

Determinant of Potential Barriers of Maternal Health Care Utilization in Rural Area in Lemo: South Region of Ethiopia

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ABSTRACT

Background: Maternal health refers to the health of women during pregnancy, childbirth, and the postpartum period. Maternal utilization is the property of attending a health centre during the ANC period. Complications of pregnancy and childbirth are a leading cause of maternal morbidities and mortalities in developing countries due to non-attending of maternal health care service utilization in the health centre.

Objective: This paper aims to analysis potential barriers for maternal health care utilization in a rural area and to identify associated factors among mothers in the rural districts.

Methods: A Primary data were collected from 309 women's those gave birth from June 2017 to June 2019 in 35 lemo districts south region of Ethiopia. A stratified simple random sampling technique was used to select the respondents s from a total of 1415 birth gave women's. The data was collected with a designed questionnaire and using interviewing the mother who gave birth in the study. Maternal health care service utilization was considered as a response variable in this study and it can be categorized as (0=utilized and 1=not utilized). A logistic regression model with a Bayesian approach was used to handle the data using both SPSS version 20 and Open BUGS version 3.2.3 software.

Results: This study revealed that the probability of not use maternal health care services in the study area was 41.5%. Age women, Maternal education, Husband education, Occupation of women, Occupation of Husband, counselling, transportation access, distance from the health centre, number of children in a family, and religion are major potential barriers influencing maternal health care service utilization in the study areas.

Keywords: Bayesian regression, Logistic regression, Maternal health care.

INTRODUCTION

A maternal death is the death of a woman in pregnant period or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related or forced by the pregnancy or its management but not from accidental. Mostly maternal death can be caused resulting from complications during pregnancy, delivery and postpartum (period) or an indirect cause, which refers to maternal deaths that result from existing diseases or diseases that developed during pregnancy which were aggravated by physiological effects of pregnancy. Maternal and infant deaths occur in the first month after birth: almost half (50%) of postnatal maternal deaths occur within the 24 hours and 66% during the first week [1].

The number of maternal deaths in a population is the product of two factors: the risk of mortality associated with a single pregnancy and the number of pregnancies or births that are experienced by women of reproductive age [2].

The World Health Organization (WHO) recommends all women with uncomplicated pregnancies to attend four ant natal care (ANC) visits during the course of the pregnancy to prevent and identify pregnancy risks and treat conditions timely through providing appropriated information to the client. About six in every ten Ethiopian women (57 percent) did not receive any antenatal care [3]. According to World health organization the major goal of focused antenatal care is to help women maintain normal pregnancies through identification of pre-existing health conditions and improving health facility then decrease maternal death rate and postnatal care helps prevent complications after childbirth. Only 17% of women age 15-49 receive a postnatal check within two days of delivery, while 81% did not have a postnatal check within 41 days of delivery [3,4].

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According to Mekonnen et al., out of total mother death, 98% of death caused due to pregnancy complication [5]. Globally, about 830 women die every day due to preventable pregnancy related cause. And World Health Organization estimates that 580,000 women of reproductive age die each year from complications arising from pregnancy and 99% of death occur on developing country [1]. A 66% high proportion of these deaths occur in sub-Saharan Africa [6]. The ratio of maternal mortality in the Ethiopia is one of the highest in the world, reaching levels of 676 per 100,000 live births, and infant mortality rate was 77 deaths per 1000 live births [7] .The death of mother among fertility age 15-49 years is high due to complication of pregnancy. Rural women are usually less educated and less exposed to knowledge and importance of maternity care. According to Fekadu et al., urban mothers had higher odds of giving birth at health facility compared to rural mothers [8]. According to Tessema et al., studies assume that socioeconomic, demographic and exposure factors have an effect on utilization of maternity care [9].

Ethiopian government and international organizations had been working for reducing maternal mortality in the previous years but maternal mortality remains increased in some digits and do not reach the target point even if the user number of health service increases from time to time and health facility improved . The researchers found that maternal health care service utilization is extremely low in rural area compared to urban areas and due this large number of women death was caused in childbearing age 15-49 years [9]. So, the main goal of this study was identify the major influencing factors of use of maternal health care service in rural areas.

METHODS

The study population of this study was mother giving birth in 35 local district of southern region of Ethiopia from June 2017 to June 2019. The primary data was obtained by interview mother released baby at study period. The study population consisted of 1415 baby released mothers and 309 of them selected using stratified sampling random sampling technique.

The response variable was maternal health care service utilization. it is dichotomized as no utilized (coded as 1) utilized (coded as 0). Mother had less than four visits considered as no utilized and Mother had four and more than four visits considered as utilized.

The independent variables such as: Maternal age: 15-19, 20-34, 35-49, Age of husband: 15-30, 31-45, 46-60, >60, Maternal education(Unable to read and Write, Read and Write, Attended primary school, Attended secondary, Certificate and above), Husband occupation (Farmer, Daily worker, Merchant, Civil servant, Other), Husband education(Unable to read and Write, Read and Write, Attended primary school, Attended secondary, Certificate and above), Maternal occupation(House wife, Merchant, Civil servant, Other), Average monthly income(<500,500-1000,1000-1500,1500-2000, >2000),Counselling during pregnancy (No, Yes), Number of child in the family(One, Two, Three, Four, Above four), Distance from health centre far(More than 4 kilometre), Average(2-4 kilometre, Near(less than more than 2 kilometre)), Religion(Orthodox, Protestant, Muslim, Other) and) and Lack of transport access (Yes, No).

Bayesian logistic regression models

Logistic regression is part of a family of models called the Generalized Linear Model use when the response variable is categorical and

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the independent variables are either continuous, categorical or both types. In binary logistic regression the dependent variable is dichotomous in to two like either or not, yes or no, agree or disagree and the independent variables are any type [10].

The response variable was maternal health care service utilization. it is dichotomized as not utilized or utilized denoted by Y, which is dichotomous with outcome either not utilized (1) with probability $p_i=P(Y_i=1|X_i)$ or utilized (0) with probability $1 \cdot p_i=P(Y_i=0|X_i)$, where X_i is a vector of r factors or predictors for each baby released mother i=1,2,3,...,n.

Bayesian logistic regression extends logistic regression in to a Bayesian framework [11]. Bayesian inference, which allows ready incorporation of prior beliefs and the combination of such beliefs with statistical data, is well suited for representing the uncertainties in the value of explanatory variables [12]. For observed data given the model parameters $\beta = \{\beta_p, \beta_2, ..., \beta_p\}$ the conditional probability and the converse conditional probability of model parameters β given observed data written as:

$$f(\beta / D) = \frac{f(\text{data} / \beta) * f(\beta)}{\int f(\text{data} / \beta) f(\beta) d\beta}$$

Where, $f(data | \beta)$: is the likelihood function, $f(\beta)$ is the joint prior probability distribution, and the $\int f(data | \beta)f(\beta)d\beta$: the normalizing constant. In Bayesian framework, there are three key components associated with parameter β : the prior distribution, the likelihood function, and the posterior distribution. The logistic regression model is given by [10]:

$$p_{i} = \frac{e^{\beta_{0} + \beta_{1} X_{i1} + \dots + \beta_{r} X_{i}}}{1 + e^{\beta_{0} + \beta_{1} X_{i1} + \dots + \beta_{r} X_{i}}}$$

where i=1,2,3,...,n; j=0,1,2,3,...,r; X_{ij} is the jth predictor of the ith child; β_0 is an intercept; β_j 's are coefficients of the predictor variables. The likelihood function $L(y|X,\beta)$ is defined as the joint probability distribution $f(y|X,\beta)$ of the independent observation vector of size n given the regression parameters β and the design matrix X. The likelihood function with the n independent observations is expressed as:

$$f(y \mid \beta) = \left[\frac{e^{\beta_0 + \beta_1 X_{i_1} + \dots + \beta_r X_{i_r}}}{1 + e^{\beta_0 + \beta_1 X_{i_1} + \dots + \beta_r X_{i_r}}}\right]^{y_i} * \left[1 - \frac{e^{\beta_0 + \beta_1 X_{i_1} + \dots + \beta_r X_{i_r}}}{1 + e^{\beta_0 + \beta_1 X_{i_1} + \dots + \beta_r X_{i_r}}}\right]^{1-y_i}$$
Prior distribution

Prior distribution

For this study, we use the most common priors for logistic regression parameters, which is a normal distribution with mean μ and covariance matrix Σ . i.e., $f(\beta) \sim N(\mu, \Sigma)$, the most common choice for μ is zero vectors, and Σ is usually chosen to be a diagonal matrix (Σ =diag($\sigma_0^2, \sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2$,)) with large variances that to be considered as non-informative prior [13].

$$f(\beta_j) = \frac{1}{\sqrt{2\pi\sigma_j}} exp\left(-\frac{1}{2}\left(\frac{\beta_j - \mu_j}{\sigma}\right)\right)$$

Posterior distribution

The likelihood and the prior distribution given above, the posterior distribution of the Bayesian logistic regression contains all the available knowledge about the parameters in the model like

The posterior distribution will be written as

$$f(\beta \mid y) \propto \left[\frac{e^{\beta_0 + \beta X_n + \dots + \beta_i X_n}}{1 + e^{\beta_0 + \beta X_n + \dots + \beta_i X_n}}\right]^{y_i} * \left[1 - \frac{e^{\beta_0 + \beta X_n + \dots + \beta_i X_n}}{1 + e^{\beta_0 + \beta X_n + \dots + \beta_i X_n}}\right]^{-y_i} * \prod_{i=0}^k \frac{1}{\sqrt{2\pi\sigma_j}} \exp\left(-\frac{1}{2}\left(\frac{\beta_j - \mu_j}{\sigma}\right)\right)$$

Where $f(\beta \mid y)$: are the posterior distribution which is the product of

likelihood and the normal prior distribution of β on the posterior distribution the posterior distribution of β on the posterior distribution

Erango M, et al.

may be difficult, for this reason we need to use non-analytic method. The Gibbs sampler algorithm is one of the Markov Chain Monto Carol (MCMC) techniques. It generates MC sequence that converges to the target distribution and the Sampling requires an initial starting point for the model parameters. A value for each parameter of interest is sampled given values for the other model parameters and data once all of the parameters of interest have been sampled, the nuisance parameters are sampled given the model parameters of interest and the observed data [14].

To check the convergence, we have used multiple chains with varying starting values give the same solution that will increase our confidence for convergence. A time series plot, autocorrelation plot and Gelman-Rubin statistic used to confirm convergence. In this study, the Statistical Package for the Social Sciences (SPSS) version 20 and Open BUGS version 3.2.3 software were used to handle and analyse the data.

RESULT AND DISSCUSION

The objective of this study was to analysis potential barriers for maternal health care utilization in a rural area and to identify associated factors among mothers in the rural districts. In the data set considered 309 births gave mothers from 35 districts.

The respondents whose age from 35-49 is 49% were use Antenatal health care service, but 51% of this age group doesn't use antenatal health care. From age 20-34, 38% of them were used antenatal health care and 62% doesn't use maternal health care from the group. From age 15-19, 12 % of them were use antenatal health care and 88% of the age group doesn't use antenatal health care. Mother whose education level unable to read and write, 10% of them were use antenatal care and 90% of the group does not use antenatal care.

Mother whose education level, enable to read and writes, 21% of them were use antenatal care and 79% of them does not use antenatal care. Mothers whose education level primary, 36% they were use antenatal care and 64% they does not use antenatal health care.

A mother at secondary education level, 21% the group was use antenatal health care and 79 % of them do not used Antenatal care. Mother whose educate level above high school is 65% were use Antenatal health care and 35% of them do not use Antenatal care.

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In the study area 59.7% women were house wife, 20% were merchant, 12.3% civil servant and 8% employed others. Among 309 mothers, 29% of the mothers have four and above child, 20% of them four child, 19% of them three child and 17% of them two child and 15% were one child. Regarding counselling service, 52% of the women's not use counselling service during antenatal Care period and 48% were use the counselling service. Among the respondent women's, 37% of them were suffered because of transport access to attend antenatal Care.

Chi-square tests were employed to find out the association between the maternal care utilization service status and the potential associated factors. Except Age of husband and age of women all the factors were significantly associated with the maternal care utilization service of women at the significant level of 5%. The results are displayed in Table 1.

Inferential analysis

The simulations of the posterior distributions are made based on the Gibbs sampler with 50,000 iterations and three different initial states of the parameters with a burn-in of 20,000 iterations considered to be sure of convergence of all the simulations. Inferences are made based on independent samples taken after convergence of the realization. Time series plots, autocorrelations and Gelman-Rubin statistics are assessed and they all confirm convergences.

The posterior means of the parameters, standard deviations, Monte Carlo errors and 95% credible intervals are estimated and odd ration of each parameter was computed to see the relative effect of the predictor and displayed in Table 2 below. The non -prior distribution used are $\beta_j \sim Normal(0,0.001)$ and variance $\sigma^2 \sim Gamma(2,0.5)$.

The parameter estimation analysis results in Table 2 below show that education level of husband, education level of women, occupation of Husband, Occupation of women, Age of women, Number of Child in the family, Distance from Health centre, Religion, Receiving counselling and lack of transportation access are significant and 95% credible interval that does not contain zero.

The Odds Ratio can be interpreted as follows: If the value exceeds 1 then the odds of an outcome occurring increase; if the value is less than 1, any increase in the predictor leads to decrease success.

	Maternal Utilization Status				
Predictors variables	Chi-square	df	P-value		
Age of Husband	0.743	2	0.389		
Education level of husband	5.091	4	0.024*		
Occupation of husband	5.591	4	0.018*		
Age of women	0.124	2	0.725		
Education level of women	2.325	4	0.012*		
Occupation of women	1.906	4	0.002*		
Number of child in the family	6.37	4	0.012*		
Sex of house leader	0.676	1	0.411*		
Distance from Health center	6.101	2	0.014*		
Counseling	9.757	1	0.002*		
Religion	9.968	3	0.002*		
Lack of Transportation	0.549	1	0.000*		

Table 1: Tests of association of predictor variables on the maternal utilization status of women.

Erango M, et al.

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	Tabl	le 2: Parameter estimation	n of Bayesian logistic regr	ession.	
Variable/Category	Mean	SD	MC Error	95% CI	Exp(Mean)
βο	5.073	1.868	0.051	(5.04,8.84)	159.65
		Education lev	el of Husband		
		β(Not read a	nd write) (Ref)		
β(Ready and write)	-0.382	0.0348	0.012	(-2.14,0.13)	0.68
β(Primary)	-0.154	0.032	0.007	(-2.4,-0.056)	0.857
β(Secondary)	-2.788	0.074	0.005	(-4.18,-0.075)	0.062
(Certificate and above)	-1.664	0.09	0.02	(-4.4,-0.87)	0.189
		Occupation	n of Husband		
		β(Farm	ner(Ref))		
β(Daily worker)	0.259	0.0527	0.014	(0.148,2.48)	1.29
β(Merchant)	0.108	0.034	0.001	(0.059,2.55)	1.115
β(Civil servant)	-3.52	0.02	0.022	(-0.926,0.093)	0.03
β(Others)	-2.636	0.039	0.025	(-3.2,1.04)	0.072
		Age of	Women		
		β(1	5-19)		
β(P20-34)	-1.38	0.021	0.007	(-3.4,-0.18)	0.25
β(35-49)	1.52	0.08	0.009	(1.27,3.62)	4.57
		Education le	evel of Women		
		β(Not read a	nd write) (Ref)		
β (Ready and write)	0.24	0.029	0.026	(0.045,2.47)	0.786
β(Primary)	1.346	0.0207	0.001	(1.156,4.273)	3.84
β(Secondary)	-0.257	0.0074	0.008	(-1.26, -0.15)	0.77
(Certificate and above)	-0.95	0.09	0.002	(-2.45,-0.09)	0.385
		Occupatio	n of Women		
		β(House	wife(Ref))		
β(Merchant)	-3.358	0.01	0.018	(-1.178,0.09)	0.035
β(Civil servant)	-2.927	0.072	0.019	(-0.78, 0.335)	0.054
β(Other)	-3.442	0.422	0.021	(-0.068,0.54)	0.032
		Number of Ch	uild in the Family		
		β(Or	ne(Ref))		
β(Two)	-1.74	0.039	0.009	(-1.9,-0.129)	0.175
β(Three)	-1.72	0.094	0.01	(-1.98, -0.054)	0.179
β(Four)	-0.675	0.0803	0.007	(-1.158,-0.045)	0.51
β(Above four)	-0.612	0.219	0.007	(-1.24,-0.42)	0.54
		Distance from	n Health Centre		
		β(Far)		
β(Average)	059	0.605	0.003	(-0.37,0.55)	1.8
β(Near)	0.89	0.605	0.003	(-0.37,0.55)	2.43
		Rel	igion		
		β(Ortho	odox(Ref))		
β(Protestant)	1.53	0.846	0	(1.25,4.29)	4.62
β(Muslim)	1.08	0.647	0.001	(0.29,2.74)	2.9
β(An Other)	0.001	0.081	0	(-0.03,2.1)	1.001
		Receiving o	f Counselling		
		β(No	o(Ref))		
β(Yes)	-1.216	0.577	0.005	(-1.81,0.285)	0.296
		Lack of Tr	ansportation		
		β(Ye	s(Ref))		
β(No)	1.371	0.037	0.003	(0 19 3 21)	3 938
P.4.107	***/14	0.001	0.005	(0.17), 0.21/	5.750

Erango M, et al.

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The odds of being not use maternal health care service were decreased by 93.8% for women her husband with secondary education levels as compared to women her husband unable to read and write. The odds of being not use maternal health care services were decreased by 81.1% for women her husband with education level certificate and above as compared to women her husband unable to read and write. The odds of being not use maternal health care service for women her husband read and write were decreased by 31.7% as compared to women her husband unable to read and write. The odds of being not use of maternal health care service for women her husband read and write were decreased by 31.7% as compared to women her husband unable to read and write. The odds of being not use of maternal health care service for women her husband read and write were decreased by 14.3% as compared to reference category.

The odds of being not use maternal health care service were decreased by 70% and 28% for women her husband occupation civil servant and other respectively as compared to women her husband occupation farmer. The odds of being not use maternal health care service for women her husband daily worker and merchant were 1.296 and 1.115 times as compared to women her husband was farmer respectively. The odds of being not use maternal health care service were decreased by 21.9% and 61.5% for women her education level read and write and certificate and above respectively compared with women her education level unable to read and write women.

The odds of being not use maternal health care service for women attended primary school decreased by 23% as compared women with education level unable to read and write. In this study occupation of women was one of factors affect maternal health care service in the study area. The odds of being not use maternal care for women occupation merchant, civil servant and other servant were decreased by 96.5%, 94.6%, and 96.8% respectively as compared to women her occupation was house wife.

Assessing convergence

In Bayesian modelling approach three parallel chains of 50000 iterations with different starting values are generated. Some sample plots of the parameters are given in Figure 1a-c below. In this study, inference was made based on posterior distributions that are taken with the thinning of 10 after burn-in 19999. In Figure 1 below, the time series plots of the history of the simulation and its mixing rate of the three chains show that a reasonable degree of randomness and they may convergence to the same value. Also, Gelman-Rubin statistics, autocorrelations and density plots are used to assess convergence.

CONCLUSION

The purpose of maternal health care facility is to improve the health of mothers it would be important to study the potential





Figure 1c: Gelman-Rubin statistic for maternal age and women education.

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Erango M, et al.

factors that can improve the performance of the service in the rural districts. The findings reveal that the probability of not use maternal health care service in the study area was 41.5%. In the study area, education of women and their husbands, Occupation of women and their Husband and religion remained strong predictors of maternal health care services utilization.

Test of association analysis of the factors indicated that education level of women and their husband, Occupation of women and their husband, Number of child in the family, sex of house leader, Distance from Health centre, receiving counselling, Lack of Transportation access and religion were significantly associated with the maternal health care utilization service of women in the study areas.

In conclusion, a significant number of women's were found in the districts which does not use maternal health care service due to lack of knowledge, due to occupation type of women and their husbands. Based on the potential determinate factors, appropriate intervention and empowering women's needed to decrease mortality rate in the study area

ETHICAL CONSIDERATION

The research proposal for this study was checked and approved by ethical clearance committee of Arba Minch University and hence, Official Ethical clearance letter was written from Research office of College of Natural Science Arba Minch University. Other written and verbal consent was obtained from each participant after thorough explanation of the purpose and the procedures of the study. Participation in the study was on a voluntary basis and responses were kept confidential and anonymous

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