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Correlates of stunting and underweight among under five children in a north-eastern district of Bangladesh

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Abstract

Sylhet is the most populated district in the north-east part of Bangladesh where half of the under-five children are either stunted or underweight. The correlates of stunting and underweight have not yet been explored extensively for the children of Sylhet district. This study aims to explore the correlates of stunting and underweight in Sylhet by selecting an appropriate logistic model for each of the indicators along with their district and sub-district level prevalence. A total of 809 children were selected in the household survey via two-stage cluster sampling design. Height-for-age and weight-for-age z-scores are used for determining stunting and underweight respectively. For each indicator, an appropriate logistic model is determined through several model selection criteria for determining the corresponding correlates. Stunting and underweight were 45.7% and 32.9% at district level, while sub-district level prevalence varied over 31.5%-60.0% and 21.6%-48.0% respectively. Children's age and recent morbidity, mothers' education and current nutrition status, and household socio-economic status are found as main correlates of stunting and underweight. Interaction of mothers' education and nutrition status has significant effect on children stunting. Study findings recommend interventions focusing on mothers and households' socio-economic improvement in the vulnerable sub-districts particularly those remote from Sylhet Metropolitan City.

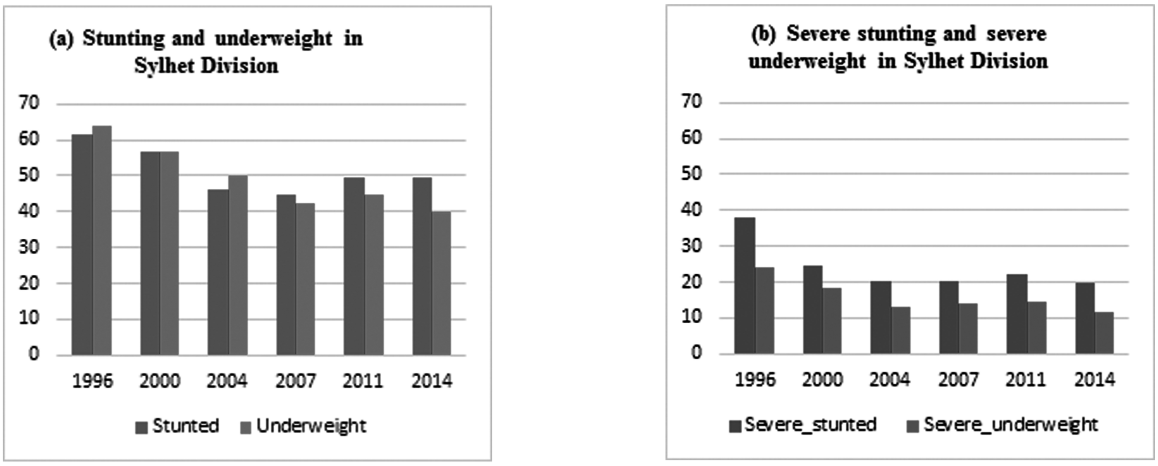
Key words: Child Undernutrition; Generalized Estimating Equation; Ordinary Logistic Regression; Population Average Logistic Regression; Random Intercept Logistic Regression.

1. Introduction

Bangladesh is one of the signatories to the Sustainable Development Goals (SDGs). Improving nutrition status is crucial to meet up the second SDG "No hunger" particularly the target of "end all forms of malnutrition" by 2030. In Bangladesh, child malnutrition is pervasive with nearly one half of all children aged under five years being either underweight or short according to their age [1]. With the target of a Millennium Development Goal (MDG) of reducing the proportion of underweight children from 66% in 1990 to 33% in 2015, Bangladesh has succeeded to meet the goal by 2014 [2]. The decline in stunting (short according to age) from 60% in 1997 [3] to 36% in 2014 [2] also shows the success of the Bangladesh. Though Bangladesh has succeeded to achieve the child malnutrition related MDG, the levels of child malnutrition at national level are still above the "high" prevalence (20-30% for underweight and 30-40% for stunting) according to WHO [4]. In 2014, the levels of stunting and underweight were higher than 30% in alldivisions except in Khulna (28.1% and 25.5%) division. The most vulnerable condition of child undernutrition has been found consistently in the Sylhet division (49.6% for stunting and 39.8% for underweight in 2014) over all the Bangladesh Demographic and Health surveys (BDHS) [2].

The trends in stunting and underweight for Sylhet division have been shown in Figure 1. The Figure 1 (a) shows that both proportions of stunted and underweight children decline significantly from about three-fifths in 1996 to about two-fifths in 2007, however there were no substantial improvement in the next two surveys. In the recent 2014 BDHS, both stunting and underweight levels are still above the WHO threshold of "Very High" prevalence (above 40% and 30% respectively) [5] in Sylhet division. Figure 1 (b) reveals that severe stunting was more prevalent than severe underweight over the whole period and after 2004 there were no substantial change in either case. These findings clearly demonstrate very poor improvement of child nutrition scenario in Sylhet division during the last two decades. To reduce malnutrition vulnerability from this highly jeopardy area, it is indispensable to observe the levels of child malnutrition particularly at the lower administrative units like district and sub-district, and also to identify the risk factors of child malnutrition at these units.

Figure 1: Trends of stunting, severe stunting, underweight and severe underweight in Sylhet Division during 1996-2014



Nationwide household surveys in Bangladesh are conducted with the aim of getting estimate of child nutrition at national and division level. The lower administrative units like districts and sub-districts are ignored in the survey sampling design and so the estimates at the district level are expected to be biased and inconsistent due to less observations. As a result, no direct estimate of child undernutrition are available for the Sylhet district, the largest sub-division of the Sylhet region in terms of population. A recent study based on a small area estimation technique using a nationwide survey data and the 2011 census data shows that 44% and 36% of the under-5 children are stunted and underweight respectively in Sylhet district [6]. These scenarios obviously reveal that child undernutrition is still a major public health problem in Sylhet district though Bangladesh has achieved a remarkable improvement in child nutrition at national level. These severe child undernutrition scenarios emphasize to estimate the prevalence of stunting and underweight at both district and sub-district levels and to find the corresponding correlates for this vulnerable Sylhet district.

The most common method of determining risk factors for a binary outcome (considering a child either undernourished or nourished) is to develop an ordinary logistic regression (hereafter referred as OLR) model assuming the outcomes are independent [7]. Since children are nested within families, families within communities, and communities within regions, in practice this independence assumption of OLR model may be violated. If the underlying assumptions of independence as well as non-existence of over-dispersion (covariances of the responses differ substantially from those under the OLR model) are violated, the corresponding regression coefficients may become unbiased but their accuracy measure (such as standard error) would be affected [8]. Generalized estimating equation (GEE) method captures the cluster-specific correlation in developing the logistic model through the correlation structure to correct the over-dispersion [9]. On the other hand, generalized linear mixed model (GLMM) is another statistical technique to capture the cluster and higher-level effects [10]. Unlike the GEE, the GLMM is not only conditional to the explanatory variables but also to the considered level-specific random effects [8].In this study, the OLR model accounting average cluster effect referred as population average logistic regression (PALR) model and cluster specific random intercept model - a special case of GLMM referred as random intercept logistic model (RILR) model are developed for both stunting and underweight.Thus,the main objectives of the study are to: (i) estimate levels of stunting and underweight in Sylhet district and in its 11 sub-districts, (ii) select appropriate logistic models for the studied stunting and underweight among the OLR, PALR, and RILR models, and (iii) determine the significant socio-economic and demographic correlates of stunting and underweight for the Sylhet district based on the appropriate logistic models.

2.0 Methods

The study utilized a small-scale household survey data collected in 2012 under a research project titled "Multilevel Modelling for Identifying Determinants of Child Malnutrition: A Case Study of Sylhet District" funded by University Grand Commission Bangladesh and SUST Research Center, Shahjalal University of Science & Technology, Sylhet. The following sub-sections provide brief discussion on the sampling design and data collection procedure, children nutrition measurement and the statistical methods used in the analysis.

2.1 Sampling design

The study followed the sampling technique used in the 2005 Child and Maternal Nutrition Survey of Bangladesh [11]. The sample size required to be representative at the sub-district level has been calculated as: $=z^2$ [P(1-P)/d^2] *Deff, where n = sample size, z = two-sided normal variate at 95% confidence level (1.96), P = indicator percentage, d = precision, and Deff = design effect. Since the level of child malnutrition varies in the range of 40%-60% in Sylhet division during the last decade (Figure 1), percentage indicator was assumed as P=0.50. Considering precision as 15%, confidence level as 95%, and design effect as 1.45, a total of 60 households is needed in each sub-district, thus at least a total of 660 households were needed to cover the study (60 households*11 Sub-districts). The sample size is consistent with 2004 Household Income and Expenditure Survey (HIES) for Sylhet division [12]. The number of children in BDHS 2014 was also about 700 for Sylhet division [2]. Distributions of sampled households and children are shown in Table 1.

Table 1: Distribution of sampled households, children, stunting, and underweight by sub-district in Sylhet District

Sub-district	Household		Children			Child malnutrition	
	PSU		Sex		Total	Stunting (HAZ < -2.0)	Underweight (WAZ < -2.0)
	Rural	Urban	Male	Female			
Sylhet Sadar	31	30	42	31	73	38.9	41.1
Balaganj	33	31	37	38	75	46.5	24.0
Beanibazar	30	30	39	35	74	40.9	21.6
Bishwanath	30	30	45	28	73	52.7	43.9
Companiganj	30	30	31	43	74	39.1	31.9
Fenchuganj	31	32	39	33	72	50.0	34.7
Golapganj	31	33	46	27	73	35.2	23.3
Gowainghat	33	30	32	40	72	53.5	32.0
Jaintiapur	33	30	36	39	75	60.0	48.0
Kanaighat	30	30	26	47	73	54.2	37.5
South Surma	33	30	41	34	75	31.5	22.7
Total	345	336	414	395	809	45.7	32.8

The households were selected following a stratified two-stage cluster sampling technique considering sub-district *(Upazilla)* as 11 strata. At the first stage, one *mouza* (village or collection of villages) from rural area and one *mohalla* (ward) from urban area were randomly selected from each sub-district as the primary sampling units (PSUs). At the second stage, at least 30 households with children aged less than five years were selected randomly from the selected *mouza/mohalla* to collect data on maternal as well as child health and nutrition. It is noted that, due to budget constraint, the PSUs which were near to any police station (thana) of a sub-district were selected randomly. The households were selected from a closely area to account the cluster effect in the data. The data were collected during the period of April-May, 2012.

2.2 Data collection

A questionnaire was designed to collect socio-economic and demographic information, access to health services and health environment, household food security, caring practice, and anthropometric information from children and their mothers (Questionnaire is available online, which link is given in the Supplementary Material S1). The questionnaire was prepared following the questionnaires of 2011 BDHS [13], and 2005 Bangladesh Child and Maternal Nutrition Survey [11]. The ethical approval of data collection was taken from the concerned body of SUST Research Center. Electronic digital scales (tested with standard weights) were utilized to measure the weight of children and mothers to the nearest 100 gm. Two stadiometers were hired from a local non-government organization to measure the lengths of children aged less than 2 years, while the heights of children aged at least 2 years and mothers were measured by using height ruler taped vertically to a hard-flat surface. Mid-upper arm circumference (MUAC) was also measured using a standard measurement tape. Length, height, and MUAC were measured to the nearest 1.0 mm. Verbal consent of household head was witnessed and formally recorded.

2.3 Children nutrition measurement

The anthropometric indices height-for-age z-score (HAZ) and weight-for-age z-score (WAZ) were calculated using WHO 2006 Child Growth Standard [14]. The SPSS macro called WHO Anthrois implemented for calculation of z-scores. A child is called stunted and underweight if HAZ and WAZ are below -2.00 standard deviation (SD) respectively. For explaining the statistical methods in the next sub-section, let us define nutrition status (either stunted or not stunted) of a child by y_{ijk} (say, 1=stunted and 0=not stunted) for the k^{th} child belonging to the j^{th} cluster of i^{th} sub-district. The corresponding values of the explanatory variables considered in the model development are denoted by a vectorX_{ijk}.

2.4 Statistical methods

Initially, chi-square test has been done to explore independently associated explanatory variables of child stunting and underweight, and then OLR, PALR, and RILR models have been developed to determine the significant predictors of child malnutrition. A number of two-way interactions have also been employed to fit better model.

2.4.1 Ordinary logistic regression (OLR) model

The OLR model predicts the probability of a child being malnourished (stunted or underweight) given the values of explanatory variables and is expressed as $\log[\pi_{ijk}/(1-\pi_{ijk})]=X_{ijk}^{T}\beta$, where $\pi_{ijk}=P_r\,(y_{ijk}=1|X_{ijk}^{T})=e^{X_{ijk}^{T}\beta}/(1+e^{X_{ijk}^{T}\beta})$ is the probability of being malnourished [15]. The overall performance of the fitted OLR model via maximum likelihood can be assessed by comparing with its competitor model families [16]. The major limitation of this model is that the response values are assumed independent.

2.4.2 Population average logistic regression (PALR) model

The issue of the non-independence or over-dispersion in OLR model is tackled by the GEE or quasi-likelihood equation method considering correlation structure among the responses as nuisance parameter [8,9]. GEE only requires the correct specification of marginal mean and variance as well as the link function which connects the covariates of interest and marginal means. The appeal of GEE in developing PALR models is that it gives consistent estimates of the parameters and standard errors even if the "working" correlation matrix is incorrectly specified [10]. The information criterion based on the quasi-likelihood method is the quasi-likelihood information Criteria (QIC).

2.4.3 Random intercept logistic model (RILR) model

The focus of the PALR models based on GEE is estimating the average response over the population. However, there can be natural heterogeneity across the clusters which may suggest varying regression coefficients from one cluster to another in the fitted PALR model [10]. In such case, the RILR is the most frequently used mixed effect model for clustered data. The RILR model can be expressed as an extension of $\log[\pi_{ijk}/(1-\pi_{ijk})]=X_{ijk}^{T}\beta+u_{ij}$ where $u_{ij}\sim N(0,\sigma_u^2)$ indicates cluster-specific random effects and σ_u^2 is the variance component. This two-level RILR is a basic example of a multilevel model. The parameters(the fixed and random effects with the cluster?specific variance component) can be estimated by a numerical approximation like adaptive Gaussian quadrature method [17]. The basic difference between the PALR and RILR is that former is population average and later is a conditional to random cluster effects. This RILR can also be referred as two-level logistic model (a basic multi-level model). The OLR, PALR, and RILR models are developed using LOGISTIC, GENMOD, and GLIMMIX statement of SAS statistical software (version of 9.4). The SAS code are given in the Supplementary Material S2.

2.5 Model selection criteria

One model cannot be claimed as superior unless of valid proof at hand because of the data structure. Furthermore, it could be possible that one model can perform better over another model due to complexity in the data. This issue leads to the selection of an appropriate logistic model among the model families for each of the nutrition indicators. However, the comparison of model families is not straightforward, some criteria have been taken in consideration for selecting a tenable model for the available data. The validity of the model families is assessed through the following criteria: (i) Hosmer-Lemeshow test (H-L test), (ii) heterogeneity factor (H-F), (iii) marginal or conditional R^2 [18] (iv) classification rate (AUC: area under curve), and (v) significance test of cluster variance component. Hosmer-Lemeshow test is performed for assessing the lack of fit of OLR models [15]. Moreover, heterogeneity factor of OLR models is calculated as the ratio of deviance statistic to the degrees of freedom to check the existence of over-dispersion. The marginal or conditional R^2 and classification rates (AUC) of the considered models are extracted for comparing model families. The significance of variance components is assessed by using likelihood ratio test (referred as LRT) to confirm the validity of cluster-specific RILR models. Several R-packages have also been employed for calculating some model selection criteria.

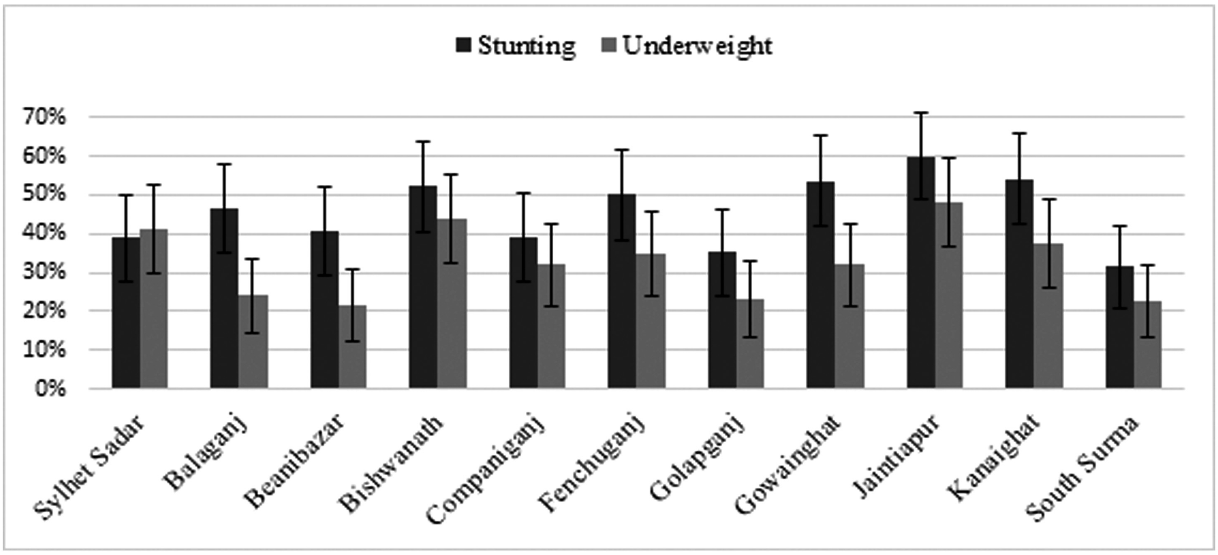
3. Results

3.1 Child malnutrition scenario in Sylhet district

Among the under-five children, about 46% and 33% were stunted and underweight respectively in Sylhet district. Table 1 and Figure 2 show that sub-district level prevalence considerably vary over 31-60% for stunting and 22-48% for underweight. The most vulnerable situation is observed in Jaintiapurupzilla where both stunting (60%) and underweight (48%) levels were highest and followed by Bishwanathupzilla (53% for stunting; 44% for underweight). Overall Nutrition scenario seems better only in South Surma (31.5% stunting; 22.7% underweight) as per WHO [4] threshold of "high prevalence" of stunting (30-39%) and underweight (20-29%).

The background characteristics of children by their nutrition status have been explored at first to find the independently associated factors of child undernutrition in bivariate relationship (Table 2). The classification of children nutrition status by their background characteristics indicates that the proportion of stunted and underweight children significantly vary by children age, occurrence of child fever during last two weeks of the survey, mother's education, mother's body mass index (BMI) and MUAC, self-reported household wealth status, and place of residence. Among the children aged 12-23 months, more than half (55%) and one-third (35%) of the children were stunted and underweight respectively. For illiterate mothers, the proportions of stunted and underweight children were about 58% and 41% respectively, while the figures are significantly lower for the higher educated mothers (stunted: 31% and underweight: 15%). About three-fifths children of mothers with lower BMI (≤18.5) and lower MUAC (≤23.5) were stunted (60.6%) and underweight (61.4%). Among the children of poor families, near about three-fifths and two-fifths were stunted (55.3%) and underweight (39.2%) respectively, whereas the levels are significantly lower for those of rich family (30% and 16% respectively). About half of the children suffering from fever in the last two weeks were stunted while the percentage was approximately 40% for underweight. The children living in rural area are more susceptible to be stunted (49.0%) and underweight (37.1%) compared to those living in urban area (39.6% and 24.8% respectively).

Figure 2: Sub-district level prevalence of stunting (%) and underweight (%) in Sylhet district with 95% confidence interval



3.2 Model selection

The significant explanatory variables found in the bi-variate relationship (shown in Table 2) are utilized to fit the OLR, PALR, and RILR models. The two-way interactions of these significant variables are also examined for both stunting and underweight. However only for stunting, interactions of mother's education and current nutrition status (based on BMI) have been found significant. The considered model selection criteria of OLR, PALR, and RILR models for stunting and underweight are shown in three parts of Table 3. The H-L tests of the developed OLR models for stunting and underweight suggest that both models are fitted well to the data of stunting (χ^2=8.49, p=0.39) and underweight (χ^2=8.26, p=0.41). However, estimated heterogeneity factors of the OLR models for stunting (1.29, p-value=0.02) and underweight (1.57, p-value=0.00) suggest existence of over-dispersion in both models and hence, the OLR models will not be reasonable for drawing valid inference. The areas under the receiver operating characteristic curves (Part-II of Table 3) indicate that the RILR models have the highest classification rates (71.22 for stunting and 74.80 for underweight) in either form of child undernutrition. Furthermore, marginal R^2 of RILR models are higher compared to the OLR and PALR models. The conditional R^2 of RILR models indicates about 5% more variations are accounted by the fitted RILR models mainly due to accounting for cluster variation in the model. Interestingly, cluster-specific variance components estimated from RILR models are almost same (0.15) for stunting and underweight (please see Part-III of Table 3). These indicate that about 5 percent variation (ICC=0.05) in child undernutrition are due to cluster-level factors. The LRT tests of variance components also indicate that between-cluster variability is statistically significant for both stunting (p-value=0.003) and underweight (p-value=0.004). In terms of the estimated standard errors of the estimated regression coefficients, there were negligible difference among the fitted logistic models, however most of the estimated regression coefficients are slightly higher in RILR models what is expected for cluster specific models (please see in Supplementary Table 1). Though comparison of AIC (QIC) values of OLR, PALR, and RILR models are not straightforward, the RILR models have comparatively the lowest AIC values. Thus, RILR models are considered as the best models for stunting and underweight. The place of residence was found insignificant in the multiple logistic regression model and so it is removed from the development of logistic regression models.

Table 2: Bivariate analysis of stunting and underweight by background characteristics in Sylhet District

Background Characteristics	n	Stunting	X^2 (p-value)	n	Underweight	X^2 (p-value)
Age of Children (in months)						
0-11	181	40.3	7.17 (0.03)	190	23.7	9.40 (0.01)
12-23	166	54.2		171	34.5	
24+	435	44.6		445	36.0	
Sex of Children						
Male	401	48.4	2.47 (0.12)	413	33.2	0.07 (0.80)
Female	381	42.8		393	32.3	
Mother's Education						
Illiterate	141	58.2	34.138 (0.00)	145	40.7	40.49 (0.00)
Class 1-5	257	53.3		266	41.4	
Class 6-9	188	41.5		194	33.0	
Higher	196	30.6		201	15.4	
Mother's BMI (in kg/m^2)						
18.5	160	60.6	18.18 (0.00)	166	49.4	26.29 (0.00)
18.5+	622	41.8		640	28.4	
Mother's MUAC (in cm)						
23.5	299	57.5	27.50 (0.00)	495	61.4	34.57 (0.00)
23.5+	483	38.3		311	38.6	
Household Economic Condition						
Poor	365	55.3	32.38 (0.00)	375	39.2	29.92 (0.00)
Lower-middle	240	42.5		248	35.1	
Middle & Rich	177	29.9		183	16.4	
Fever in Last 2-week						
Yes	399	49.6	5.18 (0.02)	411	39.7	18.15 (0.00)
No	383	41.5		395	25.6	
Place of Residence						
Rural	502	49.0	6.348 (0.01)	520	37.1	12.65 (0.00)
Urban	280	39.6		286	24.8	
Total	782	45.7	-	806	32.8	-

3.3 Risk factors of child stunting and underweight in Sylhet

The RILR models as presented in Table 4 and 5 show that most of the factors considered in the models were significantly associated with increased odds of stunting and underweight. For stunting (Table 4), these factors include children 12-23 months (OR=1.764, p-value=0.015), nourished mothers having education of Class 1-5 (OR=1.708, p-value: 0.036), undernourished illiterate mothers (OR=exp(0.478-0.455+1.425)=4.255, p-value: 0.033) and undernourished mothers having education of Class 6-9 (OR= exp(0.087-0.455+1.440)=2.921, p-value: 0.025), and household's poor economic condition (OR=2.295, p-value=0.001) (for calculation of OR please see Supplementary Material S3).For underweight (Table 5), these factors include children of 12-23 months (OR=1.776, p-value=0.024) and 24+ months (OR=2.160, p-value=0.000), children recently experienced with fever (OR=2.027, p-value=0.000), illiterate mothers (OR=2.351, p-value=0.006), mothers having education of Class 1-5 (OR=2.696, p-value=0.000), and Class 6-9 (OR=2.255, p-value=0.002), mothers with lower MUAC (OR=1.986, p-value=0.000), mothers living in poor (OR=2.091, p-value: 0.007), and lower-middle class (OR=2.225, p-value=0.002) households.

Table 3: Hosmer-Lemeshow (H-L) test and heterogeneity factor (H-F) of ordinary logistic regression (OLR) models **(Part-I)**; Model selection based on Area under the receiving operating characteristic curve (AUC), marginal and conditional R2 of OLR, population average logistic regression (PALR), and random intercept logistic regression (RILR) models **(Part-II)**; Cluster-level variance component, intra-cluster correlation (ICC), and the significance of the fitted RILR models **(Part-III)** for both stunting and underweight

Part-I: Hosmer-Lemeshow test and Heterogeneity Factor of OLR Model		
Test	Stunting	Underweight
H-L	$\chi^2_{(8)} = 8.49$, p-value =0.39	$\chi^2_{(8)} = 8.26$, p-value = 0.41
H-F	1.29, p-value =0.02	1.57, p-value =0.00

Part-II: Model Selection						
Selection Criteria	Stunting			Underweight		
	OLR	PALR	RILR	OLR	PALR	RILR
% AUC	67.54	67.34	71.22	71.39	71.40	74.80
% Marginal R^2	10.35	9.74	12.53	17.78	15.00	18.68
% Conditional R^2	-	-	16.25	-	-	22.30
AIC (QIC)	1032.47	1040.57	1027.04	935.90	939.00	930.80

Part-III: Variance Component and ICC in RILR Model		
Characteristics of the RILR	Stunting	Underweight
Variance Component, $\hat{\sigma}_u^2$	0.15	0.15
ICC: $\hat{\sigma}_u^2/(\hat{\sigma}_u^2 + 2.89)$	0.043	0.045
Test of $H_0: \sigma_u^2 = 0$	$\chi^2_{(1)} = 7.43$, p-value=0.003	$\chi^2_{(1)} = 7.13$, p-value=0.004

Table 4: Estimated regression coefficients ($\hat{\beta}$), standard error (SE), p-value, and odds ratio (OR) with confidence limits (LCL: lower confidence limit and UCL: upper confidence limit) for stunting in Sylhet district obtained from random intercept logistic regression (RILR) models

Factors	$\hat{\beta}$	SE	p-value	OR	LCL	UCL
Age of Children (in months)						
12-23 vs. 0-11	0.568	0.235	0.015	1.764	1.114	2.793
24-59 vs. 0-11	0.155	0.193	0.420	1.168	0.801	1.704
Fever						
Yes vs. No	0.289	0.157	0.065	1.335	0.982	1.814
Mother's Education						
Illiterate vs. Higher	0.478	0.304	0.115	1.614	0.890	2.927
Class 1-5 vs. Higher	0.536	0.256	0.036	1.708	1.035	2.820
Class 6-9 vs. Higher	0.087	0.254	0.733	1.090	0.663	1.793
Mother's BMI (in kg/m^2)						
≤18.5 vs. 18.5+	-0.455	0.497	0.360	0.635	0.240	1.680
Socio-economic Status						
Poor vs. Middle & rich	0.831	0.244	0.001	2.295	1.422	3.704
Low middle vs. Middle & rich	0.442	0.230	0.055	1.556	0.991	2.443
Interaction of Mother's Education Status and BMI Status						
Illiterate & BMI ≤18.5 vs. Higher & BMI 18.5+	1.425	0.669	0.033	4.157	1.120	15.425
Class 1-5 & BMI ≤18.5 vs. Higher & BMI 18.5+	0.952	0.586	0.104	2.591	0.822	8.163
Class 6-9 & BMI ≤18.5 vs. Higher & BMI 18.5+	1.440	0.644	0.025	4.222	1.195	14.9
Intercept	-1.466	0.283	0.000	0.23	0.13	0.40

4. Discussion

The study has attempted to estimate stunting and underweight levels in Sylhet district as well as for sub-district and then to explore the correlates of each indicator by selecting an appropriate logistic model for each indicator. Both stunting (46%) and underweight (33%) levels in Sylhet district were found above the WHO threshold of very high prevalence of stunting and underweight [4]. The RILR model is found as the best logistic model for both indicators and suggest that children's age and recent morbidity, mother's education and current nutrition status, and household socio-economic status are the main correlates of stunting and underweight. The RILR models indicate that the variation in stunting and underweight are also attributable to community (cluster) level variation after accounting children, mother and household levels explanatory variables in the model.

Table 5: Estimated regression coefficients ($\hat{\beta}$), standard error (SE), p-value, and odds ratio (OR) with confidence limits (LCL: lower confidence limit and UCL: upper confidence limit) for underweight in Sylhet district obtained from random intercept logistic regression (RILR) models

Factors	$\hat{\beta}$	SE	p-value	OR	LCL	UCL
Children Age (in months)						
12-23 vs. 0-11	0.574	0.254	0.024	1.776	1.080	2.920
24-59 vs. 0-11	0.773	0.215	0.000	2.166	1.422	3.301
Fever						
Yes vs. No	0.707	0.168	0.000	2.027	1.459	2.817
Mother's Education						
Illiterate vs. Higher	0.855	0.311	0.006	2.351	1.279	4.323
Class 1-5 vs. Higher	0.991	0.270	0.000	2.696	1.590	4.571
Class 6-9 vs. Higher	0.813	0.266	0.002	2.255	1.339	3.797
Mother's MUAC (in cm)						
≤ 23.5 Vs. 23.5+	0.686	0.174	0.000	1.986	1.413	2.792
Socio-economic Status						
Poor vs. Middle & rich	0.738	0.274	0.007	2.091	1.223	3.574
Low middle vs. Middle & rich	0.800	0.262	0.002	2.225	1.333	3.711
Intercept	-3.307	0.352	0.000	0.037	0.018	0.073

The stunting and underweight levels in Sylhet district are consistent with the findings of the recent small area study on child undernutrition (44% and 36% respectively in 2011) [6]. The estimated stunting and underweight in Sylhet district were also very comparable to the Sylhet division as in 2011 and 2014 BDHS surveys [2, 13]. The differences in between district and division level estimates of stunting and underweight might be due to the difference in infrastructure among the four districts under the Sylhet division. Though the district level figures seem slightly better than the Sylhet division (about 50% for stunting and 45% for underweight in 2011), the statistics significantly vary at the sub-district level over 31-60% for stunting and 22-48% for underweight. At sub-district level, the nutrition scenarios are found worst in Jaintiapur and Bishwanathsub-districts and better only in South Surma. For Sylhet Sadar which consists of the Sylhet Metropolitan city, both stunting and underweight levels were unexpectedly higher compared to its adjacent sub-districts like South Surma and Golapganj. Selection of more children from slum areas of Sylhet Sadar may be one of the reasons of such result.

For selecting the best model for stunting and underweight, three types of logistic models OLR, PALR, and RILR have been developed considering children nutrition status as either independent or correlated each other within a community. At a first glance, all the developed logistic models suggest that the main contributors in the variation of child stunting and underweight are mainly at child, mother, and household levels covariates. Based on the heterogeneity factor, AUC, R^2, and the test of cluster variance component, the multilevel RILRs are considered as appropriate than the OLR and PALR models for both stunting and underweight. In this study, only children and cluster are considered as levels for fitting the RILRs mainly due to small sample and less number of clusters considered in the sampling design (due to budget constraint of the project). In the nationwide 2011 BDHS nutrition data where 600 clusters are considered, Chowdhury et al. [19] also found significant household and cluster specific random effects on both stunting and underweight.

The findings of the study found that the odds of being stunted was about double for the children aged 12-23 months compared to the infants, while the risk of being underweight increased with the children age (about 1.8 times for 12-23 months and 2.2 times for 24-59 months). Similar findings are also reported in other nationally representative child nutrition studies [19,20,21,22]. To explore age-specific risk by sub-district, age-specific mean probabilities of being stunted and underweight have been plotted for 11 sub-districts in Supplementary Figure 1 based on the selected GLMM models. The figure shows that children of South Surma sub-district had lower mean probabilities of being stunted and underweight while children of Jaintapur sub-district had higher mean probabilities at all age groups. The scenarios are found comparatively better for the children of Golapganj sub-district particularly for the age-group 12-23 months.

Children diarrhoea and fever in last two weeks are found as significant risk factors of child stunting and underweight [23,24]. In this study, children experienced with fever also found to have 1.3 and 2.0 times higher risk of being stunted and underweight respectively compared to their counterparts.

The study has found significant interaction effects of mothers' education and their BMI on child stunting. It is observed that there is no significant difference in stunting by mothers' BMI status among the children of higher educated mothers, but significant difference in stunting among the children of nourished mothers who have education of Class 6-9. On the other hand, stunting level is found significantly higher for the children of malnourished mothers having no education and also for those mothers having education of Class 6-9 compared to those nourished mothers with higher education. However, such interaction effects are found statistically insignificant for underweight. Children of chronic malnourished mothers (MUAC?23.5) are found to have double risk of being underweight compared to the children of nourished mothers (MUAC 23.5+). These results are expected as in other studies of Bangladeshi children where mother nutrition status measured using BMI [20,21]. Felisbino-Mendes et al. [26] also showed a significant association between maternal and child nutrition status through a population based cross-sectional study in Bangladesh.

Thus, the findings of the study support the evidence that children of less educated and malnourished mothers have significantly higher risks of being stunted and underweight compared to those of higher educated and nourished mothers. Such findings are expected since educated mothers are more likely to have better socio-economic condition, employment opportunity, access to better food supply, and efficient management skills to implement the strategies that might meet the nutritional needs for their children and family members [25]. Other nutrition studies considering Bangladeshi children also found a strong relationship of mother's education and nutrition status with child nutrition vulnerability [19,20,21,22]. Involvement in longer education can aid mothers to prevent early marriage, to conceive baby at a better stage, to acquire better childcare skills over time which are essential for meeting the nutritional needs of their children.

The odds of having stunted and underweight children largely vary with household socio-economic status. The children who belong in a poor family have about double risk of being stunted and underweight than those belong to a middle/rich family. Even children from low-middle class families have more than double risk of being underweight. Some previous studies also support a strong association between household economic wellbeing and child nutrition status [19,21,27,28]. The households with well socio-economic status may have capacity to lessen food insecurity and better access to sufficient health care facilities which ultimately ensure better child nutrition.

The small number of sampled clusters can be considered as one of the main limitations of this study for developing complex models like PALR and RILR; however, the results are reasonable compared to other relevant studies using nationwide data [29]. Though a number of significant factors are independently associated with child undernutrition status, many of them are not observed as significant in the multivariate model. Such findings may be due to the interrelationship among these explanatory variables. Having less significant explanatory variables may be one of the reasons of overdispersion in fitting OLR models. However, finding significant interaction effects of mother's education and nutrition status on stunting is one of the strengths of this study. Regarding consistency and reliability of the survey data, it is expected less reporting bias since the data were collected by a group of university graduate students. On the other hand, both stunting and underweight are based on anthropometric measurements which are free from subjectivity and have internal validity to calculate children anthropometric indices.

5. Conclusion

The findings of the study indicate that the levels of stunting and underweight in Sylhet district were very high though Bangladesh succeeded to achieve the MDG 4 in time. The scenario at sub-district level confirms that district level estimates highly mask the significant variation of child malnutrition at disaggregated administrative units. The selection procedure of an appropriate model for predicting child malnutrition status recommends to account clustering effect in model specification via multilevel analysis even though small number of clusters are covered in the survey. Children age and their current morbidity status, mother's education and their current nutrition status, and household socio-economic condition are the main contributors in the inequality of child stunting and underweight in Sylhet district considering the community effects in the model. In addition, the significant interaction effect of mother's education and nutrition status on their children chronic malnutrition recommends the necessity of effective maternal education for their children and own health. Hence, local stakeholders should take interventions focusing on mothers and households' improvement for the prevention of child malnutrition in the vulnerable sub-districts particularly in those sub-districts distant from the Sylhet Metropolitan City belongs to Sylhet Sadarupzila.

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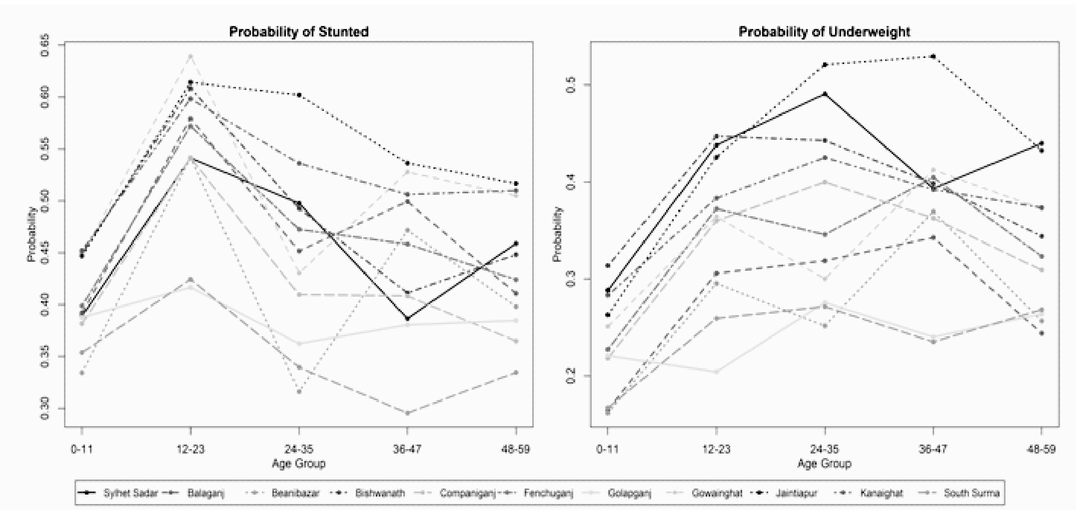
Supplementary Table 1: Regression coefficients ($\hat{\beta}$) and their standard error (se) of ordinary logistic regression (OLR), population average logistic regression (PALR), and random intercept logistic regression (RILR) models for stunting and underweight in Sylhet district

Factors	Stunting						Underweight					
	OLR		PALR		RILR		OLR		PALR		RILR	
	$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE	$\hat{\beta}$	SE
Age of Children (in months)												
12-23 vs. 0-11	0.52	0.24	0.55	0.23	0.57	0.23	0.54	0.25	0.56	0.22	0.57	0.25
24-59 vs. 0-11	0.19	0.20	0.16	0.19	0.16	0.19	0.75	0.21	0.75	0.24	0.77	0.22
Fever												
Yes vs. No	0.30	0.16	0.28	0.15	0.29	0.16	0.67	0.16	0.69	0.15	0.71	0.17
Mother's Education												
Illiterate vs. Higher	0.49	0.31	0.52	0.25	0.48	0.30	0.85	0.30	0.84	0.32	0.85	0.31
Class 1-5 vs. Higher	0.50	0.26	0.47	0.30	0.54	0.26	1.05	0.26	0.99	0.30	0.99	0.27
Class 6-9 vs. Higher	0.09	0.25	0.09	0.25	0.09	0.25	0.78	0.26	0.80	0.29	0.81	0.27
Mother's BMI (in kg/m²)												
≤18.5 vs. 18.5+	-0.39	0.51	-0.44	0.49	-0.45	0.50	-	-	-	-	-	-
Mother's MUAC (in cm)												
≤ 23.5 vs. 23.5+	-	-	-	-	-	-	0.72	0.17	0.68	0.18	0.69	0.17
Socio-economic Status												
Poor vs. Middle & rich	0.71	0.24	0.81	0.24	0.83	0.24	0.63	0.26	0.72	0.25	0.74	0.27
Low middle vs. Middle & rich	0.45	0.23	0.43	0.23	0.44	0.23	0.78	0.25	0.79	0.25	0.80	0.26
Mother's EducationX Mother's BMI												
Illiterate & BMI ≤18.5 vs. Higher & BMI 18.5+	1.31	0.68	1.38	0.66	1.42	0.67	-	-	-	-	-	-
Class 1-5 & BMI ≤18.5 vs. Higher & BMI 18.5+	0.88	0.60	0.93	0.58	0.95	0.59	-	-	-	-	-	-
Class 6-9 & BMI ≤18.5 vs. Higher & BMI 18.5+	1.37	0.66	1.40	0.63	1.44	0.64	-	-	-	-	-	-
Intercept	-1.41	0.27	-1.44	0.28	-1.47	0.28	-3.22	0.33	-3.25	0.36	-3.31	0.35

Supplementary Figure 1: Average probabilities of being stunted and underweight for the under-5 children according to their age group and sub-district based on the fitted random intercept logistic regression (RILR) models for stunting and underweight



according to their age group and sub-district based on the fitted random intercept logistic regression (RILR) models for stunting and underweight

Supplementary Materials

S1. Questionnaire

Please see the Technical Report for the Questionnaire of the research project
https://www.researchgate.net/publication/335527049_Multi-level_Modeling_for_Identifying_Determinants_of_Child_Malnutrition_A_Case_Study_of_Sylhet_District

S2. SAS Code

```
LIBNAME CLS 'C:\Users\Research paper';
PROC IMPORT DATAFILE='C:\Users\ Research paper
5\Data_final.sav' OUT=cls.r5;
run;
proc contents data=cls.r5;
run;
procfreq data=cls.r5;
run;

/***Multiple Logistic for stunting***/
proclogistic data=cls.r5;
title '1.Binary logistic regression for Stunting';
title2 'with PROC LOGISTIC';
class age_cat_new_GEE (ref='0-11 Months')
mot_edu_glmixbmi_mot_glmix (ref='BMI 18.5+') m3_q36_glmix
(ref='No') m1_q12_recoded (ref='Middle/Rich')/ param=ref;
model stunt(event='Stunted') =
age_cat_new_GEEmot_edu_glmixbmi_mot_glmix m3_q36_glmix
m1_q12_recoded /Lackfit;
run;
/*** GLMM for stunting***/
PROC GLIMMIX DATA=cls.r5 METHOD=laplace OR;
TITLE 'GLMM binary data random intercept (full)';
CLASS age_cat_new_GEE (ref='0-11 Months')
mot_edu_glmixbmi_mot_glmix (ref='BMI 18.5+') m3_q36_glmix
(ref='No') m1_q12_recoded (ref='Middle/Rich') PSU_UNIQUE_ID;
MODEL stunt
(event='Stunted')=age_cat_new_GEEmot_edu_glmixbmi_mot_glmix
m3_q36_glmix m1_q12_recoded/ dist=bin solution;
RANDOM intercept / subject=PSU_UNIQUE_ID g;
covtest/wald;
RUN;
18.5+') m3_q36_glmix (ref='No') m1_q12_recoded (ref='Middle/Rich')
PSU_UNIQUE_ID;
model
stunt(event='Stunted')=age_cat_new_GEEmot_edu_glmixbmi_mot_glm
ix m3_q36_glmix m1_q12_recoded/ dist=b type3;
repeated  subject =PSU_UNIQUE_ID/ type=exchcorrwmodelse;
run;
/*** GEE for stunting ***/
procgenmod data=cls.r5;
title '12. GEE logistic regression for Stunting';
title2 'weighted + clustered';
class  age_cat_new_GEE (ref='0-11 Months')
mot_edu_glmixbmi_mot_glmix (ref='BMI
```

```
/***Multiple Logistic for underweight***/
proclogistic data=cls.r5;
title '1.Binary logistic regression for underweight;
title2 'with PROC LOGISTIC';
class age_cat_new_GEE (ref='0-11 Months') mot_edu_glmix
m2_q15_c_recoded (ref='MUAC > 23.5') m3_q36_glmix
(ref='No') m1_q12_recoded (ref='Middle/Rich')/ param=ref;
model under(event='Underweight') =
age_cat_new_GEEmot_edu_glmix m2_q15_c_recoded
m3_q36_glmix m1_q12_recoded/lackfit;
run;
/***GLMM for underweight ***/
PROC GLIMMIX DATA=cls.r5 METHOD=laplace OR;
TITLE 'GLMM binary data random intercept (full)';
CLASS age_cat_new_GEE (ref='0-11 Months')
mot_edu_glmix m2_q15_c_recoded (ref='MUAC > 23.5')
m3_q36_glmix (ref='No') m1_q12_recoded
(ref='Middle/Rich') PSU_UNIQUE_ID;
MODEL
under(event='Underweight')=age_cat_new_GEEmot_edu_glm
ix  m2_q15_c_recoded m3_q36_glmix m1_q12_recoded/
dist=bin solution;
RANDOM intercept / subject=PSU_UNIQUE_ID g;
covtest/wald;
RUN;
/*** GEE for underweight ***/
procgenmod data=cls.r5;
title '12. GEE logistic regression for underweight';
title2 'weighted + clustered';
class  age_cat_new_GEE (ref='0-11 Months') mot_edu_glmix
m2_q15_c_recoded (ref='MUAC > 23.5') m3_q36_glmix
(ref='No') m1_q12_recoded (ref='Middle/Rich')
PSU_UNIQUE_ID;
model
under(event='Underweight')=age_cat_new_GEEmot_edu_glm
ix  m2_q15_c_recoded  m3_q36_glmix m1_q12_recoded/
dist=b type3;
repeated  subject =PSU_UNIQUE_ID/
type=exchcorrwmodelse;
run;
```

S3. Calculation of odds ratio

For explaining the calculation of odds ratio when an interaction effect is added in the logistic model, lets define two dummy variables as $X_1 = 1$ for "Illiterate Mother" and $X_1 = 0$ for "Higher educated mother"; $X_2 = 1$ for "Malnourished Mother (BMI $\leq$ 18.5)" and $X_2 = 0$ for "Nourished Mother (BMI = 18.5+)". Then the logistic model is written as

$$\log(\text{odds}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$$

With the results from Table 4, the fitted model can be written as

$$\log(\text{odds}) = -1.466 + 0.478\, X_1 + (-0.455) X_2 + 1.425\, X_1 X_2$$

where the regression coefficient of X_1 (0.478) is the log-odds ratio comparing illiterate ($X_1 = 1$) with higher educated ($X_1 = 0$) mothers amongst nourished mothers ($X_2 = 0$). Similarly, the regression coefficient of X_2 (-0.455) is the log-odds ratio comparing malnourished mother ($X_2 = 1$) with nourished mothers ($X_2 = 0$) amongst higher educated mothers ($X_1 = 0$). While the regression coefficient of X_1X_2 (1.425) is the difference between "the log-odds ratio comparing Illiterate ($X_1 = 1$) vs higher educated ($X_1 = 0$) mothers" amongst malnourished mothers ($X_2 = 1$)" and "the log-odds ratio comparing Illiterate ($X_1 = 1$) vs higher educated ($X_1 = 0$) mothers amongst nourished mothers ($X_2 = 0$)". Thus, the interpretation of β_3 (interaction effect) is difficult to interpret in a straightforward way for the non-technical people.

For calculating the odds ratio for "Illiterate & malnourished mothers" ($X_1 = 1$and $X_2 = 1$) compared to "Higher educated & nourished mothers" ($X_1 = 0$ and $X_2 = 0$), at first we calculated log-odds for these two groups as below:

Log-odds for "Illiterate & malnourished mothers" = $-1.466 + 0.478\,(X_1 = 1) + (-0.455)\,(X_2 = 1) + 1.425\,(X_1X_2 = 1) = -1.466 + 0.478 - 0.455 + 1.425$

Log-odds for "Higher educated & nourished mothers" = $-1.466 + 0.478\,(X_1 = 0) + (-0.455)(X_2 = 0) + 1.425\,(X_1X_2 = 0) = -1.466$

Hence, odds-ratio for "Illiterate & malnourished mothers" compared to "Higher educated & nourished mothers" will be OR = $e^{-1.466+0.478-0.455+1.425}/e^{-1.466} = e^{0.478-0.455+1.425}$.