Determinants of Undernutrition among Children under Five Years of Age in Ethiopia

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Abstract

Background: Child undernutrition is still a persistent health problem in developing country like Ethiopia. Several cross-sectional studies have used the three anthropometric indicators separately to identify the factors associated to undernutrition of children. This study aimed at identifying the factors associated with undernutrition of children using a single composite index of anthropometric indicators. Methods: Ethiopia Demographic and Health Survey of 2016 was used for the analysis. A single composite index of undernutrition indicators was created using principal component analysis and recode into ordinal outcome. For this ordinal outcome, partial proportional odds model was fitted to identify significant determinants of undernutrition and its relative performance was compared with some other ordinal regression models. Results and conclusion: The Brant test of proportional odds model indicated that the null hypothesis that states the model parameters are equal across categories was rejected. Based on Akaike information criterion, partial proportional odds model suggested an improved fit compared to ordinal regression models that do not need parallel regression assumption. Hence, the fitted partial proportional odds model revealed child's age, maternal education, region, source of drinking water, number of children under five years, wealth index, anemic status of child, multiple birth, child's sex, fever, mother's age at birth, body mass index of mother and husband's education were significantly associated with children undernutrition. Finally, authors recommend that responsible bodies take interventions on improving household wealth index and food security, educating mothers and their partners, improving maternal nutritional status, and increase access to health care

Keywords: Stunting; underweight; wasting; partial proportional odds model

Introduction

Malnutrition includes undernutrition, or over nutrition. However, in developing countries, malnutrition is usually used specifically to refer to under nutrition [1]. The indicators of childhood under nutrition are stunting, wasting and underweight. Stunting, wasting and underweight refer to children from the ages of 0-59 months who are below 2 standard deviations from the median height-for-age, weight-for-height and weight-for-age, respectively as determined by the World Health Organization (WHO) Child Growth Standards [2].

Prevalence of childhood undernutrition is still a persistent health problem in Sub-Saharan countries The prevalence of stunting, wasting and underweight for children under five years of age are 39% , 10% and 25% , respectively in this sub-Saharan countries [3]. Undernutrition has both short- and long-term effects. The short-term effects of childhood undernutrition are mortality and morbidity. Global report showed that around 45% of child deaths in developing countries are related to undernutrition [4]. The long-term effects are like preventing children from reaching their full developmental potential and poor cognitive performance, which in turn has consequences for the country's economic productivity [5]. The conceptual framework shoed the general effects on the childhood undernutrition (Figure 1).

Ethiopia remains an extremely undernourished country even if it has showed progress in the decrement of undernutrition prevalence in the past decade. In 2000, 55.70% of Ethiopian children were stunted. This figure decreased to 43.4% in 2011 and to 40% in 2014 [6]. Child underweight prevalence was around 41% in 2000. This declined to 25% in 2014. Child wasting is also relatively higher than 10 % in 2014 [9].

Several cross-sectional studies have used the three anthropometric indicators separately to identify the factors associated to undernutrition of children [7-11]. To date, the researcher did not find a study in Ethiopia that finds a single composite index of three anthropometric indices and thereafter identify the factors associated with undernutrition of children less than five years. Thus, this study had a purpose of creating a single composite index from the classical anthropometric indices; and identified the risk factors associated with childhood undernutrition in Ethiopia.

Methodology

Data source

2016 Ethiopia Demographic and Health Survey (EDHS) data was used for the analysis. The 2016 EDHS sample was stratified in to urban and rural areas and selected in two stages. A total of 645 enumeration areas (EAs) having an average of 181 households were selected in the first stage of selection with probability proportional to EA size. 202 of them are from urban and 443 are from rural areas. In the second stage of selection, a fixed number of 28 households per EA were selected using systematic sampling. In all the selected households, height and weight measurements were collected from children age 0-59 months [12]. The data set used in the analysis was Children's Data with complete anthropometric and valid age based on woman and household questionnaires.

Variables

Dependent variables

The three anthropometric variables are measured through z-scores for height-for-age, weight-for height and weight-for-age and are defined as: (see Formula 1 in the Supplementary Files) where AI_i is the child anthropometric indicator, μ and σ refer respectively to median and standard deviation of the reference population.

A single composite index was created from HAZ, WHZ and WAZ using principal component analysis [13-15]. The first component alone explains 65.7% of the total variation of all anthropometric indices and this is a significantly high figure to create a single index of undernutrition [16]. Therefore, the first component of principal component analysis was taken as a new composite index of undernutrition and further it was classified as nutrition status (severely undernourished if z-score <-3, moderately undernourished if -3≤ z-score <-2.0 and nourished if z-score ≥ -2.0). Finally, the transformed variable was re-coded into ordinary outcome as ‘1’ = nourished, ‘2’= moderately undernourished and ‘3’ =severely

undernourished. The methodology for computing the indicators was based on the 2006 WHO Child Growth Standards [2].

Explanatory variables

The selection of explanatory variables are theoretically driven and supported through prior research on factors affecting children nutritional status. Previous research works have been referenced in the creation of categories for naturally continuous and discrete variables [17-21] (Table 1).

Table 1: Description of independent variables

Variables	Codes=Categories
Region	1=Tigray 2=Afar 3=Amhara 4=Oromiya 5=Somali 6=Benishangul 7=SNNPR 8=Gambela 9=Harari 10=Addis Ababa 11=Dire Dawa
Place of residence	1=Urban 2=Rural
Sex of a child	1=Male 2=Female
Age of child in month	0=0-5 1=6-11 2=12-23 3=24-35 4=36-47 5=48-59
Birth order	0=First 1=2-3 2=4-5 3=6 and more
Wealth Index	1=Poorest 2=Poorer 3=Middle 4=Richer 5=Richest
No of children under five years in the household	0=1 2=2 & 3=3 or more

Variables	Codes=Categories
Multiple birth	0= Single birth 1= 1st of multiple birth 2= 2nd of multiple birth
Educational level of mother	0= No education 1=Primary 2=Secondary and higher
Age of mother at first birth	0=<20 1=20-34 2 = 35- 49
Mother's Body mass index	0= Thin 1= Normal 2= Overweight
Anemia level	0= Non-Anemic 1= Anemic
Had cough in last two weeks	0= No 1= Yes
Had diarrhea recently	0= No 1= Yes
Had fever in last two weeks	0=No 1= Yes
Husband/partner's education	0=No education 1= Primary 2= Secondary and Higher
House hold size	0= 1-4 (small) 1= 5-9 (medium) 2= 10 and more (large)
Source of drinking water	0=Improved source 1=Unimproved source

Statistics Analysis

Ordinal Logistic Regression Model

Logistic regression may be useful to model a categorical dependent variable as a function of one or more independent variables. The dependent variable may have two categories or more than two categories. If it

has more than two categories they may be ordered or unordered. Proportional Odds Model is used as a tool to model the ordinal nature of a dependent variable by defining the cumulative probabilities differently instead of considering the probability of an individual event. The proportional odds model is used to estimate the odds of being at or below a particular level of the response variable. It considers the probability of that event and all events that are ordered before it. The proportional odds model is the usual (or default) form of ordinal logistic regression provided by statistical software [13, 14]. The proportional odds model with the logit or log-odds of the first cumulative probabilities is modeled as a linear function of the explanatory variables as: (see Formula 2 in the Supplementary Files)

If the proportional odds assumption is not met, then different models would be needed to describe the relationship between each pair of outcome groups [16].

Generalised Ordered Logit Model

The proportional odds assumption (**β** is independent of response level) may be too strict and should tested, in any case, tested. The generalized ordered logit model relaxes the parallel lines assumption for all C outcome categories. That is, it allows the slope coefficients to differ for each of C-1 binary regressions [16]. The generalised ordered logit model (GOLM) is defined as: (see Formula 3 in the Supplementary Files)

The GOLM retains the nature of the POM by considering simultaneously the effects of a set of independent variables across successive dichotomizations of the outcome [22], yet setting free the slope coefficients to vary across the categories.

Partial Proportional Odds Model

A model that relaxes the assumption of proportional odds is referred to as a partial proportional odds or non-proportional odds model. When the proportional odds assumption applies to some but not all of the covariates, the partial proportional odds model may be used. This model allows some co-variables to be modeled with the proportional odds assumption, but for those variables in which this assumption is not satisfied, the effect associated with each cumulative logit adjusted by the other co-variables is increased by a coefficient . The general form of the model is the same as the POM, but now the coefficients are associated with each category of the response variable and in this study the partial proportional odds model (PPOM) was employed. The PPOM is formulated by Peterson and Harrell [23] imposes constraints for parallel lines only where they are needed. The GOLM equation is now extended to accommodate the unconstrained parameters which violated the assumption: (see Formula 4 in the Supplementary Files)

Here x is the vector containing the full set of independent variables. $\mathbb{X}$ is a vector containing a subset of independent variables which violate the parallel assumption and are the regression coefficients associated with the variables in $\mathbb{X}$. The predicted probabilities of belonging to a certain category are defined as: (see Formula 5 in the Supplementary Files)

Parameter Estimation

McCullagh and Thompson and Baker treated cumulative link models as multivariate generalized linear models [24, 25]. McCullagh presented a Fisher scoring algorithm for ML estimation using cumulative probabilities. McCullagh showed that sufficiently large *n* guarantees a unique maximum of the likelihood. Burridge 1981 and Pratt 1981 showed that the log likelihood is concave for many cumulative link models, including the logit, probit, and complementary log-log. Iterative algorithms usually converge rapidly to the ML estimates [26].

All the models described above were fitted to the data set using STATA (version 14) software. Purposeful method of variable selection was used. The first step in the model estimation is to evaluate the parallel assumption. Firstly, a POM was fitted with command “ologit” and then the “brant” test was performed to evaluate the parallel assumption. This test compares the beta coefficients from *C-1* binary logits and gives a list of which variables are violating the parallel assumption. The commands “**gologit2**” was used to estimate the GOLM. The PPOM was estimated using the **gologit2** command with the **autofit** option to impose constraints on the variables where the parallel assumption is not violated.

All the ordinal logistic models are estimated through the procedure of maximum likelihood estimation. Maximum likelihood estimates are the values of the parameters that have the “maximum likelihood” of generating the observed sample. The likelihood equations are non-linear functions of the unknown parameters. The ordinal logistic regression model is fitted to the observed responses using the maximum likelihood approach. In general, the method of maximum likelihood produces values of the unknown parameters that best match the predicted and observed probability values.

Model selection

To compare the ordinal logistic models the log-likelihood were calculated. A model with a higher log-likelihood should be considered as a better-fitting model. It is much better to compare models based on their results, reasonableness, and fit as measured, e.g. by the Akaike Information Criterion (AIC) and Baye’s Information Criterion (BIC) [27]. Models with the smaller absolute AIC and/or BIC values should be preferred. From a set of competing models, the best model is the one with lowest value of AIC and BIC.

Test of overall model fit

The null hypothesis for an overall model fit test may be stated as “All independent variables considered together do not explain the variation in the response any more than the size alone”. In other words, the null hypothesis is stated as “all the regression parameters are zero” and the alternative hypothesis is “at least one regression coefficient (parameter) is not zero”. To keep use of the selected mode the null hypothesis must be rejected and possibility for examining the significance for the individual parameters.

In testing the goodness of fit of a model, the null and alternative hypotheses can also be stated as “the observed data are consistent with the fitted model” and the alternative hypothesis is “the observed data are not consistent with the fitted model”. This can be tested by the deviance test with degrees of freedom, where *k* is the difference in number of parameters between the current model and the model

with only intercept. The deviance statistic is the difference in -2*log (likelihood) values for the fitted model and a model with only intercept: (see Formula 6 in the Supplementary Files)

Results

Ordinal logistic regression models

Test of parallel regression assumption

All the significant explanatory variables (at 5% significance level) from uni-variable generalized ordered logistic regression models were included and assessed their significance in the proposed ordinal logistic regression models. The Brant test of parallel regression assumption from POM yielded a Chi-Square value of 90.27 with p-value=0.000, indicating that the proportional odds assumptions for the full-model was not upheld. This suggested that the effect of one or more of the explanatory variables was likely to differ across separate binary models fit to the cumulative cut points. This indicates that the null hypothesis that states the model parameters are equal across categories (i.e. parallel regression assumption) can be rejected. When the parallel regression assumptions are violated, models based on the parallel assumption for all the independent variables cannot be accurately applied to the whole population (the parameters of the model are said to be biased). Consequently, proportional odds were excluded from further analysis. Generalized ordered logit model and partial proportional odds models were fitted to the data and comparison of model was done.

Goodness of fit and model selection

Table 2: Log-likelihood and likelihood ratio estimates

Model	Obs	LL(null)	LL (model)	DF	LR chi2	Prob>chi2
GOLM	7910	-8049.262	-7269.128	84	1560.27	0.000
PPOM	7910	-8049.262	-7283.187	54	1532.15	0.000

From Table 2 one can conclude that both of the full model improves significantly over their null model (model only with intercept term) since there are evidences against the null hypothesis that all the coefficients of the predictors are zero (Prob>chi-square =0.000).

The model which represents the best fit according to AIC and BIC is PPOM as it has the smallest AIC (GOLM: 14710.26 and PPOM: 14678.37) and BIC (GOLM:15310.18 and PPOM: 15069.02). Partial proportional odds model is also more parsimonious than GOLM as it has fewer parameters. Thus, PPOM was used to identify significant determinants of undernutrition and parameter estimates of the PPOM are presented and interpreted for the significant predictors.

Results of Partial Proportional Odds Model

There are two result panels in Table 3 and 4. The first panel (Table 3) contrasts the moderately undernourished and severely undernourished categories with the nourished category. That is, the signs of the coefficients in the first panel imply how likely a child is nourished as opposed to the remaining two categories of undernutrition. Similarly, the second panel (Table 4) contrasts the severely undernourished category with nourished and moderately undernourished categories. Hence, positive coefficients indicate that higher category values on the explanatory variable make it more likely that the respondent will be in a higher category of Y than the current one, whereas negative coefficients indicate that higher category values on the explanatory variable increase the likelihood of being in the current or a lower category.

From the partial proportional odds model the categories Afar, Oromia, Somali, SNNPR, Gambela, Harari, Dire Dawa of the region; the category richest of wealth index; the category primary of husband's education; the categories 2-3 and 4-5 of birth order and the variable sex were found to violate the parallel lines assumption. The partial proportional odds model therefore allows the coefficients of these variables to vary across the two equations. From PPOM results the predictors region, mother's education, source of drinking water, number of children under five years, wealth index, anemia level, multiple birth, sex of a child, age of a child, fever, mother's age at birth, body mass index of mother and husband's education level were found to be significantly related to undernutrition.

Table 3: Maximum likelihood estimates of Partial proportional odds model

Predictors		Moderate and severe undernourished versus nourished					
		Coefficient	Std.Error	Z	P>|z|	Odds ratio	95% CI for OR
Region	Afar	-0.060	0.114	-0.53	0.597	0.942	(0.754, 1.177)
	Amhara	0.328	0.101	3.25	0.001	1.389	(1.140, 1.693)
	Oromia	-0.372	0.096	-3.86	0.000	0.689	(0.571, 0.833)
	Somali	-0.670	0.108	-6.21	0.000	0.512	(0.414, 0.632)
	Benishangul	0.117	0.112	1.05	0.295	1.124	(0.903, 1.401)
	SNNPR	-0.355	0.100	-3.54	0.000	0.701	(0.576, 0.853)
	Gambela	-0.715	0.127	-5.65	0.000	0.489	(0.382, 0.627)
	Harari	-0.213	0.127	-1.68	0.092	0.808	(0.630, 1.036)
	Addis Ababa	-0.812	0.173	-4.69	0.000	0.444	(0.316, 0.6236)
	Dire Dawa	-0.097	0.138	-0.70	0.485	0.908	(0.692, 1.191)
Residence	Rural	-0.138	0.104	-1.32	0.186	0.871	(0.711, 1.069)
Mother's education	Primary	-0.100	0.061	-1.62	0.105	0.905	(0.803, 1.021)
	Secondary & >	-0.547	0.116	-4.72	0.000	0.579	(0.461, 0.726)
Drinking water	Unimproved	0.102	0.051	2.01	0.045	1.108	(1.002, 1.224)
House hold size	5-9	0.054	0.069	0.78	0.434	1.055	(0.922, 1.207)
	10 and more	0.208	0.123	1.70	0.089	1.232	(0.969, 1.567)
No children <5 years	2	-0.144	0.076	-1.90	0.057	0.866	(0.746, 1.004)
	3 and more	0.150	0.055	2.72	0.007	1.162	(1.043, 1.294)
Wealth index	Poorer	0.082	0.070	1.18	.238	1.085	(0.947, 1.244)
	Middle	-0.204	0.076	-2.67	0.008	0.815	(0.702, 0.947)
	Richer	-0.453	0.083	-5.44	0.000	0.636	(0.540, 0.748)
	Richest	-0.447	0.113	-3.96	0.000	0.639	(0.512, 0.798)
Anemia	Anemic	0.197	0.050	3.95	0.000	1.218	(1.105, 1.3435)

Husband's Education	Primary	-0.087	0.059	-1.47	0.141	0.916	(0.816, 1.0296)
	Secondary & >	-0.171	0.086	-2.00	0.045	0.924	(0.769, 1.109)
Birth order	2-3	-0.059	0.074	-0.79	0.428	0.943	(0.816, 1.090)
	4-5	-0.035	0.091	-0.38	0.701	0.966	(0.809, 1.154)
	6 and more	-0.079	0.093	-0.85	0.395	0.924	(0.769, 1.109)
Multiple birth	1st of multiple	0.725	0.210	3.45	0.001	2.066	(1.369, 3.117)
	2nd of multiple	0.796	0.222	3.58	0.000	2.216	(1.430, 3.427)
Sex	Female	-0.110	0.049	-2.26	0.024	0.895	(0.814, 0.985)
Age of child in month	6-11	0.583	0.123	4.74	0.000	1.792	(1.408, 2.281)
	12-23	1.646	0.107	15.37	0.000	5.185	(4.203, 6.395)
	24-35	2.057	0.107	19.19	0.000	7.819	(6.338, 9.647)
	36-47	1.980	0.107	18.44	0.000	7.244	(5.869, 8.941)
	48-59	1.859	0.107	17.33	0.000	6.415	(5.199, 7.916)
Fever	Yes	0.237	0.077	3.06	0.002	1.267	(1.089, 1.475)
Cough	Yes	-0.019	0.074	-0.26	0.793	0.981	(0.849, 1.133)
Mother's age at birth	20-34	-0.110	0.049	-2.24	0.025	0.895	(0.813, 0.986)
	35-49	0.296	0.562	0.53	0.599	1.344	(0.447, 4.046)
BMI of mother	Normal	-0.349	0.055	-6.36	0.000	0.705	(0.633, 0.785)
	Overweight	-0.939	0.106	-8.87	0.000	0.391	(0.318, 0.481)
Constant		-0.805	0.189	-4.26	0.000	0.447	(0.309, 0.647)

Table 4: Maximum likelihood estimates of Partial proportional odds model

Predictors		Severely undernourished versus nourished and moderately undernourished					
		Coefficient	Std.Error	Z	P>|z|	Odds ratio	95% CI for OR
Region	Afar	0.198	0.115	1.73	0.084	1.219	(0.974, 1.525)
	Amhara	0.328	0.101	3.25	0.001	1.389	(1.139, 1.693)
	Oromia	-0.152	0.102	-1.49	0.136	0.859	(0.704, 1.049)
	Somali	-0.312	0.113	-2.76	0.006	0.732	(0.586, 0.914)
	Benshangul	0.293	0.114	2.57	0.010	1.341	(1.073, 1.677)
	SNNPR	-0.007	0.105	-0.07	0.946	0.993	(0.808, 1.220)
	Gambela	-0.439	0.141	-3.12	0.002	0.645	(0.489, .849)
	Harari	-0.213	0.127	-1.68	0.092	0.808	(0.630, 1.036)
	Addis Ababa	-0.812	0.173	-4.69	0.000	0.444	(0.316, 0.624)
	Dire Dawa	0.237	0.143	1.66	0.097	1.267	(0.958, 1.676)
Residence	Rural	-0.138	0.104	-1.32	0.186	0.871	(0.711, 1.069)
Mother' education	Primary	-0.100	0.061	-1.62	0.105	0.905	(0.803, 1.021)
	Secondary & >	-0.547	0.116	-4.72	0.000	0.579	(0.461, 0.726)
Drinking water	Unimproved	0.102	0.051	2.01	0.045	1.108	(1.002, 1.224)
House hold size	5-9	0.054	0.069	0.78	0.434	1.055	(0.922, 1.207)
	10 & more	0.208	0.123	1.70	0.089	1.232	(0.969, 1.566)
No children < 5 years	2	-0.144	0.076	-1.90	0.057	0.866	(0.746, 1.004)
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	Richest	-0.612	0.121	-5.06	0.000	0.542	(0.428, 0.688)
Anemia	Anemic	0.197	0.050	3.95	0.000	1.218	(1.105,

							1.343)
Husband's education	Primary	-0.188	0.063	-3.01	0.003	0.828	(0.732, 0.936)
	Secondary & >	-0.171	0.086	-2.00	0.045	0.843	(0.712, 0.996)
Birth order	2-3	-0.059	0.074	-0.79	0.428	0.943	(0.816, 1.090)
	4-5	0.096	0.093	1.03	0.302	1.101	(0.917, 1.320)
	6 and more	0.050	0.095	0.53	0.598	1.052	(0.872, 1.268)
Multiple birth	1st of multiple	0.725	0.210	3.45	0.001	2.066	(1.369, 3.112)
	2nd of multiple	0.796	0.222	3.58	0.000	2.216	(1.433, 3.427)
Sex	Female	-0.214	0.053	-4.07	0.000	0.808	(0.729, .895)
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BMI of mother	Normal	-0.349	0.055	-6.36	0.000	0.705	(0.633, 0.785)
	Overweight	-0.939	0.106	-8.87	0.000	0.391	(0.318, 0.481)
Constant		-1.929	0.191	10.09	0.000	0.145	(0.100, 0.211)

Key: *the reference category for predictors is: Region (Tigray), Residence (urban), mother's education (no education), source of drinking water (improved source), house hold size (1-4), number of children <5 years (1), wealth index (poorest), anemia (no), husband's education (no education), birth order (1), multiple birth (single), sex (male), age of child (0-6), diarrhea (no), cough (no), fever (no), mother's age at birth (<20), BMI (thin).*

Predictors that do not violate the parallel line assumption

The results of PPOM revealed a child who lived in Amhara was 1.4 (OR=1.4; CI: 1.14 - 1.69) times more likely to be in moderate or severe undernutrition status than nourished status as opposed to a child in Tigray, holding all variables constant. Similarly, a child born in Amhara was 1.4 (p-value =0.0001) times more likely to be in severe undernutrition status than moderate or nourished status compared to a child in Tigray. The odds of being worse undernourished was 2.3(OR=0.44; CI: 0.32-0.62) times in Tigray's children as opposed to children of Addis Ababa, holding all other variables constant.

The fitted model showed the risk of having worse undernutrition status was 1.7= $(0.58)^{-1}$ (OR=0.58; CI: 0.46 - 0.73) times higher for children born to mother without education compared to children born to mother with secondary or higher education. Children with secondary or higher educated fathers were around 8% (OR=0.92; p-value =0.045) less likely to be in the worst nutrition status, compared to the children with illiterate fathers. The risk of being in worse undernutrition status was decreased by 11% (OR=0.89; p-value =0.025) in a child born to a mother aged 20-34 years as compared to a child born to a mother aged <20 years. A child with mother of BMI<18.5 was 1.4 (OR=0.71; CI: 0.63 - 0 .79) and 2.6 (OR=0.39; CI: 0.31 - 0.65) times more likely to be in worse undernutrition status as opposed to a child who had normal and obese mother respectively, keeping all other variables constant.

The results of this study revealed that the odds of being in worse undernutrition status were 1.2 (OR=1.2; p-value =0.007) times higher for children from families having 3 or more under five years children compared to children from families having one child aged under five years. The risk of being worse undernourished was decreased by 18% (OR=0.82; p-value =0.008) in children from families with middle wealth index and 36% (OR=0.64; p-value=0.000) in children from families with richer wealth index, respectively as opposed to children from households with poorest wealth index. The children born who were first of multiple and second of multiple births were 2.1 (OR=2.1; p-value =0.001) and 2.2 (OR=2.2; CI: 1.43-3.43) times more likely to be in worse undernutrition status respectively as compared to single birth. The children aged 6-11, 12-23, 24-35, 36-47 and 48-59 months were 1.8 (OR=1.8; CI: 1.4-2.3), 5.2 (CI: 4.2-6.4), 7.8 (CI: 6.3-9.6), 7.2 (CI: 5.9-8.9) and 6.4 (CI: 5.2-7.9) times more likely to be in worse undernutrition status respectively as opposed to children aged 0-6 months, holding all other variables constant.

Holding all variables constant, the fitted model indicated the risk of having worse undernutrition status was 1.2 (OR=1.2; CI: 1.1-1.3) times higher among anemic children when compared to the non-anemic children. The risk of being in worse undernutrition status was 1.3 (OR=1.3; p-value=0.002) times higher for children who had fever in the last two weeks before the survey as compared to children who had no fever. The odds of being undernourished was increased by 10% (OR=1.1; p-value=0.045) in children from household who have not consumed water from improved source compared to children from household who have consumed water from improved source.

Predictors that violate the parallel regression assumption

The results of PPOM showed a child from Tigray region was 1.4 (OR=0.69; CI: 0.58-0.83), 2 (OR=0.50; CI: 0.41-0.63), 1.4 (OR=0.70; CI: 0.58-0.85) and 2 (OR=0.49; CI: 0.38-0.63) times more likely to be in moderate or severe undernutrition status than nourished status as opposed to a child from Oromia, Somali, SNNP and Gambella respectively. A child who lived in Tigray was 1.4 (p-value =0.006) and 1.5 (p-value =0.002) times more likely to be in severe undernutrition status than nourished or moderate undernutrition status as compared to a child in Somali and Gambella respectively. A child born in Benshangul was 1.34 (p-value =0.01) times more likely to be in severe undernutrition status than nourished or moderate undernutrition status as opposed to a child in Tigray. The children from families with poorest wealth index were found 1.5 (OR=0.64; CI: 0.51-0.80) times more likely to be in moderate or severe undernutrition status than nourished status when compared to children who had richest wealth index households. The children who had families with poorest wealth index were found 1.8 (OR=0.54; CI: 0.43-0.69) times more likely to be in severe undernutrition status than nourished or moderate undernutrition status as opposed to children from families with richest wealth index, keeping all other variables constant.

The fitted model had showed that male children were 1.1 (p-value =0.024) times more likely to be in moderate or severe undernutrition status than nourished status when compared to female. The risk of male child being in severe undernutrition status was 1.2 (OR=0.81; CI: 0.73-0.89) times higher than being in nourished or moderate status as opposed to female child. The risk of children born to husband without education being in severe undernutrition status were 1.2 (p-value =0.003) times higher than being in nourished or moderate status as compared to children born to husband with secondary or higher education, holding all other variables constant.

Discussion

In this study, a single composite index of undernutrition was created based on principal component analysis technique and recode into ordinal outcome. Thereafter, an attempt has been made to develop a method that can help to identify factors that affect children undernutrition. Firstly, Proportional odds model was fitted and parallel regression assumption was evaluated. It was found that parallel regression assumptions were violated. Consequently, models that need assumption of parallel regression assumption were excluded from further analysis. Generalized ordered logit model, partial proportional odds model, unconstrained continuation ratio model and stereotype ordered logit models were fitted to the data and comparisons of model were done. PPOM suggested an improved fit as compared to the rest of ordinal logistic models as it has the smallest AIC. Furthermore, the choice of model should depend on the research question and event under study. If the main goal is to understand the nature and direction of the predictor effects by exploiting the ordinal nature of nutritional status, one should pick the model that best interprets the event of interest under study, especially in this study where there was little difference in terms of goodness of fit and performance between the four models considered. Moreover, the directions of the estimates were very similar between models, although the interpretation of the odds ratios varied from one model to another. Thus, PPOM was used to identify significant determinants of undernutrition and estimates of parameters for the identified predictors were interpreted. Child’s sex, age of a child, region, mother’s education level, source of drinking water, number of children under five years, wealth

index, anemia level, multiple birth, fever, mother's age at birth, body mass index of mother and husband's education level were identified to be significant factors that were associated with child undernutrition in this study.

This study had found age of the child was found to be significantly associated with nutritional status. This finding is consistent with studies conducted in Ethiopia and Bangladesh [18, 21, 28, 29] which revealed that the risk of being undernourished would increase as the age of a child increases. One conceivable clarification could be because of the late introduction of supplementary food with low nutritional quality [30]. The study showed male was significantly more likely to be underweight, stunted or wasted than female in children under five years in Ethiopia. This result is supported by previous studies done in Ethiopia and Burkina Faso [11, 18, 31]. One possible explanation for this could be that childhood morbidity is higher among male than female in early life, even after adjusting for gestational age and body size [31]. This finding was negated by previous studies [28, 32] which reported female children as being more prone to undernutrition. However, a study conducted in Ethiopia reported male children as being more susceptible to stunting while female to underweight [33].

Maternal education was identified as potential determinant factor of undernutrition by this study. The risk of a child being in worse undernutrition was higher for lower maternal education than higher maternal education. Several previous studies done in Ethiopia, Bangladesh, Tanzania and Uganda are consistent with this finding which revealed that children of mothers with a higher education were less likely to be undernourished than children of mothers with no/or lower education [17, 21, 29-31, 34-37]. Maternal education might be an essential factor in proper infant feeding practices. This is realistic because the higher-educated mother has better knowledge of child health and nutrition. Educated mothers might also be more conscious about their children's health; and they tend to look after their children in a better way [38]. Besides maternal education, father's education was also significantly associated with childhood undernutrition. Those children whose fathers had attended formal education had less chance of being undernourished. Similar findings have been reported by other studies [31]. Those fathers with formal education might be more knowledgeable on proper child feeding and hygiene practices, which have a positive effect on preventing childhood undernutrition [39].

The present study observed a significant association between maternal BMI and child's nutritional status. A child who had thin mother is more likely to be in worse undernutrition status compared to a child born to normal and obese mother. Mothers who had a lower BMI were marginally associated with higher odds of childhood undernutrition as opposed to mothers with normal BMI. Previously conducted studies are in agreement with this study results [17, 18, 29, 31, 35, 36, 40]. Maternal BMI is an important determinant of child undernutrition and is influenced by maternal nutrition, therefore proper nutrition for the mothers during the prenatal and postnatal period is essential in order to improve child growth. This indicates that healthier mothers have less risk of having undernourished children [35]. In this study, mother's age at birth was identified as a determinant factor of undernutrition. Comparable results have been reported in Democratic Republic of Congo which revealed that compared to the children with mothers below 20 years

of age at childbirth, children with the mothers aged 20– 34 years had significantly lower odds of being stunted [19].

The study had found region as a significant factor of undernutrition. The finding is in agreement with study done previously in Ethiopia [21, 28]. A child living in Tigray was at higher risk of undernutrition compared to a child in Addis Ababa, Oromia, Somali, SNNP, and Gambella, whereas a child who lives in Tigray was at lower risk of undernutrition as opposed to a child living in Amhara and Benshangul. This finding is comparable with other study conducted in Ethiopia [21]. The study had also showed that wealth index is significantly associated with nutritional status. A child from a household belonging to the lower category of wealth index is at higher risk of being undernourished, which is consistent with the findings of previous studies carried out in different developing countries [18, 21, 29-31, 35]. This could be due to the fact that increased income improves dietary diversity [41], which in turn improves the adequacy of nutrient intake and nutritional status.

The study findings showed the higher the number of children under five years in the household, the higher the risk of a child being undernourished. There are studies conducted in Ethiopia that are in lined with this finding [18, 20] which found under-five children per household was critical and significant determinant in aggravating undernutrition. The present study revealed the risk of having worse undernutrition status was higher among anemic children when compared to the non-anemic children. This finding coincides with previous studies [31, 42]. The risk of being in worse undernutrition status was higher for children who had fever in two weeks before the survey compared to children who had no fever in the last two weeks before the survey. This result is in agreement with previous studies conducted in Ethiopia and Burkina Faso [18, 20]. The children born who are of multiple births were more likely to be in worse undernutrition status as opposed to singleton child at birth. Similar findings are consistent with this study [18, 42]. Source of drinking water is an environmental factor that was identified to be significant factors of undernutrition. Children from a family who do not have improved source of water were more likely to be in worse undernutrition status compared to those children who have improved source. This result is supported by previous studies done [18, 20, 37].

Conclusions

The partial proportional odds model suggested an improved fit compared to GOLM, UNCRM and SORM based on AIC. Since the main goal of the study was to understand the nature and direction of the predictor effects by exploiting the ordinal nature of nutritional status and PPOM is preferred to GOLM in accordance with the principle of parsimony, PPOM was selected and significant predictors of undernutrition were identified. The determinant factors that significantly affect undernutrition in this study were almost consistent with research findings conducted from developing countries. In this study, the potential identified determinants of undernutrition are age of the child, maternal education, region, source of drinking water, number of children under 5 years, wealth index, anemic status of a child, multiple birth, child's sex, incidence of fever, mother's age at birth, body mass index of mother and father's education.

Male child was significantly more likely to be undernourished than female in children under five years of age in Ethiopia. The risk of a child being in worse undernutrition was higher for lower maternal education than higher maternal education. Those children whose fathers had attended formal education had less chance of being undernourished. Mothers who had a lower BMI were marginally associated with higher odds of childhood undernutrition compared to mothers with normal BMI. The higher the number of children under five years in a house hold, the higher the risk of a child being undernourished. The risk of having worse undernutrition status was higher among anemic children when compared to the non-anemic children. The risk of being in worse undernutrition status was higher for children who had fever in the last two weeks before the survey as opposed to children who had not have fever. Multiple (twin) children at birth were more likely to be in worse undernutrition status as compared to singleton child at birth. The children from a household who do not have improved source of water were more likely to be in worse undernutrition status compared to children who have consumed improved source.

Authors finally recommended that the improvement of nutritional status of children requires multi-factorial interventions. A policy is also needed to address the provision of essential services and increasing access to health care to reduce burden of diseases that increase vulnerability to undernutrition. Further research may explore the specific factors that are responsible for gender and region disparities in the prevalence of undernutrition among children and study will also be important to assess the spatial epidemiology of child undernutrition in Ethiopia to identify the regions with high hotspots of child undernutrition.

Abbreviations

AIC: Akaike Information Criteria; BIC: Bayesian information criteria; BMI: Body mass index; CI: Confidence Interval ; CSA: Central Statistical Agency; EAs: Enumeration Areas; EDHS: Ethiopia Demographic and Health Survey; GOLM: Generalized Ordered Logit Model ; HAZ: Height for age z-score; LL: Log Likelihood; Logit: Log of Odds ; ML: Maximum Likelihood; MLE: Maximum Likelihood Estimation ; OLS: Ordinary Least Square; OR: Odds Ratio; PCA: Principal Component Analysis; POM: Proportional Odds Model; PPOM: Partial Proportional Odds Model; UN: United Nation; UNICEF: United Nations Children's Fund; WAZ: Weight for age z-score ; WHO: World Health Organization; WHZ: Weight for height z-score

Declarations

Ethics approval and consent to participate

The ethical clearance for the survey was approved by Ethical Review Board of Central Statistical Agency (CSA), Ethiopia and all participants who agreed to take part in the survey signed a consent form. Hence, we author asked the CSA permission to use data via on line form and the data manager of CSA give permission to use for this article.

Consent for publish

Not Applicable.

Availability of data and materials

The data set supporting the conclusions of this article is held by the authors and the Central Statistical Agency, CSA, Ethiopia, and the de-recognized data may be made available if a unique request is crafted from CSA website (www.csa.gov.et).

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

GW wrote the proposal, analyzed the data and manuscript writing. DL accredited the proposal with revisions, analysis the data and manuscript writing. Both GL and DL read and approved the very last manuscript.

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Figures

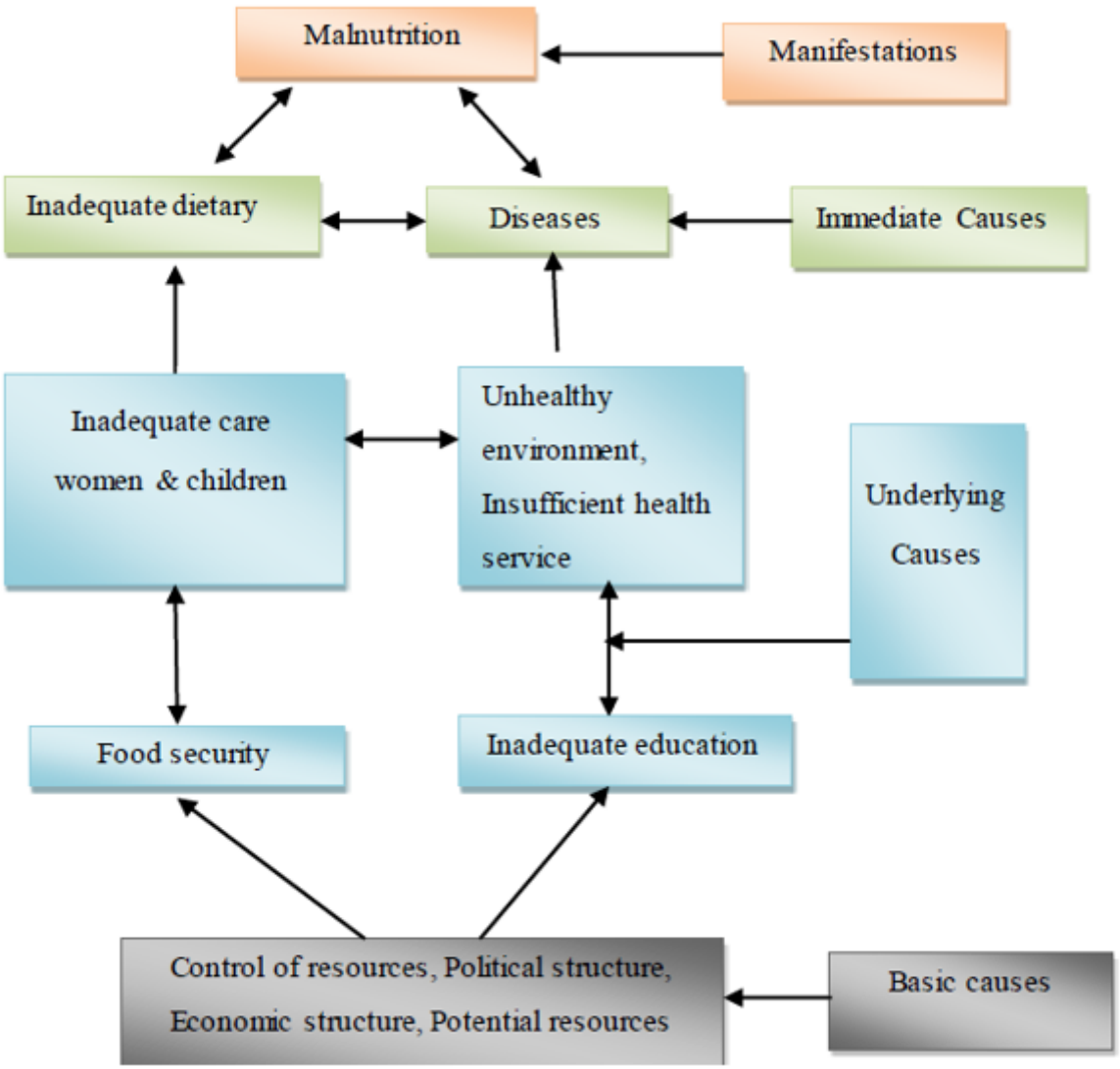

Figure 1

Conceptual framework of determinants childhood malnutrition

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