Significant Risk Factors Associated With Stunting for Children Under the Age of 5-years in Malawi: the Application of Proportional Odds Model Using DHS Datasets.

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Research Article

Keywords: Malnutrition, Stunting, Children under-five, proportional odds model, Malawi

Posted Date: April 23rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-415157/v1

Title Page

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Article Title

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Abstract

Background

Child malnutrition is perhaps the one of the main medical condition influencing general human wellbeing, mainly in non-industrial nations. The improvement of legitimate evaluations of malnutrition is one of the difficulties encountered by policymakers in numerous countries worldwide. In this manner, the current study was embraced with the essential goal of evaluating and determining all potential determinants of childhood malnutrition in Malawi, using the Demographic and Health Survey (DHS) data 2015/16. The study seeks to reveal some of the significant factors that are perpetuating the incidence of malnutrition in children of Malawi. It also designed to offer deeper insights on how the probability of being diagnosed with this medical condition (malnutrition) evolves across the different levels of the found significant factors.

Methods

The proportional odds (PO) model was the best model to utilize, motivated by the design of the current study's data set. The PO model is an alternative to conceptualize how the ordinal designed data can be sequentially into dichotomous groups without losing the ordinal nature of response variables. The model is an extension of logistic regression models with two outcomes, it is one of the best models to deal with ordinal response variable comprising of more than two categories. The PO model, as well as the logistic regression models are common classes of generalised linear models (GLMs) mostly used to model association between dependent variable and independent variables.

Results

The observations derived from fitting the PO model on the Malawi DHS data to investigate risk factors associated with malnutrition (stunting) suggested that: the age of the child; birth type (singleton/multiple births), parents' level of education, household's type of resident; mother's age at the time of birth, mother's BMI, incident of diarrhoea in the last two weeks before the survey, are the most significant independent risk factors of malnutrition (stunting).

Conclusions

All the aforementioned risk factors are controllable, and they can be improved through intervention strategies. The policies that undergird the country are required to counteract this condition, as the majority of the risk factors need the coherent actions of several governing authorities.

Keywords

Malnutrition, Stunting, Children under-five, proportional odds model, Malawi

1. Background

Statistically, nearly one in three persons globally suffer from under-nutrition, micronutrient deficiency, overweight, and/or obesity (1). Sub-Saharan Africa has probably the highest level of child malnutrition globally. Hence, a critical look at the distribution of malnutrition within its sub-regions is required to determine the factors that escalate the worst nutritional status in these areas.

Determinants of child malnutrition remain an interest of several researchers. In 2017, according to the World Health Organization (WHO) Statistics data visualizations dashboard (2018), the regional average of the prevalence of stunting in the regions of Africa was found to be 33.6% above the global average, which is 22.2%. Furthermore, in 2017, internationally, there were 51 million who were wasted, 151 million kids under five years old who were stunted, and 38 million kids were overweight (2). These numbers support the fact that the prevalence of stunting remains the most problematic form of malnutrition globally.

Several studies, internationally, have endeavored to disclose elements that influence childhood malnutrition so that relevant measures can be put in place to improve the circumstance straightforwardly (3,4). The WHO has also implemented a United Nations Decade of Action plan on Nutrition. Also, the WHO members have embraced worldwide targets for improving maternal, baby, and little youngster's nourishment and are focused on supervising the progress. These targets are crucial in recognizing need zones for actions and speeding up worldwide change as specified in the global nourishment targets 2025. For example, expanding select breastfeeding in the initial six months of the infants resulted in a 40% to 50% decrease in the quantity of stunted under-five kids (5). These are a few territories, as per WHO, which should be improved to accomplish the target.

In response to the call of the United Nations Decade of Action on Nutrition, there are positive and unique worldwide execution guides to battle the issue of malnutrition, one of a few such cases in Norway, turning into the primary nation to set up an activity network as a component of the United Nations (UN), the Decade of Action on Nutrition 2016-2025 on 6 June 2017 (1,6) and the Global Action Network on Sustainable Food from the Ocean for Food Security and Nutrition purposes for living for higher need to be given to fisheries and hydroponics in an endeavor to improve worldwide food security (7). Among other activities, part states focused on improving practical food frameworks by creating rational public approaches from creation to utilization across pertinent areas to give all year admittance to food that meets individuals' sustenance needs, advance protected and differentiated sound eating regimens (8).

The administrations of Italy, the Russian Federation, Japan, the United Kingdom, and Northern Ireland co-supported an uncommon occasion on reinforcing public obligation to end malnutrition in the entirety of its structures. This occasion was upheld by the Food and Agriculture Organization of the United Nations and the WHO and occurred on 20 September 2016 at the UN Headquarters (9). Many other reports presented by the WHO show how fighting malnutrition is being conducted worldwide, and researchers are also working to identify all the key factors (1).

The African region has the largest population accounting for 33.6% of the stunted children globally and a minimum of 20.0% prevalence of wasting in all the regions, according to the WHO's 2018 report (10). As a result, several studies on children's maturational status under five years have been carried out across the regions of Africa, using different methods. These studies' objective was to examine the risk components of children's malnutrition within the African continent. Habyarimana (2017) utilized the proportional odds model to discover malnutrition's main factors, less than five children in Rwanda (11). Another recent study conducted by Taluder (2017) endeavored to reveal the related elements of lack of healthy sustenance among under-five Bangladeshi youngsters by utilizing BDHS information to utilize the PO model (12). Several researchers have already revealed that factors such as mother's and father's level of education, mother's BMI, wealth index, residence's location, antenatal consideration administration during pregnancy, and the interval between successive birth are regular reasons for a poor nourishing status among children under five across the African mainland (11–14).

A descriptive and econometric analysis done by Kabubo-Mariara (2008) in Kenya, amplified by policy limitations, was employed to research the effect of the child, parental, family unit, and local area attributes kids' tallness and the likelihood of stunting (15). Critical discoveries from this examination were that male children experience more malnutrition than young ladies, and kids from multiple births are bound to be malnourished than singletons. Various investigations have found that even the age of the kid and youth ailment are critical factors influencing kid dietary status in Africa (13,16)

The prevalence of stunting in under-five children is very high in Malawi (37.1% on average), which is above the regional average in Africa (33.6%), according to the joint child malnutrition estimates by the United Nations Children's Fund, the WHO, and the World Bank Group (10). According to the UNICEF global site (2018), in Malawi, 4% of youngsters, particularly those under five years old, experience the ill effects of acute malnutrition, and the more significant part of Malawian kids experience the ill effects of chronic malnutrition, bringing about stunting (17). These numbers are empirical evidence that Malawi is one of the nations with the highest malnutrition occurrence within the Southern and Eastern parts of Africa. Several causes have been attributed to this: food insecurity within public and families, substantial workloads and nourishment of moms, subsequent infections, health-less dietary patterns, and HIV diseases prompting repeated ailment (16). Childhood malnutrition is devastating, and it can be the single most significant contributor to under-five child mortality. In Malawi, unfortunately, there has been only a slight change in children's nutritional status (stunting) since 1992 (48.7%), and stunting rates remain unacceptably high thus far (37.1%), according to the WHO.

In Malawi, similar to what other countries are doing worldwide, various stakeholders are attempting to mitigate the impact of malnutrition. Throughout the time frame 2012–2018, UNICEF focused on deterrence of stunting and faltering, the two of which are significant hindrances to children's development and even survival. The initiative was more coordinated towards sound sustenance for pregnant ladies and infants during their initial two years of life. Some strategies to prevent stunting in the country include, but not limited to, supporting the government to develop the Nutrition Act and educating the people living with pregnant women on how to support and encourage the behavioural change for maternal Nutrition and young child and infants nourishing practices (18). All these efforts seem to be promising in ensuring that the average level of stunting is decreasing in the country.

In addition to these strategies aimed at preventing the disease, an alternative and effective approach to this endeavor would be to clearly understand the exact factors that escalate the incidence of malnutrition. This study's primary objective is to reveal those factors associated with childhood malnutrition in Malawi using the PO model. An almost similar study by Chirwa (2008) was conducted in Malawi, the researcher used multivariate analysis to investigate factors that determine child malnutrition. The study was conducted using the three anthropometric measures of malnutrition, WAZ for underweight, HAZ for stunting, and WHZ for wasting. Consequently, it was revealed from the Chirwa (2008) study that stunting is the most significant contributor to malnutrition problems amongst the three measures of malnutrition. The current research is fashioned to narrow deep into understanding causes of the most common symptom of malnutrition in Malawi, which stunting, and through the use of the most recent available Demographic Health Survey (DHS) data. We have also taken a deep dive into the specifically addressing the impact of each factors of stunting across different levels. Possible factors are going to be selected, this factors has been used in the different studies conducted across the African continent (4,11,13,16). The study uses association statistics and further uses the regression analysis to analyse information that cannot be revealed by association.

2. Study methodology and Utilised material

2.1. Data and Definition of variables

Malawi is a landlocked state in south-eastern Africa. Endowed with extensive lakes and spectacular highlands, it is within a narrow, bending piece along with East African Rift Valley land. Lake Nyasa, also recognized as Lake Malawi within Malawi, represents significantly more than one-fifth of Malawi's overall zone. The nation's exports are comprised of production from both minor landholdings and tobacco and tea bequests. The country has achieved an impressive level of worldwide capital in the sort of advancement help that has contributed essentially toward the abuse of its natural assets and has made it feasible for Malawi to, on occasion, produce a food surplus. Notwithstanding, the nation's populace has suffered from persevering malnutrition, especially children under the age of five years, elevated paces of new-born child mortality, and devastating poverty – an oddity regularly connected to an agricultural framework that has supported significant estate proprietors.

The data sets used in this study are from the nationwide Malawi DHS 2015 (MWDHS-2015). This data includes an anthropometric component where all children under five listed in the Household Questionnaire were weighed and measured. The study utilized 5092 children, whose complete and plausible anthropometric data were available.

2.2. Dependent variable

This study's dependent variable is the anthropometric measure of height-for-age z-score as an indicator of chronic malnutrition known as stunting. Stunting of children is considered as the best general indicator to gauge the level of wellbeing of children. Moreover, stunting is imperially the highest pervasive form of childhood malnutrition, there is an estimation of around 161 million kids globally, falling under 2 Standard Deviation (SD) from the World Health Association Child Growth Standards middle, height-for-age (19).

As a result, in the current study, we considered only the height-for-age anthropometric index to represent a child's nutritional status throughout our investigations. The Z-scores extracted from the height-for-age anthropometric index for each child were calculated to understand the association, if any, between nutritional status and all the selected independent variables. Children's nutrition status (represented by the calculated Z-score) was considered to be a categorical variable with three different ordered levels: severely malnourished (for children with Z-score < -3.0), moderate malnourished (for children with $-3.0 \leq$ Z-score < 2.0), and nourished (for children with Z-score ≥ -2.0). Hence the response variable (nutritional status) was considered an ordinal response variable grouped from a continuous variable.

2.3. Explanatory/independent variables.

The explanatory variables considered are child characteristics and recent child illness, household characteristics, and community characteristics. The child characteristics include the child's age, the gender of the child, birth order, and whether the child is a twin or not. The sex of the child is recorded by a dummy variable equal to 1 for a male and 2 for a female child. If there is gender inequality concerning children's care, we expect female children to be better nourished than male children if female children are favoured and vice-versa. In other studies, female children were found to have a better nutrition status than male children (16). Then we also took into consideration the characteristic of whether a child is from multiple births or not. It was recorded by a dummy variable equal to 1 for a child from multiple births and zero for a single born child.

The child's age has an upper boundary of five years, which was measured in months since stunting is the failure to grow optimally and is first detected in children who are considered short for their age group when they are two years old . Therefore, we expect the children who are two years or more to have worse nutrition status than those younger than two years. The child's birth order and recent illness are also characteristics that we are to access against the Nutrition of status of the child. The child's illness was the recent incident of diarrhoea. Whether the child had a fever in the last two weeks or not, both were captured with a dummy variable equal to zero for no incident of diarrhoea or fever. A dummy variable equal to 1 represents a yes; there was recently an incident of diarrhoea or fever.

The household characteristics include the household's wealth status, mother's BMI, mother's age at birth of a respective child, mother's working status, mother's highest level of education, father's highest level of education, and father's main occupation grouped. The wealth index of household economic status was constructed in the MWDHS-2015 report by using the information on household ownership of assets and dwelling characteristics. The wealth index was recorded with dummies representing the three categories of poor, middle, and rich. The mother's BMI was captured in two categories, Thin (BMI≤18.5) and Normal

(BMI>18.5). The expectation was that an underweight mother would result in worse nutrition status for the child since she would lack the fat needed to produce adequate milk for her child.

The female parent's age at the birth of the respective child was also categorized in five different levels. There is evidence elsewhere that children born to mothers below 18 and above 34 years of age are more likely to be malnourished when compared with the children born to mothers aged 18 to 34 (20).

The mother's current working status was captured by a dummy variable equal to one for the currently working mother and 0 for a non-working mother. The highest level of education of a mother was measured with dummies representing four categories: no education, primary, secondary and higher education. The highest level of education for a father was captured in the same manner. Education affects caregiving practices through the ability to process information, acquire skills, and model behaviour. It can be hypothesized; therefore, those educated parents are associated with the child's high nutritional status. They can better use healthcare facilities and ensure a high standard of environmental sanitation (16).

Five dummy variables of a father's occupation measure different types of employment. Thus, this independent variable is categorized as not working, professional, business, agriculture, and other occupational sectors. The prevalence of stunting was significantly lowest among the children of fathers who were service holders in a study of predictors of chronic child malnutrition in Bangladesh by Das (2011). One would expect children of fathers who hold professional positions (such as managerial positions) to have better nutritional status since in professional occupations; parents usually get maternity leave to care for their new-born baby, which may help them ensure an early healthy lifestyle for the child.

The community variables used in this study include water sources and the type of residence of the household. Source of water is captured with dummy variables for piped water, well water, and other sources (such as rain, tank, etc.). The residence household is captured by dummy variables equal to one for urban and two for rural areas. The expectation is that children from urban areas would be associated with better nutritional status since the availability of health and educational facilities is greater in urban areas compared with rural areas. The duration of breastfeeding was also added to the independent variables to assess the effect of breastfeeding. Breastfeeding is captured by dummies categorized into three groups: ever breastfed, then stopped, never breastfed, and still breastfeeding.

Recent several other studies (21–23) utilised the following variables were mostly found to be significant predictors of malnutrition; Socio-economic and demographic characteristics, such as family size, monthly family income, mother can read and write, mother's educational status, mother's marital status feeding practices, diarrhoea in the past two weeks, and age of child variables include. The current study have used some of this variables to investigate association with childhood malnutrition in Malawi.

3. Statistical Analysis

3.1. Descriptive statistics

The study utilized a quantitative research methodology appropriate for investigating the relationship between two or more variables known as cross-tabulation through version 25.0 of the SPSS statistics application. The use of cross-tabulation enabled us to examine associations within our selected independent variables and the ordered categorical response variable (child nutrition status). Pearson's chi-square test or the Chi-square test of association was used to discover if there is a relationship between the level of stunting and each independent variable. The results of these descriptive statistics are displayed in **Table *1***. The test provided a necessary additional understanding of the data as we were able to isolate the most critical variables (with p-value < 0.005). The chi-square test results show that some of the independent variables are highly significant with the response variables. It is from descriptive statistics results as presented in **Table *1*** we were able to select variables to be fitted in the PO model (introduced in section 3.2).

Please insert **Table *1*** here.

3.2 Model development

Wedderburn and Nelder (1972) led the concept of generalized linear models (GLMs). This type of model expands classical linear models that permit the population to rely upon a linear indicator through a nonlinear link function where the response probability distribution belongs to the exponential distribution family. Wedderburn and Nelder formulated the GLMs with the objective of merging different statistical models, including but not limited to logistic regression, linear regression, and Poisson regression (24). Extensive and deep theory on introduction to GLMs was provided in the book published in 1983 by Nelder and McCullagh. Other different good books can provide excellent references that are giving good examples of the application of GLMs (24–26)

3.2.1 Components of generalized linear models

A proper kick-off on the discussion of GLMs is to briefly discuss its traditional models from which they emanate, which are known as classical linear models. We consider an observation vector $\boldsymbol{y}$ possessing n components, which is presumed to be a design of arbitrary variable $\boldsymbol{Y}$ whose components are distributed independently with μ, the mean of the random variables. The essential technical part of the current model is the classification of the vector μ through the use of a smaller number of unknown parameters $\beta_1, \cdots, \beta_p$. For ordinary linear models, we have:

$$\mu = \sum_{j=1}^{p} \boldsymbol{x}_j \beta_j$$

Where the βs are unknown parameters and the values of these unknowns are estimated from the empirical data set.

Suppose that, for generality, i is observations index, then the essential technical part of the model can be represented by:

$$E(\boldsymbol{Y}_i) = \mu_i = \sum_{j=1}^{p} x_{ij}\beta_j, \quad i = 1, \dots, n$$

$\boldsymbol{x}_{ij}$ represent the value of the jth covariate of the observation i. This can be written in matrix form as $\mu = \boldsymbol{X\beta}$ (where $\boldsymbol{X}$ is $n \times p$, μ is $n \times 1$, and β is $p \times 1$), $\boldsymbol{\beta}$ is the parameters' vector, and $\boldsymbol{X}$ is the matrix of the model. This completes the specification of the systematic part of the model.

3.2.2 The generalization

The simple path to describe the shift from classical linear models to GLMs is through rearranging the first expression in 3.2.1. The first expression in 3.2.1 is required to have three-part characteristics know as: The systematic component – which is qualified when the covariates $x_1, x_2, \cdot\cdot\cdot, x_p$ produce a linear predictor $\boldsymbol{\eta}$, given by $\sum_{j=1}^{p} \boldsymbol{x}_j \beta_j$; the random component - which is qualified when the components of $\boldsymbol{Y}$ are independently normally distributed with the parameters, $\mu = E(\boldsymbol{X})$ and the constant variance σ^2; the link function linking the systematic and random components that is $\mu = \boldsymbol{\eta}$. The latter generalization brings about a new character η which is signifying the linear predictor. The third component of the generalization stipulates that $\boldsymbol{\eta}$ and μ are identical. Suppose that we express $\eta_i = g(\mu_i)$ then $g(\cdot)$ is called the link function. GLMs permit two fundamental extensions, the first being; the distribution of the link function may come from the exponential family other than the Normal. Secondly, the link function may be any monotonic differentiable function. In other words, GLMs can be considered as natural generality of classical-linear-models that permits the mean of the population to entirely rely on linear predictor by means of the (possibly nonlinear) link function. The latter permits the probability distribution of the response to be within the exponential family of distributions.

3.2.3 Model Fitting

In general, when one is working with data that possesses a categorical response variable, and the categories are more than two, the GLMs provide two choices to be considered by the model developer. The current study utilizes the approach that generalizes the logistic regression through the dichotomous categories of the response into either ordinal or nominal responses. The alternative approach, which is not discussed herein, uses counts or frequencies to model the covariate designs for response variables through Poisson distribution.

This choice was motivated by the design of the response variable, which is a continuous variable z that measures the severity of disease (malnutrition). Children under the age of five with small values of z are classified as children suffering from "severe malnutrition" or "moderate malnutrition," while children with large or normal values of z are classified as not suffering from malnutrition. The z cut-off points represented by $C_1, \dots, C_{j-1}$ defines j categories with associated probabilities $\pi_1, \dots, \pi_j$, where $\sum \pi_j = 1$.

Since the possible outcomes for our response variable consist of three categories, and ordinal in design, the use of logistic regression, which is usually model the probability of one of the outcome, named "success" is not applicable. However, there exist regression models that are specifically designed for this situation; these are the expansions of the logistic-regression-model with a response a binary response. The intricacy in fitting ordinal regression models arises to some degree because there are countless opportunities for how "success" and the resulting likelihood of "success" may be represented in the model. Below we discuss one of the commonly used procedures modelling categorical, ordinal response variables.

3.2.4 Proportional odd model (POM)

The investigation that mimics this strategy for dichotomizing the response variable, where the progressive dichotomizations result in cumulative "splits" within the data set, is commonly known as proportional or cumulative odds (27,28). It is one approach to conceptualize how the information may be consecutively divided into dichotomous categories without losing the ordinal nature of those categories (26). The application of this methodology is interesting and easy to execute, because the ordinal feature of the data set similar as dealing with dichotomous data through logistic regression. The PO model's primary objective is to concurrently study the impact of different explanatory variables across the data's conceivable successive cumulative splits.

The proportional odds model's applications is only valid when the assumption that the dependent variables have the same impact on the odds (29). This assumption is called proportional odds. When this assumption of proportionality is violated, this implies that we have a portion of $\boldsymbol{X}$ effects with p_1 parameters which fulfils the proportional odds assumption (that is, they have equal slopes), and a portion of $\boldsymbol{Z}$ effects with p_2 parameters which does not fulfil the proportional odds assumption, hence it cannot be fitted by a proportional odds model. The letter situation can be dealt with by other models such as the partial proportional model (PPOM) (13). The functional form of POM has the form described below (13);

$$\boldsymbol{\phi}(x) = ln\left\{\frac{\mathrm{P(Y = 1}|x) + \cdots + \mathrm{P(Y = j}|x)}{\mathrm{P(Y = j + 1}|x) + \cdots + \mathrm{P(Y = k}|x)}\right\} = \ln\left\{\frac{\sum_1^j \mathrm{P(Y = j}|x)}{\sum_{j+1}^k \mathrm{P(Y = j}|x)}\right\}$$

$$\phi(x) = \alpha_{\mathrm{j}} + \left(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p\right), j = 1,2, \ldots, k - 1$$

where $\boldsymbol{Y}$ is our response variable, $\boldsymbol{x}$ is the vector of dependent variables = $(x_1, x_2, \ldots, x_p)$, α_j are intercepts and $(\beta_1, \beta_2, \ldots, \beta_p)$ are logit coefficients. The above equation is only valid when the response variable's original design was continuous, then subsequently grouped into categories, and the proportional odds assumption is satisfied. This assumption needs to be tested, and when they are not satisfied, one will have to use alternative models, such as PPOM or others, depending on the design of the response.

The connection between the proportional-odds cumulative model and the idea of continuous response variable is one of the reasons behind the common usage of this model. Since the response variable (stunting) of the current study is continuous, and categorised into three regions (nourished, moderate and severe) by to cut-points, as defined by the WHO parameters of measuring malnutrition. Hence the regression model of stunting on the chosen explanatory variables take the form:

$$\boldsymbol{\phi}(\text{Stunting}) = \alpha_j + \beta_1 * \text{Child's age} + \beta_2 * \text{Sex of child} + \beta_3 * \text{Birth order} + \beta_4 * \text{Type of birth} + \beta_5 * \text{Type of residence} + \beta_6 * \text{Mother's education level} + \beta_7 * \text{Father's education level} + \beta_8 * \text{Household wealth index} + \beta_9 * \text{Mother's BMI} + \beta_{10} * \text{Mother's age at birth} + \beta_{11} * \text{Mother's working status} + \beta_{12} * \text{Mother's age at birth} + \beta_{13} * \text{Source of water} + \beta_{14} * \text{Duration of breastfeeding} + \beta_{15} * \text{Had diarrhea recently} + \beta_{16} * \text{Had fever in last two weeks}, j = 1, \dots, 16,$$

4. Results and discussion

4.1. Model assumptions testing

The study has an ordinal response variable which is nutritional status. As discussed above, the ordinal response variable was derived by grouping a continuous variable; the height-for-age anthropometric index. Statistically, when one has such a data design, it is appropriate to formulate a PO model. The chi-square score has then utilized to test the appropriateness of developing the PO model; testing the PO assumption. This test is primarily conducted to confirm whether the main PO model assumptions are violated or not. However, there are empirical concerns about the chi-square score test; it tends to result in a too-small p-value. As a result, the current study conducted, above the chi-square score test, a supporting technique for investigating the PO assumption. This technique computes the single score tests for each covariate as an alternative method of testing whether the PO assumption is violated (30). Results of the test are displayed in **Table *2***.

Firstly, from **Table *2***, the chi-square score test for testing the PO assumption is not significant at a 5% level of significance (χ^2= 36.94, p-value = 0.3347). Therefore, the design of our data set does not violate the PO assumption. In addition, this demonstrates that for every one of the picked covariates, one parameter may be utilized for separate modelling logits of cumulative probabilities. However, to confirm the chi-square test results' correctness, we have conducted the alternative or supporting testing technique; single covariate score test. The outcome of the letter test is displayed in the last column of **Table *2***. The outcome indicates that all the covariates were insignificant (p-value ≤ 0.005), and hence, they satisfy the PO assumption. From the latter results, we were able to make a final decision that our dataset satisfies the PO assumption for POM.

4.2. Discussions

The observations from fitting the PO model for determining risk factors for childhood stunting in Malawi are displayed in **Table *2***. We have evaluated the goodness-fit test to assess the PO model's overall adequacy on the data set. The test results suggested that the overall model did not lack any type of fit, with p-value = <.0001 (see the last row of **Table *2***). The data set used in the current study was collected in 2015/16 DHS. Hence, the study results must be read as a likelihood that similar conditions are still evident in Malawi. This is a strong assumption motivated by the argument of no evidence, which suggests that the risk factors of stunting revealed by the current study have already been addressed.

The column labelled odds ratio in **Table *2*** displays the values of the estimated adjusted odds ratios. Therefore, the interpretation of our results is based on adjusted odds ratios. The PO model results revealed that the odds of possessing worse nutrition status (stunting) are 3.62, 4.19, and 3.91 higher among children belonging to the age group 12-23, 36-47, and 48+ months respectively when compared with the infants. This result supports the earlier hypothesis; stunting can be clearly identified when the child is two years old. Moreover, this result supports evidence from a study on childhood malnutrition conducted by Das (2008) in Bangladesh. It can be surmised that when a child is growing, the mother's milk alone becomes insufficient for feeding. As a result, we can confidently state that the reason for increased odds of stunting in children of 12 or months is attributed to inadequate supplementary foods when breastfeeding is no longer adequate. The odds of stunting in children younger than five years can worsen as age increases; however, this is evident up to a certain age (47 months), beyond which then the odds of stunting improve materially.

The results of the PO model displayed in **Table *2*** also suggest that kids from multiple births have 3.66 (odds) times higher odds of possessing stunting compared to children of single births (with p-value = <.0001). The observation could be attributed to the low birth weight for children from multiple births, insufficient food intake from breastfeeding, and competition for nutritional intake, which will distress the offspring of multiple births. Furthermore, we can attribute this to the fact that, in general, parents can care more for fewer kids, which can be added as a justification for the high risk of stunting in multiple birth children. As an individual, I also applaud the Human Fertilization and Embryology Authority in its efforts to reduce multiple births through the "one at a time" campaign (31); African nations can also follow other countries in imposing a single embryo transfer policy – this alone may play a significant role in decreasing the risk of childhood medical complications caused by multiple births, possibly even the prevalence of stunting.

The results from **Table *2*** also reveal that the difference in a mother's education level plays a significant role in the risk of poor nutritional status of a child. The children of illiterate mothers (with no education) have a high likelihood of having a poor nutritional status (about 2.0 times) when compared with mothers with higher educational qualifications. Compared with children of fathers with higher education levels, the risk of stunting was found to double (2.144) for children of fathers with only primary school as their highest level of education. These results highlight the importance of education as an essential determinant of child malnutrition in Malawi. This finding is common, and many studies have attempted to explain this difference in malnutrition in relation to parents' education levels (e.g., (13,16)). There is a common belief that educated mothers may be more conscious about the health of their children. As a result of their educated status, they can easily research, identify and adopt new feeding practices, which may help to significantly improve the nutritional status of their children.

Household factors make a substantial contribution to the nutritional status of under-five children. Usually, children in households with the lowest income have the worst nutritional status, and this improves with the increased wealth status of the household (13). In the current study, the results indicate that children from households with a poor wealth index status are 1.55 times more at risk of a poor nutrition status as compared with children from households classified under the rich wealth index status (**Table *2***). However, there was no significant difference in the likelihood of a poor nutrition status between children from households with either moderate or rich wealth index status. The results support the statement; "growth of infants and younger children throughout the world is related to the socio-economic environment in which they live" (14).

Another interesting observation from the results from the PO model is that odds of the stunting condition are observed to be significantly different between children of mothers with normal (BMI $\geqslant$ 18.5) and thin (BMI < 18.5) body mass index (BMI). Children of mothers with a BMI indicating underweight (BMI < 18.5), compared with those with a normal body mass index, are about 1.5 times more likely to be severely stunted. There are prolific number of research studies available also showing the association of BMI and malnutrition (13,32–34). Furthermore, the model reveals that the odds of having malnutrition (stunting), for the under-five children in Malawi, are lower for children born to mothers over 18 years of age at birth when compared with mothers who gave birth when under 18. **Table *2*** reveal that children born to mothers aged 19-23, 24-29, and 30-34 were 0.89, 0.577, and 0.57 less likely to have chronic malnutrition (stunting) when compared with children of mothers who gave birth when they were below the age of 18 years. The results support the inherent results that generally, children born to mothers below 18 and above 34 are more susceptible to malnourishment than children born to mothers aged within 18-34 years (20,35).

Within the two weeks before the survey, children who suffered from diarrhoea were at a 1.2 times higher risk of being malnourished than children who did not suffer from diarrhoea during the same time period (**Table *2***). This suggests that the illness history of the child can serve as one of the determinants of malnutrition. Number of studies have also postulated the reciprocal relationship between malnutrition and diarrhoea (36,37).

Inset **Table *2*** here.

Conclusions

The current research was conducted with the primary goal of revealing factors that might be associated with the condition of high childhood malnutrition in Malawi. The study revealed the risk factor of malnutrition in Malawi and deeper insights on how the probability of stunting evolves across the different levels of risk factors. The risk factors of malnutrition from the current study are found to be; the age of the child; birth type (singleton/multiple births), parents' level of education, household's type of resident; mother's age at the time of birth, mother's BMI, the incident of diarrhoea in the last two weeks before the survey. From the results of the current study, we can deduce that Malawi's economic state is possibly the centre of the causal. However, this can be subjective as it was not proven by any statistical model utilized herein. All the risks mentioned above factors are controllable, and they can be improved one way or another. In US Government launched the Feed the Future Guide, describing its strategy to address global hunger and food security. The strategy emphasizes that investments in addressing the root causes of under-nutrition can improve the lives of mothers and their children. Likewise in Malawi, collective government's interventions are required to counteract this condition

List of Abbreviations

All acronyms were qualified on the text.

Declarations

See below

Ethics approval and consent to participate

Before each interview is conducted, an informed consent statement is read to the respondent, who may accept or decline to participate. A parent or guardian must provide consent prior to participation by a child or adolescent. Participation was voluntary, and all individuals provided verbal informed consent according to approved survey protocols. This article features a secondary analysis of publicly available DHS data which does not require further ethics approval.

Procedures and questionnaires for standard DHS surveys have been reviewed and approved by Informed Consent Form (ICF) Institutional Review Board (IRB). Additionally, country-specific DHS survey protocols are reviewed by the ICF IRB and typically by an IRB in the host country. ICF IRB ensures that the survey complies with the U.S. Department of Health and Human Services regulations for the protection of human subjects (45 CFR 46), while the host country IRB ensures that the survey complies with laws and norms of the nation. In Malawi, the survey protocol, including biomarker collection and testing procedures were reviewed and approved by the National Health Sciences Research Committee in Malawi and the ICF Institutional Review Board.

Details on ethical procedures are provided in the annexes to DHS reports and on the DHS website: https://dhsprogram.com/What-We-Do/Protecting-the-Privacy-of-DHS-Survey-Respondents.cfm.

Consent for publication

Not Applicable

Availability of data and materials

The dataset used in the current study can obtained from DHS website upon request. Please register and request the Malawi DHS 2015-16 data at: http://www.dhsprogram.com/data/dataset_admin/login_main.cfm. The data must not be passed on to others. All DHS data should be treated as confidential, and no effort should be made to identify any household or individual respondent interviewed in the survey

Competing interests

The authors declare that they have no competing interests

Funding

Thanks to SASA-NRF for funding my UKZN studies

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Authors' Contributions:

MME: is the primary author, responsible for implementation and application of all the conceptualisations of the study.

SR: 'contributed' in the design and conceptualisation of the study. He is my supervisor, he does all the reviews and validation of the findings. He validated the statistical parameters and model appropriateness for the current study.

FH: 'contributed' in the design and conceptualisation of the study as well. He is my co-supervisor, his technical contributions to the writing and coding has made it possible for us to come up with robust findings. He validated all the findings and the interpretations thereof.

Acknowledgements

Not applicable

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Tables

Table 1: Children's nutritional status according to selected independent variables

Level of Stunting (Height-for-Age)					
Covariates	**Severe** (z-score < -3.00)	**Moderate** (-3.00 ≤ z < -2.00)	**No stunting** (z-score ≥ -2.00)	**Total**	**Chi-square** χ^2 **(p-value)**
	Independent Variables of Stunting (%)				
Child's age (in months)					
6	11 (1.9)	43 (7.5)	518 (90.6)	572	175.8(0.000)
7-11	14 (3.2)	63 (14.4)	359 (82.3)	436	
12-23	81 (7.7)	280 (26.6)	690 (65.7)	1051	
24-35	70 (6.9)	219(21.5)	729 (71.6)	1018	
36-47	114 (10.8)	243 (23.0)	701 (66.3)	1058	
48-59	78 (8.2)	217 (22.7)	662 (69.2)	957	
Sex					
Male	190 (7.6)	526 (21.0)	1784 (71.4)	2500	1.15(0.562)
Female	178 (6.9)	539 (20.8)	1875 (72.3)	2592	
Birth order					
1	87 (6.9)	279 (22.0)	901 (71.1)	1267	7.5(0.279)
2-3	134 (6.8)	394 (20.0)	1439 (73.2)	1967	
2-3	83 (7.2)	235 (20.5)	831 (72.3)	1149	
6^+	64 (9.0)	157 (22.1)	488 (68.8)	709	
Residence					
Rural	327 (7.7)	947 (22.2)	2996 (70.2)	4270	37.5(0.000)
Urban	41 (5.0)	118 (14.4)	663 (80.7)	822	
Mother's education level					
No education	73 (11.6)	150 (23.8)	408 (64.7)	631	62.7(0.000)
Primary	246 (7.4)	725 (21.8)	2355 (70.8)	3326	
Secondary	49 (4.6)	183 (17.3)	823 (78.0)	1055	
Higher	0 (0.0)	7 (8.8)	73 (91.3)	80	
Father's education level					
No education	30 (7.6)	95 (23.9)	272 (68.5)	397	

Primary	199 (8.4)	516 (21.7)	1658 (69.9)	2373	50.0(0.000)
Secondary	69 (5.2)	252 (19.2)	994 (75.6)	1315	
Higher	5 (2.6)	15 (7.9)	171 (89.5)	191	
Wealth status					
Poor	214 (9.5)	552 (24.6)	1480 (65.9)	2246	93.9(0.000)
Middle	61 (6.1)	223 (22.2)	721 (71.7)	1005	
Rich	93 (5.1)	290 (15.8)	1458 (79.2)	1841	
Mother's BMI					
Thin (BMI < 18:5)	24 (9.3)	66 (25.6)	168 (65.1)	258	6.1(0.047)
Normal (BMI 18:5)	342 (7.1)	998 (20.7)	3477 (72.2)	4817	
Mother's age at birth of the respective child (years)					
18	17 (8.8)	36 (18.7)	140 (72.5)	193	19.4(0.013)
19-23	109 (8.0)	319 (23.3)	941 (68.7)	1369	
24-29	96 (6.0)	315 (19.8)	1177 (74.1)	1588	
30-34	64 (6.5)	190 (19.2)	738 (74.4)	992	
35+	82 (8.6)	205 (21.6)	663 (69.8)	950	
Mother's working status					
Currently working	248 (7.4)	727 (21.6)	2393 (71.1)	3368	3.3(0.193)
Not working	120 (7.0)	338 (19.6)	1266 (73.4)	1724	
Father's occupation					
Not working	31 (8.6)	72 (19.9)	258 (71.5)	361	25.0(0.002)
Professional	17 (5.0)	52 (15.4)	269 (79.6)	338	
Business	18 (6.4)	47 (16.7)	216 (76.9)	281	
Agriculture	127 (7.5)	399 (23.6)	1168 (68.9)	1694	
Other+	113 (6.9)	316 (19.4)	1199 (73.6)	1628	
Birth type					
Singleton	342 (6.9)	1015 (20.6)	3578 (72.5)	4935	38.0(0.000)
Multiple birth	26 (16.6)	50 (31.8)	81 (51.6)	157	
Duration of breastfeeding					
Ever, then stopped	262 (8.5)	691 (22.4)	2127 (69.1)	3080	36.0(0.000)
Never breastfed	4 (4.9)	19 (23.5)	58 (71.6)	81	
Still breastfeeding	102 (5.3)	355 (18.4)	1474 (76.3)	1931	
Source of water					
Piped water	48 (4.3)	175 (15.8)	887 (79.9)	1110	
Well water	284 (7.8)	821 (22.4)	2558 (69.8)	3663	

Rainwater, tank, other	36 (11.3)	69 (21.6)	214 (67.1)	319	52.8(0.000)
Had diarrhea in the last two weeks					
No	258 (7.3)	730 (20.6)	2558 (72.1)	3546	0.8(0.663)
Yes	109 (7.1)	334 (21.7)	1096 (71.2)	1539	
Had a fever in the last two weeks					
No	289 (7.2)	823 (20.5)	2903 (72.3)	4015	1.8(0.402)
Yes	77 (7.3)	236 (22.3)	743 (70.4)	1056	

Table 2: Results of the fitted PO Model

Covariates	Regression Coefficient	Standard Error	p-value	Odds Ratios	Single Score test (p-value)
Intercept1	-2.1226	0.2037	<.0001	-	-
Intercept2	-0.4293	0.1993	0.0313	-	-
Child's age (in months) [0-11 months as a reference]					
12-23	0.2632	0.0894	0.0032	3.620	**0.056**
24-35	0.0074	0.0776	0.9236	2.803	
36-47	0.4106	0.0818	<.0001	4.195	
48-59	0.3420	0.0877	<.0001	3.917	
Sex of child [Male as a reference]					
Female	-0.0241	0.0351	0.4932	0.953	**0.382**
Birth order [First as a reference]					
2-3	-0.0227	0.0685	0.7397	1.087	**0.673**
3-6	0.0248	0.0758	0.7433	1.140	
6+	0.1043	0.1089	0.3381	1.235	
Type of birth [Singleton as a reference]					
Multiple	0.6485	0.0901	<.0001	3.658	**0.718**
Type of residence [Rural as a reference]					
Urban	-0.0143	0.0656	0.8279	0.972	**0.446**
Mother's education level [higher as a reference]					
No education	0.3083	0.1437	0.0319	1.735	**0.130**
Primary	-0.0188	0.1247	0.8804	1.251	
Secondary	-0.0471	0.1298	0.7168	1.216	

Father's education level [higher as a reference]					
No education	0.1389	0.1197	0.2458	1.921	**0.358**
Primary	0.2488	0.0879	0.0047	2.144	
Secondary	0.1263	0.0896	0.1585	1.897	
Household wealth index [Rich as a reference]					
Poor	0.2279	0.0516	<.0001	1.551	**0.274**
Middle	-0.0173	0.0591	0.7698	1.213	
Mother's BMI [Normal as a reference]					
Thinness (BMI < 18:5)	0.1867	0.0775	0.0160	1.453	**0.862**
Mother's age at birth [18 years as a reference]					
19-23	0.2347	0.0895	0.0087	0.894	**0.565**
24-29	-0.2028	0.0820	0.0134	0.577	
30-34	-0.2150	0.0991	0.0301	0.570	
35+	-0.1638	0.1211	0.1762	0.600	
Mother's working status [Not working as a reference]					
Currently working	0.0343	0.0407	0.3992	1.071	**0.575**
Father's type of occupation [Professional as a reference]					
Not working	-0.0136	0.1135	0.9049	0.921	**0.530**
Business	-0.0855	0.1259	0.4972	0.857	
Agriculture	0.0401	0.0711	0.5731	0.972	
Other	-0.0093	0.0679	0.8910	0.925	
Source of water [Piped water as a reference]					
Well water	-0.0002	0.0620	0.9975	1.141	**0.161**
Other, rainwater, tank, etc.	0.1327	0.0970	0.1711	1.304	
Duration of breastfeeding [Still breastfeeding as a reference]					
Ever, then stopped	0.0581	0.1081	0.5908	0.966	**0.291**
Never breastfed	-0.1510	0.1916	0.4306	0.784	
Had diarrhea recently [No as a reference]					
Yes	0.0898	0.0453	0.0472	1.197	**0.503**
Had fever in last two weeks [No as a reference]					
Yes	0.0105	0.0392	0.7883	1.021	**0.489**

Score test for the Proportional Odds Assumption: Chi-Square (χ^2) = 36.94, df = 34, p-value = 0.3347

Goodness-of-fit of overall model (Likelihood Ratio): Chi-Square (χ^2) = 330.60, df = 34, p-value = <.0001