Bayesian Multilevel Analysis of Children Vaccination Coverage in Ethiopia

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BAYESIAN MULTILEVEL ANALYSIS OF CHILDREN VACCINATION COVERAGE
IN ETHIOPIA

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Abstract

Background: Vaccine preventable diseases (VPDs) account for 17% of the global under-five mortality per annum and more than half of these deaths have occurred in sub-Saharan Africa. Ethiopia is one of the ten countries which account for about 62% of unprotected children and one of the three countries (Ethiopia, Nigeria, and the Democratic Republic of Congo) in which half of the world's child deaths have occurred are in sub-Saharan Africa. The main objective of this study is to understand the current status of complete immunization coverage and examine its determinant factors among children in Ethiopia.

Method: Bayesian multilevel logistic regression models have been utilized to realize the objectives of the research. The dataset used for this study comes from the 2016 Ethiopian Demographic and Health Survey (EDHS). The convergences of parameters are checked by using Markov chain Monte-Carlo (MCMC) using SPSS and MLwiN software.

Results: The descriptive result revealed that, out of the 1929 children who are supposed to complete all basic childhood vaccines, 699 (36.2%) children were completely vaccinated, while 1230 (63.8%) children were incompletely vaccinated. Moreover, regions Afar, Somali and Gambela have the least proportion of vaccination coverage. Among the multilevel models, Bayesian random coefficient model is found to be a better model to estimate the vaccination coverage of children. Using this model, it has been found that factors like place of residence, maternal educational, mother occupation type, Antenatal Care (ANC) utilization, Postnatal Care (PNC) utilization, type of pregnancy, household wealth index, and field worker visit were found to be the significant factors that influences the vaccination coverage.

Conclusion: In general, it has been estimated that the vaccination coverage in the country is relatively low and there was significant variation in the level of vaccination coverage in regions of the country.

Key words: Vaccination coverage, Immunization, Bayesian multilevel analysis, Ethiopian Demographic and Health Survey, Markov chain Monte-Carlo

Background

Vaccination is the administration of a vaccine using a biological substance intended to stimulate a recipient's immune system to produce antibodies or undergo other changes that provide future protection against specific infectious diseases [1].

Vaccination is the stimulation of changes in the immune system through which that protection occurs. It is one of the prevention strategies for common childhood illnesses. It prevents morbidities and mortalities from diphtheria, hepatitis B, measles, mumps, pertussis, pneumonia, polio, rotavirus diarrhea, rubella, cervical cancer, and tetanus. It is also one of the most powerful and cost-effective of all health interventions. It prevents debilitating illness and disability and saves millions of lives every year. Vaccination is also a key to achieve the Millennium Development Goals (MDGs) commitments made by world leaders in 2000 to reduce poverty and improve human development. The contribution of immunization is especially critical to achieving the goal to reduce deaths among children under five years old (MDG 4). Vaccines have the power not only to save, but also to transform lives giving children a chance to grow up healthy, go to school, and improve their life prospects [2]. Vaccines protect the future health of all populations.

Universal immunization of children against six common vaccine-preventable diseases, namely tuberculosis, diphtheria, whooping cough (pertussis), tetanus, polio, and measles, is crucial in reducing infant and child mortality. Other childhood vaccines given in Ethiopia protect against hepatitis B, and *Haemophilus influenzae* type b (Hib). The government of Ethiopia introduced the pneumococcal conjugate vaccine (PCV 13) and monovalent human rotavirus vaccine (RV1) into the nation's infant immunization programme in November 2011 and October 2012, respectively. The pneumococcal vaccine protects against *Streptococcus pneumoniae* bacteria, which cause severe pneumonia, meningitis, and other illnesses. Rotavirus causes gastroenteritis, an inflammation of the stomach and intestines. If left untreated, it can lead to severe dehydration and death [3].

Vaccine Preventable Diseases (VPDs) account for 17% of the global under-five mortality per annum. In 2019, 5.2 million children died, and about 14,000 children still die every day worldwide. Children continue to experience widespread geographic inequalities in their chances of survival. Sub-Saharan Africa is still the region with the highest child mortality rate in the

world. The region had an average child mortality rate of 76 deaths per 1000 live births in 2019. Over 80% of the 5.2 million child deaths occurred in sub-Saharan Africa and Central and Southern Asia. More than half of these deaths have occurred in sub-Saharan Africa. Three of the five countries (Ethiopia, Nigeria, and the Democratic Republic of Congo) in which half of the world's child deaths have occurred are in sub-Saharan Africa [4].

On the basis of the [5] estimates of national immunization coverage, Ethiopia is 5th of the ten countries which account for the 62% of unprotected children following Nigeria, India, Democratic republic Congo and Pakistan.

The aim of this study is to understand the current status of vaccination coverage of children in Ethiopia and to reveal the various factors influencing the vaccination coverage in the country. The findings from this study would help the policymakers in understanding current status of vaccination coverage and the determinant of its coverage in the country and serve as an important input for any possible intervention aimed at improving the coverage in the country. This study covered children in the age range of 12- 23 months from all 9 regions and 2 city administrations of the country.

Methods

Study Area

Ethiopia is the oldest independent country, located in the North Eastern part of Africa, also known as the Horn of Africa, lies between 3 and 15 degrees north latitude and 33 and 48 degrees east longitude. Ethiopia is officially known as the Federal Democratic Republic of Ethiopia and is a landlocked country located in the Horn of Africa. It is the second-most populous nation in Africa, with 117,876,227 populations according to united nation estimate of 2021. The total surface area of Ethiopia is about 1.1 million square kilometers and bordered by Djibouti, Eritrea, the republic of the Sudan, the republic of the Southern Sudan, Kenya, and Somalia. At present Ethiopia is administratively structured in to ten regional states Tigray, Afar, Amhara, Somali, Benishangul-Gumuz, Southern Nations Nationalities and Peoples (SNNP), Gambela, Sidama and Harari and two city administrations, Dire Dawa and Addis Ababa. There are topographic-induced climatic variations broadly categorized into three: the “Kolla”, or

hot lowlands, below approximately 1,500 meters, the “Wayna Degas” at 1,500-2,400meters and the “Dega” or cool temperate highlands above 2,400 meters [6].

Data source and Description

The data source for this study was secondary data from [6] which is the fourth Demographic and Health Survey (DHS) conducted in Ethiopia, following the 2000, 2005, and 2011 EDHS surveys. The [6] provides valuable information on trends in key demographic and health indicators over time. Information on vaccination coverage was obtained in three ways in the 2016 EDHS: written vaccination records (including the infant immunization card and other health cards), mothers’ verbal reports, and health facility records. In the [6], for each child born in the 3 years before the survey, mothers was asked to provide information about the vaccinations that her child has received. Unlike the previous EDHS surveys, in the [6] a separate team visited the health facility to collect complementary vaccination records if the mother was not able to present the infant immunization card and the child had visited a health facility. Consent was obtained from mothers prior to contacting the facilities and verifying child vaccination records.

The purpose of obtaining information at the health facility was to complement the information collected by mother’s recall. The information collected through this [6] was intended to assist policy makers and program managers in evaluating and designing programs and strategies for improving the health of the country’s population. Additionally, the [6] included a health facility component that recorded data on children’s vaccinations, which were then combined with the household data on children’s vaccinations. It was implemented by the Central Statistical Agency (CSA) at the request of the Ministry of Health (MoH).

Sampling Frame and Technique

The sampling frame used for the [6] is the Ethiopia Population and Housing Census (PHC), which was conducted in 2007 by the Ethiopia Central Statistical Agency. The census frame is a complete list of 84,915 enumeration areas (EAs) created for the 2007 PHC. An EA is a geographic area covering on average 181 households. The sampling frame contains information about the EA location, type of residence (urban or rural), and estimated number of residential households. With the exception of EAs in six zones of the Somali region, each EA has accompanying cartographic materials.

The sample for the 2016 EDHS was designed to provide estimates of key indicators for the country as a whole, for urban and rural areas separately, and for each of the nine regions and the two administrative cities. The 2016 EDHS sample was stratified and selected in two stages. Each region was stratified into urban and rural areas, yielding 21 sampling strata. Samples of EAs were selected independently in each stratum in two stages. Implicit stratification and proportional allocation were achieved at each of the lower administrative levels by sorting the sampling frame within each sampling stratum before sample selection, according to administrative units in different levels, and by using a probability proportional to size selection at the first stage of sampling.

In the first stage, a total of 645 Enumeration Areas (EAs) (202 in urban areas and 443 in rural areas) were selected with probability proportional to EA size (based on the 2007 PHC) and with independent selection in each sampling stratum.

Inclusion and exclusion criteria

Inclusion Criteria

As the study is related to children vaccination coverage in Ethiopia, children of age 12-23 month from all 9 regions and 2 city administrations were included.

Exclusion Criteria

In the 2016 EDHS, for each child born in the 3 years before the survey, mothers were asked to provide information about the vaccinations her child has received.

The following children were excluded from the study:-

- Children less than the age of 11 months.
- Children greater than the age of 23 months.

Study variables

Dependent Variables

The dependent variable is the complete vaccination status of children aged 12–23 months. As WHO recommended, basic childhood vaccines consists of polio, pentavalent (diphtheria, tetanus, pertussis, Haemophilus influenza, and hepatitis B vaccine), measles, and Bacillus Calmette

Guerin (BCG) that can prevent common childhood infections. Complete basic childhood vaccination achieved when the child received one dose of BCG vaccine, three doses of penta-valent vaccines, three doses of polio vaccines and one dose of measles vaccine. Additionally, three doses of the pneumococcal vaccine (PCV) and two doses of the rotavirus vaccine (RV) introduced by the government of Ethiopia.

The child who received all the above doses of each vaccine was categorized as “completely vaccinated”. While those who failed to take the recommended doses of vaccine were categorized as “incompletely vaccinated”.

A random variable Y_i represents the i^{th} child response variable with two categories.

$$Y_{ij} = \begin{cases} 1, & \text{if the } i^{th} \text{ child in } j^{th} \text{ region is completely vaccinated} \\ 0, & \text{if the } i^{th} \text{ child in } j^{th} \text{ region is incompletely vaccinated} \end{cases} \quad (1)$$

With $P_{ij} = P(Y_{ij} = 1/X_{ij})$ is the probability i^{th} child in region j fully vaccinated, X_{ij} is the observed characteristic of the i^{th} child in the j^{th} region and $1 - P_{ij} = P(Y_{ij} = 0/X_{ij})$ is the probability of incomplete vaccination coverage for i^{th} child in region j .

Independent Variables

Vaccination level of children is influenced by socio-economic and demographic factors. These includes maternal educational level, marital status, wealth Index, age of mother, place of delivery, child lives with who (care giver), women Occupation, ANC follow up, baby Post natal care, place of residence, sex of the child, type of pregnancy, field worker visit and husband educational level. These variables are supported with literatures.

Method of Statistical Data Analysis

Multilevel Linear Models

When the data was collected in hierarchical or clustered structures the suitable model is multilevel models. Multilevel models are used to account for the correlation of observations within a given group by incorporating group specific random effects. These random effects can be nested (individuals nested in regions, with random effects at the women and region levels) [7]. The dependent variable must be examined at the lowest and highest level of analysis.

Bayesian Multilevel Logistic Regression Model

Two- level model

This model considers the lack of independence across levels of nested data (i.e., individuals nested within regions). All experimental units are assumed to be independent which means that any variable which affects level of vaccination have the same effect in all regions, but these models are aiming at examining whether the effect of variables vary from region to region. The probability of ‘success’ or ‘failure’ is the same for all individuals in the group [7].

The random variable Y_{ij} has a Bernoulli distribution is one of the standard assumption of the model. Similar to logistic regression the p_{ij} is modeled using the link function logit. The two level models are given by:

$$\text{logit}(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \sum_{h=1}^k \beta_{hj} x_{hij} + U_{0j} + \sum_{h=1}^k U_{hj} x_{hij} \quad (2)$$

Where $X_{hij} = (X_{1ij}, X_{2ij}, \dots, X_{kij})$ represents the first and the second level of covariates for k variables, $\beta = (\beta_0, \beta_1, \dots, \beta_k)$ are regression parameter coefficients, and $U_{0j}, U_{1j}, \dots, U_{kj}$ are the random cluster effects of model parameter at higher levels with the assumption that follows normal distribution with mean zero and variance σ_u^2 . Therefore, conditional on $U_{0j}, U_{1j}, \dots, U_{kj}$, the Y_{ij} can be assumed to be independently distributed as Bernoulli random variables [7].

Bayesian Multilevel Analysis of Empty Models

The null two-level model or empty two-level model for a dichotomous outcome variable indicates to a population of groups (level-2 units) and dictates the probability distribution for group dependent probabilities p_j in $Y_{ij} = p_j + \varepsilon_{ij}$ without taking further explanatory variables into account. Thus, in the population groups, the log-odds have a normal distribution, which is given by:-

$$f(p_j) = \beta_0 + u_{0j} \quad (3)$$

218 Where $p_j = \frac{e^{\beta_0 + u_{0j}}}{1 + e^{\beta_0 + u_{0j}}}$, β_0 is the population average of the transformed probabilities and u_{0j} are
 219 regional level random effects that are i.i.d. normally distributed with zero means and constant
 220 variances σ_u^2 . This model does not constitute a different parameter for the level-one variance,
 221 because the level-one error variance of the Y_{ij} follows Bernoulli distribution straight from the
 222 success probability, as indicated by $\text{Var}(\epsilon_{ij}) = p_j(1-p_j)$ [7].

223 The likelihood function of empty model is

$$224 \quad L(p_j/y_{ij}) = \prod_j (p_{ij})^{y_{ij}} (1 - p_j)^{1-y_{ij}} \quad (4)$$

225 ***Prior distribution***

226 The prior distributions are default non-informative uniform distribution for the intercept β_0 and
 227 gamma for the random part σ_{u0}^2 of the model. For the parameters. It is written as; $P(\beta_0) \propto 1$ and
 228 $P(\sigma_{u0}^{-2}) \propto \text{gamma}(\alpha, \beta)$ where α and β are scale and shape parameters which are fixed constants
 229 [7].

230 ***Posterior Distribution***

231 From the posterior distribution $P(\sigma_{u0}^2, \beta_0/y_{ij})$, we can estimate random parameters by using
 232 MCMC methods.

233 The full conditional distribution for parameter β_0 is given by,

$$234 \quad P(\beta_0/\sigma_{u0}^2, y_{ij}) \propto \prod_{ij} \left(\frac{e^{\beta_0 + u_{0j}}}{1 + e^{\beta_0 + u_{0j}}} \right)^{y_{ij}} \left(\frac{1}{1 + e^{\beta_0 + u_{0j}}} \right)^{1-y_{ij}} \quad (5)$$

235 The full conditional distribution for parameter σ_{u0}^2 is given by,

$$236 \quad P(\sigma_{u0}^2/\beta_0, y_{ij}) \propto \text{gamma}(N/2 + N(\alpha-1), N\beta) \quad (6)$$

237 Where N is the total number of individual respondents interviewed in all regions of the country
 238 that is calculated from $\sum n_j$ and the scale and shape parameters are α and β respectively which
 239 are both fixed constants [7].

240

241 Variance Components Model

242 The variance components model has the form;

$$243 \quad Y_{ij} = \beta_0 + u_{0j} + \epsilon_{ij} \quad (7)$$

244 Where the vaccination status of the i^{th} women in j^{th} region is Y_{ij} , the regional level random
245 effects u_{0j} 's are i.i.d. normally distributed with mean zero and constant variances σ_u^2 . The error
246 terms ϵ_{ij} are i.i.d. normally distributed with zero means and constant variances σ_ϵ^2 and β_0 is the
247 overall mean.

248 The total variance is partitioned into two the region and children levels variances, representing
249 between and within region variability's in the utilization of antenatal care services [8]. The
250 interclass correlation (ICC) that measures correlation between observations within cluster
251 (region) is given by:

$$252 \quad ICC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\epsilon^2} \quad (8)$$

253 where σ_u^2 is the 'between-region' variance and σ_ϵ^2 is the 'between-children' variance .

254 Bayesian Multilevel Analysis of Random Intercept Models

255 In this model, the intercept is the only random effect that differ with respect to the average value
256 of the response variable, but the relationship between explanatory and response variables cannot
257 differ between groups. It shows the heterogeneity between groups in the overall response [7].

258 There is an assumption that there are variables which are potential explanation for observed
259 success or failure. These variables are denoted by:-

$$260 \quad X_h = \{X_{hij}, i = 1, 2, \dots, n_j, h = 1, 2, \dots, k \text{ and } j = 1, 2, \dots, N, k \text{ is the number of predictors}\}$$

261 The logit of p_{ij} which is called log odds is the sum of a linear function of the explanatory
262 variables and a random group-dependent deviation u_{0j} .

$$263 \quad \text{logit}(p_{ij}) = \beta_0 + \sum_{h=1}^k \beta_h x_{hij} + u_{0j} \quad (9)$$

264 Where the fixed part is $\beta_0 + \sum_{h=1}^k \beta_h x_{hij}$ and the remaining part u_{0j} is the random part of the
 265 model [9] and the success probability is

$$266 \quad p_{ij} = \frac{e^{\beta_0 + \sum_{h=1}^k \beta_h x_{hij} + u_{0j}}}{1 + e^{\beta_0 + \sum_{h=1}^k \beta_h x_{hij} + u_{0j}}} \quad (10)$$

267 **Bayesian Multilevel Analysis of Random Coefficients Models**

268 In this model, the coefficients of lower-level predictors are modeled. It indicates the unobserved
 269 heterogeneity in the effects of explanatory variables on the response variable [7].

270 We represent the variables that are potential explanations for the observed outcomes variables by
 271 $X_h = \{X_{hij}, i = 1, 2, \dots, n_j, h = 1, 2, \dots, k \text{ and } j = 1, 2, \dots, N\}$. The success probability is not
 272 constant for all individuals in a given group, as some or all of these variables could be level-one
 273 variable. Therefore, the success probability depends on the individual as well as the group, and is
 274 symbolized by p_{ij} .

$$275 \quad \text{logit}(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \beta_0 + \sum_{h=1}^k \beta_h x_{hij} + u_{0j} + \sum_{h=1}^k u_{hj} x_{hij} \quad (11)$$

276 In the above model, the part $\beta_0 + \sum_{h=1}^k \beta_h x_{hij}$ is the fixed part and $u_{0j} + \sum_{h=1}^k u_{hj} x_{hij}$ is the
 277 random part [8]. The remaining part $\sum_{h=1}^k u_{hj} x_{hij}$ can be considered as a random interaction
 278 between group and the explanatory variables. In other words, the groups are characterized by two
 279 random effects: their intercept and slopes [7].

280 ***Prior Distribution***

281 Let us represent the parameters $\beta_0, \beta_1, \dots, \dots, \beta_k$ and Ω_u as prior distribution as follows.

282 $P(\beta_0) \propto 1, P(\beta_1), \dots, \dots, P(\beta_k) \propto 1$ and $p(\Omega_u) \sim \text{inverse-Wishart}_k(s_u, h)$ distribution. Where Ω_u
 283 is the variance covariance matrices, s_u is an estimate for the true value of Ω_u , k is dimension of
 284 Ω_u , that denotes the degree of freedom, so this prior is essentially as uninformative prior. In
 285 statistics, Wishart distribution is a generalization to multiple dimensions of the chi-squared
 286 distribution, or, in the case of non-integer degrees of freedom, of the gamma distribution [17].
 287 Then Ω_u is positive definite with probability density function ;

$$f(\Omega_u) = \frac{|s|^{\frac{h}{2}}}{|\Omega|^{\frac{h+p+2}{2}} \frac{hk}{2} \frac{h}{2} \text{gamma}(k)^{\frac{h}{2}}} \exp \left\{ -\frac{1}{2} \text{tr}(s^{-1}\Omega) \right\} \quad (12)$$

The posterior distribution for the parameters $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ is given by:-

$$P(\beta_{\hat{h}}/\Omega_u, y_{ij}) \propto \prod_{ij} ((p_{ij})^{y_{ij}} (1 - p_{ij})^{1-y_{ij}}) \quad (13)$$

Where $\hat{h} = 0, 1, 2, \dots, k$. The full conditional distribution for the parameter Ω_u is given by;

$$f(\Omega_u/\beta_{\hat{h}}, y_{ij}) \propto p(y_{ij}/\Omega_u, \beta_{\hat{h}})(f(\Omega_u)) \quad (14)$$

Estimation Techniques for MCMC

The software MLwiN, a specialized program for performing multilevel analysis was used to run the Bayesian estimation. The general simulation method Markov chain Monte Carlo (MCMC) is used for sampling from posterior distributions and computing posterior quantities of interest [7].

The Deviance Information Criterion (DIC) which is hierarchical modeling generalization of the AIC is used for model selection. Assessing goodness of fit involves examining how close the values are predicted by the model with that of observed values [9]. The comparison of observed to predicted values using the likelihood function is based on the statistic called deviance.

$$D = -2 \sum [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)] \quad (15)$$

Where the predicted value for observation i is p_i . The rule is, the larger deviance, the poorer the fitness of the model [7].

Missing Data

Missing data is a problem since nearly all standard statistical methods presume complete information for all the variables is included in the analysis. A relatively few absent observations on some variables can dramatically shrink the sample size. As a result, the precision of confidence intervals is harmed, statistical power weakens and the parameter estimates may be biased. Appropriately dealing with missing can be challenging as it requires a careful examination of the data to identify the type and pattern of missing data, and also a clear understanding of how the different imputation methods work.

Several different methods and strategies are available to handle missing data. First, the method should yield unbiased estimates of a variety of different parameters. Second, the method should include a way to assess the uncertainty about the parameter estimates, and third, the method should have good statistical power. It is further good to remember that the goal of any missing data procedure is not to recreate the missing observations but rather to retain the characteristics of the data and the associations between variables such that valid and efficient inferences can be made [10].

Multiple imputations are the popular method for handling missing values in a data. The advantage of the method is that once the imputed data set have been generated, the analysis can be carried out using procedures in virtually any statistical package, which makes the analysis simple. Also, standard error or p-value obtained from MI is generally valid because they incorporate uncertainty due to missing values. MI can be highly efficient even if the number of imputations is relatively small, especially when between-imputation variance is not too large. The multiple imputation inference involves three distinct phases [10].

As a rule of thumb, if less than 5% of the observation are missing, the missing data can be simply be deleted without any significant ramifications [10]. For this particular study, the percentage of mission observation is less than 5%. However, if more than 5% of the data is missing, deleting the missing data will result in a reduced sample size and an increased standard error of the parameter estimate. In this case it is strongly suggested to use imputation of the mean, mode or median or multiple imputations, to fill in the missing data.

Result and Discussion

Descriptive Statistics

The results displayed in Table 1 below shows the percentages and counts of vaccination services with respect to socioeconomic and demographic variables. All computations were conducted in Statistical Package for Social Sciences (SPSS) version 20.0 and MLwiN version 2.36. Out of the 1929 children who received vaccination service, 699 (36.2%) children were fully vaccinated (completely vaccinated), while 1230 (63.8%) children were not fully vaccinated (incompletely vaccinated) at the time of data collection.

340 **Table 1: Chi-square analysis output depicting the relationship between vaccination status and some**
341 **socio-economic and demographic variables**

Variable	Category	N	Percent (%)	Vaccination status		Df	Chi-square	p-value
				Complete (%)	Incomplete (%)			
Region	Tigray	216	11.2	114(52.78)	102(47.22)	10	243.41	P≤0.001
	Afar	171	8.9	11(6.43)	160(93.57)			
	Amhara	178	9.2	70(39.32)	108(60.68)			
	Oromia	287	14.9	92(32.05)	195(67.95)			
	Somalia	223	11.6	41(18.38)	182(81.62)			
	Benishangul-Gumuz	156	8.1	66(42.31)	90(57.69)			
	SNNPR	231	12.0	94(40.69)	137(59.31)			
	Gambella	138	7.1	28(20.28)	110(79.72)			
	Harari	117	6.1	39(33.33)	78(66.67)			
	Addis Abeba	102	5.3	78(76.47)	24(23.53)			
	Dire dawa	110	5.7	66(60)	44(40)			
Residence	Urban	409	21.2	236(57.7)	173(42.3)	1	103.50	P≤0.001
	Rural	152	78.8	463(30.5)	1057(69.5)			
Maternal Educational level	No education	1170	60.65	312(26.67)	858(73.33)	3	136.75	P≤0.001
	Primary	508	26.33	233(45.86)	275(54.14)			
	Secondary	162	8.4	95(58.64)	67(41.36)			
	Higher	89	4.6	59(66.29)	30(33.71)			
Wealth index	Poorest	664	34.42	117(17.62)	547(82.38)	4	180.56	P≤0.001

	Poorer	373	19.33	140(37.53)	233(62.47)			
	Middle	339	17.57	144(42.48)	195(57.52)			
	Richer	287	14.87	151(52.61)	136(47.39)			
	Richest	266	13.78	147(55.26)	119(44.74)			
Field worker visit	No	129	66.93	308(23.85)	983(76.15)	1	258.87	P≤0.001
	Yes	638	33.07	391(61.29)	247(38.71)			
Wanted last child	Wanted	154	80.14	544(35.18)	1002(64.81)	2	18.26	P≤0.001
	Wanted later	271	14.05	126(46.49)	145(53.51)			
	Wanted no more	112	5.8	29(25.89)	83(74.11)			
Sex of the child	Male	946	49.04	318(33.62)	628(66.38)	1	5.52	0.019
	Female	983	50.96	381(38.76)	602(61.24)			
Mother occupation type	No work	111	58	364(32.53)	755(67.47)	4	19.04	P≤0.001
	Gov'tal and skill	257	13.32	115(44.75)	142(55.25)			
	Agricultural	386	20.01	149(38.60)	237(61.40)			
	Household and domestic	35	1.81	13(37.14)	22(62.86)			
	Other	132	6.8	58(43.94)	74(56.06)			
ANC follow up	Yes	855	44.32	478(55.91)	377(44.09)	1	257.15	P≤0.001
	No	107	55.68	221(20.58)	853(79.42)			
Place of delivery	Home	115	59.82	373(32.32)	781(67.68)	1	19.04	P≤0.001
	Health facility	775	40.18	326(42.06)	449(57.94)			
Baby PNC	No	168	87.24	577(34.28)	1106(65.72)	1	21.77	P≤0.001

check up	Yes	246	12.76	122(49.59)	124(50.41)			
Husband/ partner education level	No education	891	46.19	284(31.87)	607(68.13)	4	30.54	P≤0.001
	Primary	620	32.14	226(36.45)	394(63.55)			
	Secondary	224	11.61	87(38.84)	137(61.16)			
	Higher	189	9.79	99(52.38)	90(47.62)			

342

343 On the basis of p-value in the table 1 above, the vaccination coverage of children is associated
 344 with region, residence type, educational level of the mother, wealth index, field worker visit, sex
 345 of the child, wanted child, mother occupation, antenatal care service follow up, place of delivery,
 346 baby postnatal care, husband/partner educational level.

347 Bayesian Multilevel Logistic Regression Analysis output

348 In the multilevel analysis, a two-level structure is used with regions as the second-level units and
 349 children as the first level units. The expectation is that there would be differences in the level of
 350 vaccination coverage among regions. The nesting structure is children within regions with a total
 351 of 1929 children.

352 Model Comparison

353 Table 2: Bayesian Deviance Information Criteria

$\bar{D}$	$D(\bar{\theta})$	pD	DIC	Model
2037.71	1778.89	258.82	2296.53	Bayesian multilevel null model
1767.29	5703.45	207.53	1974.82	Random intercept model
1514.14	5606.13	340.11	1854.26	Random Coefficient model

354

Statistically significance at 5%

From Table 2, the measure $\bar{D}$ indicates the average deviance from the complete set of iterations. $D(\bar{\theta})$ indicates the deviance at the expected value of the unknown parameters and pD (the estimated degrees of freedom consumed in the fit or it is the difference between the average deviance from the complete set of iterations and the deviance at the expected value of the unknown parameters. Also the deviance information criterion is the sum of $\bar{D}$ and pD. For comparing models, we use the DIC (Deviance Information Criteria). The random intercept model reduced by 321.71 than the null model. Thus, the random intercept model with the fixed explanatory variables shows a highly significant improvement suggesting that it is better than the null model and the DIC diagnostics of random coefficient model is reduced by 120.56 and 442.27 from the random intercept model with the fixed explanatory variables and null model respectively. Therefore this smallest value of DIC criteria indicates that Bayesian multilevel logistic regression for random coefficient model is the most significant model as compared to the null and random intercept model with the fixed explanatory variables. Therefore, this study employs the Bayesian multilevel logistic regression for random coefficient model.

Bayesian Multilevel Logistic Regression Analysis using Empty Model

The empty (null) model in table 3 contains no explanatory variables and it can be considered as a parametric version of assessing heterogeneity of children vaccination coverage among regions. Here also non informative priors were used for the fixed intercept and for the variance. The following table 3 value was calculated from the posterior distribution by storing 50000 actual iterations and from which the overall mean of vaccination coverage is estimated at $\beta_0 = -0.660$ and significant at 5% level of significance.

Table 3: Bayesian Multilevel Logistic Regression Empty Model

Model	Coefficient	Standard error	Z-value	P-value
Fixed intercept(β_0)	-0.660	0.084	-7.86	$P \leq 0.001$
Random effect				
Variance = σ_{u0}^2	1.739	0.309	5.63	
ICC	0.3458			

Using table 3 above, it is possible to test the following hypothesis:

Ho: there is no regional variation on vaccination coverage of the children.

H1: there is a regional variation in the coverage of vaccination.

By using the p-value from the above table, which is $P \leq 0.001$, we reject the null hypothesis and conclude that there is a regional variation (heterogeneity) on vaccination coverage of the children.

The variances σ^2_ϵ and σ^2_u in table 3 estimate the variation among individual child and among regions of the country. The individual (level-1) variance was fixed to $\pi^2/3 = 3.29$ for the logit model. Also, to examine how much variation in the coverage of vaccination of child was attributable to the region level factors, it is useful to see the intra-region correlation coefficient $ICC = \frac{\sigma^2_u}{\sigma^2_u + \sigma^2_\epsilon} = 1.739/1.739 + 3.29 = 0.3458$, which measures the proportion of variance of complete coverage of vaccination that is between regions, not within regions. The intra-region correlation coefficient (ICC) in the intercept-only model is 0.3458 which is significant at a 5% level of significance. This means that 34.58% of the variation in coverage of vaccination exists between regions, whereas the remaining 65.42% attributable to an individual (children) level, i.e. within region variation.

Bayesian Multilevel Logistic Regression Random Intercept Model

To identify the effect of explanatory variables, a Bayesian multilevel binary logistic model with random intercept and fixed explanatory variables was estimated and displayed in table 4 below. The following table is the output from MLwin 2.36 for the Bayesian multilevel random intercept model.

Table 4: Results of Random Intercept Bayesian Multilevel Logistic Regression Model

Variable	Category	Coefficient	Standard error	Z-value	P-value
Fixed	Intercept	-2.305	0.819	-2.81	$P \leq 0.001$
Residency	Rural	-1.216	0.221	-5.50	$P \leq 0.001$
	Urban (ref)				
Age of the	20-24	-0.012	0.303	-0.04	0.497

mother	25-29	0.150	0.323	0.46	0.326
	30-34	0.163	0.331	0.49	0.331
	35-39	0.393	0.367	1.07	0.173
	40-44	0.381	0.411	0.93	0.218
	45-49	0.709	0.698	0.99	0.158
	15-19 (ref)				
Education	Primary	0.456	0.162	2.81	0.003
	Secondary	0.637	0.269	3.94	0.009
	Higher	0.224	0.372	0.60	0.274
	No education (ref)				
	Poorer	0.760	0.203	3.74	P≤0.001
Wealth index	Middle	0.814	0.221	3.68	P≤ 0.001
	Richer	1.372	0.232	5.92	P≤0.001
	Richest	1.460	0.251	5.82	P≤0.001
	Poorest(ref)				
Sex of the child	Female	0.100	0.131	0.76	0.224
	Male (ref)				
	Wanted later	0.465	0.183	2.54	0.007
Child wanted	Wanted no more	-0.713	0.321	-2.22	0.016
	Wanted (ref)				
Field worker visit	Yes	1.685	0.140	12.04	P≤0.001
	No (ref)				

Marital status	Married	0.406	0.751	0.54	0.318
	Living with partner	0.707	1.024	0.69	0.252
	Widowed	0.767	1.002	0.76	0.227
	Divorced	0.336	0.831	0.40	0.362
	No longer living together	0.429	1.111	0.39	0.355
	Never in union (ref)				
Number of child		-0.030	0.107	-0.28	0.390
Baby PNC	Yes	0.579	0.191	3.03	P≤0.001
	No (ref)				
ANC	Yes	1.777	0.141	12.6	P≤0.001
	No(ref)				
Place of delivery	Health facility	-0.008	0.148	-0.054	0.477
	Home (ref)				
Occupation type	Gov'tal and skill	-0.160	0.207		0.221
	Agricultural	0.425	0.179		0.009
	House hold	-0.395	0.518		0.225
	Other	0.321	0.260		0.110
	No work (ref)				
Random effect					
Variance		1.093	0.255	4.29	
ICC		0.2493			

From table 4 above, we can understand that the covariates type of residency, women educational level, wealth index, child wanted (desired), field worker visit in last 12 months, baby postnatal care, antenatal care and women were also found to be significant and also contributing factors for variation in children vaccination among the regions of Ethiopia.

Bayesian Multilevel Logistic Regression of Random Coefficient Model

The effect of level one covariate can be incorporated in the model through adding random coefficients in front of some of the individual-level covariates of the model. In random intercept model we allowed the intercept only vary across regions by fixing explanatory covariates, but the relationship between explanatory and dependent variable cannot differ between groups. The following table depicts some random coefficients and fixed explanatory variables which had significant effect on the vaccination coverage of children in Ethiopia.

Table 5: Results of Random Coefficient Bayesian Multilevel Logistic Regression Model

Fixed effect	Category	Estimate	Standard error	Z	p-value	OR
Constant		-2.377	0.325	-7.31	P≤0.001	0.093
Residency	Rural	-1.451	0.247	-5.87	P≤0.001	0.234
	Urban(ref)					
Maternal educational level	Primary	0.591	0.174	3.40	P≤0.001	1.81
	Secondary	0.787	0.292	2.69	0.003	2.19
	Higher	0.072	0.399	0.18	0.425	1.07
	No education (ref)					
Wealth index	Poorer	1.124	0.255	4.41	P≤0.001	3.077
	Middle	1.188	0.243	4.89	P≤0.001	3.281
	Richer	1.779	0.263	6.76	P≤0.001	5.924
	Richest	1.959	0.307	6.38	P≤0.001	7.092
	Poorest(ref)					

Child wanted (desired)	Wanted later	0.536	0.210	2.55	0.005	1.709
	Wanted no more	-0.995	0.348	-2.86	0.002	0.3697
	Wanted(ref)					
Field worker visit	Yes	0.291	0.158	1.84	0.033	1.337
	No(ref)					
Baby Postnatal	Yes	0.650	0.217	3.00	P≤0.001	1.9155
	No(ref)					
ANC follow up	Yes	2.139	0.217	9.86	P≤0.001	8.491
	No(ref)					
Mother occupation type	No work (ref)					
	Gov'tal and skill	-0.075	0.238	0.32	0.381	0.927
	Agricultural	0.428	0.204	2.10	0.005	1.534
	Household and domestic	-0.512	0.614	0.84	0.205	0.599
	Other	0.428	0.294	1.45	0.070	1.534
Random effect	Estimate	Standard error	Z	p-value		
Var (constant)= $\sigma^2 u_{0j}$	3.229	0.851	3.79			
Var (poorer)= $\sigma^2 u_{5j}$	1.851	0.812	2.28			
Var (richest)= $\sigma^2 u_{8j}$	3.270	1.122	2.91			
Var (ANC)= $\sigma^2 u_{13j}$	5.137	1.196	4.29			
Cov (u _{0j} , u _{5j})	-1.281	Corr (u _{0j} , u _{5j})	-0.531			
Cov (u _{0j} , u _{8j})	-1.908	Corr(u _{0j} , u _{8j})	-0.567			
Cov(u _{0j} , u _{13j})	-3.020	Corr(u _{0j} , u _{13j})	-0.739			

$\text{Cov}(u_{5j}, u_{8j})$	0.761	$\text{Corr}(u_{5j}, u_{8j})$	0.315
$\text{Cov}(u_{5j}, u_{13j})$	0.881	$\text{Corr}(u_{5j}, u_{13j})$	0.291
$\text{Cov}(u_{8j}, u_{13j})$	-0.192	$\text{Corr}(u_{8j}, u_{13j})$	-0.063
ICC	0.495		

As depicted in table 5 above, some of the independent variables were found to have significant effect on the vaccination coverage of children. These are women educational level, wealth index, type of residency, child wanted, field worker visit in last 12 month, baby postnatal care, antenatal care for current child and women occupation found to be significant at 5% significant level.

By adding level 1 predictors, the ICC depicted in table 5 increased to 0.4953 which indicates that roughly 49.53% of the total variability in child vaccination coverage is attributable to the random factor and region in random coefficient Bayesian multilevel binary logistic model. From table 5, the random coefficient estimates for intercepts and the slopes vary significantly at 5% significance level, which implies that there is a considerable variation in the effects of wealth index and antenatal care; these variables differ significantly across the regions.

Using the OR value in table 5, the odds of vaccination coverage of children who dwell in rural areas was 0.234 indicating that a 76.6% decrease in coverage than children who dwell in urban.

Similarly in table 5 above, the odds of vaccination coverage among children having mother who had primary and secondary level of education was 1.81 and 2.19 respectively. This indicates that the odds of vaccination coverage of children of mothers with primary and secondary education are 1.81 and 2.19 times than children of mothers with no education at 5% level of significance and keeping all the other variables in the model constant.

As depicted in table 5 above, the odds of vaccination coverage of children in the poorer, middle, richer, richest wealth index category were 3.077, 3.281, 5.924 and 7.092 respectively which illustrates that the odds of vaccination coverage for children living in the poorer, middle, richer, richest wealth index category families are 3.077, 3.281, 5.924 and 7.092 times that of children living poorest household at 5% level of significance and keeping all the other variables in the model constant.

436 As provided in table 5 above, the odds of vaccination coverage among children with mothers
437 who need pregnancy later and who wanted no more children were found to be 1.709 times and
438 0.3697 times than those children with mothers who need more children later respectively. Thus,
439 children with mothers who do not need more children later are 63.03% less likely to cover
440 vaccination than children with mothers who want to deliver more children later at 5% level of
441 significance and keeping all the other variables in the model constant.

442 Similarly in table 5, the odds of vaccination coverage among children whose households had
443 been visited by field worker in the last 12 month was found to be 1.337 compared to households
444 who are not the visited by the field worker (ref). Therefore, children whose household are visited
445 by field worker are 33.7 % more likely to cover vaccination than those whose household was not
446 visited by field worker at 5% level of significance and keeping all the other variables in the
447 model constant.

448 As shown in table 5 above, the odds of vaccination coverage among children whose mother had
449 attended postnatal care found 1.9155 indicating that they are 91.55% more likely to cover
450 vaccination compared to children whose mother had not attended postnatal care services (ref) at
451 5% level of significance and keeping all the other variables in the model constant.

452 With regard to the variable ANC service shown in table 5, it has been found that the odds of
453 vaccination coverage among children having mothers who attended antenatal care service was
454 found 8.491 indicating that their odds is 8.491 times than that of children whose mother did not
455 attend the ANC services at 5% level of significance and keeping all the other variables in the
456 model constant.

457 As it has been depicted in table 5, the odds of vaccination coverage among children having
458 mother who had working in agriculture was found 1.534 compared to a women who had not
459 working (ref). This shows that children with mother working in agriculture are 53.4% more
460 likely to cover vaccination than children with mother who did not work in agriculture at 5% level
461 of significance and keeping all the other variables in the model constant.

462 The estimated variance of intercept, slope of household wealth index and antenatal care follow
463 up depicted in table 5 varies significantly. This showed that the factors household wealth index
464 and antenatal care follow up have brought a variation in the vaccination coverage across regions

of the country. Some of the variances of the interaction terms between intercepts and slopes of explanatory variables are also found significant.

In Table 5, the value of $\text{var}(u_{0j})$, $\text{var}(u_{5j})$, $\text{var}(u_{8j})$ and $\text{var}(u_{13j})$ are the estimated variance of intercept, slope of wealth index and antenatal care follow up. From the output, we can understand that there is a significant variation in the effects of these explanatory variables across the regions. Some of the variances of the interaction terms between intercepts and slopes of explanatory variables are also found significant. Interpretation of significant covariance terms can be easily made in terms of the correlation coefficients displayed in Table 5, and the correlation matrix contains the estimated correlation coefficients between random intercept and slopes (-0.531, -0.567, -0.739 for poorer, richest and ANC follow up respectively) which are negatively correlated. The negative sign for the correlation between intercepts and slopes indicates that regions with higher intercepts tend to have on average lower slopes on the corresponding predictors.

Discussion

The purpose of this study was to understand the current status of complete vaccination coverage and associated factors among children in Ethiopia by using Bayesian Multilevel logistic regression Analysis. This study employed three multilevel logistic regression models for the response variable on the status of vaccination coverage. The Bayesian multilevel logistic regression empty model, Bayesian multilevel logistic regression random intercept, and Bayesian multilevel logistic regression for the random coefficient model were applied to explain the vaccination coverage among children of 12-23 month based on EDHS 2016 data.

Bayesian multilevel logistic regression random coefficient model was identified to be a better fit for the vaccination dataset. This model was also considered to be the best model to check the antenatal care service utilization in national level [12].

The upward trend in immunization coverage in recent years in Ethiopia was due to tremendous efforts of the government to realize the millennium development goal of reducing child mortality from vaccine preventable diseases. A study conducted by [13] in Afar, Somali and Tigray regions showed that the full vaccination coverage was 20.6%, 36.6% and 51% respectively.

The place of residence was found to be significantly associated with the complete coverage of vaccination. This shows that children who were living in rural areas were less likely to complete vaccinations than children living in urban areas. This difference might be due to the fact that urban children are more accessible to health services and mothers of children have information and education about vaccination than women in the rural area as indicated by studies in [13,14].

Children with mothers having primary and above education level are associated with an increased in full immunization. In other words, as mothers' level of education increase the probability of having a full immunization of children increased. This has been confirmed with the finding of [14].The importance of maternal education in children's health is universally recognized. Children of more educated mothers are more likely to be fully immunized.

Childhood immunization is also influenced by the household wealth index. A child from a family with poor wealth has a higher chance of being incompletely immunized. This might be associated with lack of money that results in poor health seeking behavior. Household income and wealth index influences the likelihood that children receive complete immunization. This result is similar to the results from [14, 15]. This might be due to the indirect cost needed for travel to health facilities or time spent away from income generating activity to make it difficult for the poorest households to avail themselves of services that exist in the community [16].

The study also found that the type of pregnancy had significant effect on status of vaccine completion. On the basis of this study finding, a child that was born from mothers who wanted pregnancy was more likely to get complete vaccination. This finding matches with the finding from [1] that was conducted in Debre Markos town in Ethiopia.

The finding from this study also shows that the use of health care service (ANC and PNC) by mothers contributes to the improvement in the immunization status of children. Children with mothers who attended antenatal care have higher chance of being fully immunized compared to those whose mothers did not attend any antenatal care. Attending antenatal care may puts women in a better position of obtaining adequate information about routine immunization for children and other health facility services. Also, the processes undergone during antenatal care prepare a mother towards having positive inclination to health care utilization not only for themselves but also their children. According to the study maternal antenatal care follow up and baby post natal

care are possible reasons for having better vaccination completion. Mothers who have more frequent contact with health professionals seem to be more aware of their children's health as they receive more information about immunization and child health. A study conducted by [4, 14, 15, 17] confirmed this truth.

This study depicts that worker visit of the family in the last 12 months was significantly associated with the status of vaccine completion. This might be related with sharing of information to mothers about immunization, including immunization schedules and side effects during their visit. The finding is in conformance with a study done in Indonesia by [15].

The study also identified some socio-economic indicators of the region as predictors that affect the status of vaccine completion. Variables like wealth index and antenatal care service utilization are considered as region level factors. According to the random coefficient model, these level-two variables explain 46.24% of the variation in vaccination completion status of children in the country.

Strength and limitations

The statistical model used for the research need the application of various softwares. In this regard, the contribution from authors is of high value and the findings of the research have less standard error and high accuracy. Some important variables that would affect the vaccination coverage have been missed from the dataset.

Conclusion and Future Implication

The study identified some socioeconomic and demographic factors that affect the status of vaccine completion of children. Based on the findings, at the individual level, variables like maternal (caregiver's) education level, household wealth index, mother occupation, ANC and PNC service utilization were found to be the significant factors affecting complete coverage of children vaccination. These days, the number of women attending education is increasing. As a result the coverage of vaccination would definitely increase in the near future. In this regard, all stakeholders particularly the government should act to raise women's educational level and promote the importance of using ANC and PNC to mothers of children. Moreover, the government and other stakeholders working on health and related sectors should work on the accessibility of health facilities around places where women lives so that they can save

551 transportation cost and minimize waste of time. Finally, health extension workers should make
552 have a regular schedule to visit family having children taking vaccination.

553 **Abbreviations**

554	AIC	Akaike information criteria
555	ANC	Antenatal care
556	BCG	Bacillus-Calmette-Guerin (Tuberculosis Vaccine)
557	BIC	Bayesian information criterion
558	CSA	Central Statistical Agency
559	DIC	Deviance information criteria
560	DPT	Diphtheria, pertussis, tetanus vaccine
561	EAs	Enumeration areas
562	EDHS	Ethiopia Demographic and Health Survey
563	EPHC	Ethiopian Population and Housing Census
564	EPHI	Ethiopia Public Health Institute
565	FMOH	Federal Ministry of Health
566	GAVI	Global Alliance for Vaccine and Immunization
567	GVAP	Global vaccine action plan
568	GIVS	Global Immunization Vision and Strategies
569	HepB	Hepatitis B (vaccine)
570	Hib	Haemophilus influenzae type B (vaccine)
571	ICC	Interclass correlation
572	MDG	Millennium Development Goal
573	MCMC	Markov chain Monte Carlo
574	MCSE	Monte Carlo standard error
575	ML	Maximum Likelihood
576	MLE	Maximum likelihood estimation
577	OR	Odds Ratio

578	OPV	Oral Polio Vaccine
579	PACF	Partial autocorrelation function
580	PCV	Pneumococcal Conjugated Vaccine
581	PNC	Post natal care
582	RED	Reaching Every District
583	RV	rotavirus vaccine
584	SPSS	Statistical package for social science
585	USAID	United States Agency for International Development
586	VPD	Vaccine Preventable Diseases
587	WHO	World Health Organization

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596 **Availability of data and materials**

597 In this study, we used the information from the fourth Demographic and Health Survey
598 conducted of Ethiopia from January 18, 2016, to June 27, 2016 by Central Statistical Agency
599 (CSA) focusing on all children in the age range 12–23 months.

600 **Declaration**

601 **Ethics approval and consent to participate**

602 Not applicable.

603 **Consent for publication**

604 Not applicable.

605 **Competing interests**

606 The authors declare that they have no competing interests.

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