age and Anaemic status (HB) are more important than the earlier three factors mentioned based on the value of the Wald Statistic. Also, considering the Wald value for Age and HB grouping, both are statistically significant since their p-values (0.000) < 0.05 while that of the Level of Education, Gender and RDT status are not statistically significant.

7.0 Conclusion

In conclusion, it could be observed that hb grp 1, RDT 1, RDT 2, RDT 3 and age group 1 are statistically significant Also, the Wald test value of level education 1 and level education 6 are very important in the model while level education 3 is fairly important in the model for wasting nutritional status. However, in the case of stunting nutritional status for adolescents in Nigeria, it is clearly indicated that RDT 1, RDT 2 and age group 1 are statistically significant Also, level education, 1, 2, 3, 4, 5, 6, 8 as well as hb group1 and hb group 2 are very important in the model while the highest and lowest standard error for the categorical variables are level education 8 and gender lab 1 with zero standard errors from RDT 3 and 4 respectively

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