American Journal of Life Sciences
2018; 6(6): 80-88
http://www.sciencepublishinggroup.com/j/ajls
doi: 10.11648/j.ajls.20180606.12
ISSN: 2328-5702 (Print); ISSN: 2328-5737 (Online)

Bayesian Modelling on Incidence of Pregnancy among HIV/AIDS Patient Women at Adare Hospital, Hawassa, Ethiopia

Yenesew Fentahun Gebrie[1, *], Ayele Taye Goshu[2, *]

[1]Department of Statistics, Debre Markos University, Debre Markos, Ethiopia

[2]School of Mathematical and Statistical Sciences, Hawassa University, Hawassa, Ethiopia

Email address:

yenefenta@gmail.com (Y. F. Gebrie), ayele_taye@yahoo.com (A. T. Goshu)

[*]Corresponding author

To cite this article:

Yenesew Fentahun Gebrie, Ayele Taye Goshu. Bayesian Modelling on Incidence of Pregnancy among HIV/AIDS Patient Women at Adare Hospital, Hawassa, Ethiopia. *American Journal of Life Sciences*. Vol. 6, No. 6, 2018, pp. 80-88. doi: 10.11648/j.ajls.20180606.12

Received: December 4, 2018; **Accepted**: January 9, 2019; **Published**: January 28, 2019

Abstract: HIV/AIDS is the most serious diseases human kind has ever faced and a public problem, particularly, for women of childbearing age. For HIV infected women, the prospects of getting pregnant and having an HIV negative baby could be significantly improved with the increasing of the availability of Antiretroviral Therapy (ART). Even though, ART treatment has shown significant effect of clinical importance to reduce the risk of mother to child transmission of HIV but, HIV infected Women remain poorly understood or they fear to be pregnant and having HIV negative child. To the authors' knowledge, no study examined incidence of pregnancy among women on ART follow-up in Ethiopia. In response, we conducted a study to explore the incidence and potential predictors of pregnancy. The objective of this study was to investigate the incidence of pregnancy among HIV/AIDS patient women under ART follow-up. A retrospective cohort study was conducted based on secondary data that reviews or visits medical chart of HIV/ADIS patient women aged 15-49 years under ART follow-up from April 2008 to February 2015. Out of 720 total patient women, a sample of size 328 was selected by using simple random sampling technique. Bayesian estimation were used for binary logistic regression model to identify the significant factors of incidence of pregnancy. The Gibbs sampler algorithm was implemented by WinBUGS software to solve approximate properties of the marginal posterior distributions for each parameter in Bayesian estimation. The results of this study revealed 21.3% of women got pregnancy during the follow-up. From Bayesian logistic regression analysis, significant predictors of incidence of pregnancy were: WHO clinical stage, marital status, contraception use, number of child alive before ART follow-up, CD4 cell count, time of Antiretroviral Therapy (ART) follow-up, educational level, spouse's HIV status, occupation and age (at p=0.05). In this study, when age of the women increased, the probability of becoming pregnant was decreased and advanced WHO clinical stage were associated with decreased incidence of pregnancy. Time on ART was a strong predictor of becoming pregnant: longer time on ART was associated with increased probability of becoming pregnant. Educational level of women was positively related with incidence of pregnancy that is, women who had college and above educational level was more likely to become pregnant. When CD4 count increased, incidence of pregnancy also increased and married women had more chance to become pregnant. The predictors identified in this study can be used to care for those HIV/AIDS patient women who want to have baby.

Keywords: Antiretroviral Therapy, Bayesian, Incidence of Pregnancy

1. Introduction

HIV/AIDS is one of the most critical diseases human kind has ever faced as well as a social dilemma. It has become one of the world's most serious health and development challenges, as well as a social problem particularly among women of childbearing age [1]. HIV/AIDS patient compromises their immunity which further aggravates their chances of conception and supporting pregnancy to term. AIDS epidemic has now spanned nearly three decades and it was first recognized by the United States Centres for Disease Control and Prevention in 1981 through its cause and HIV was

identified in the early 1980s. The estimated 35.3 (32.2–38.8) million people were living with HIV worldwide by 2012. In 2012 the number of deaths due to AIDS is decrease with 1.6 (1.4–1.9) million deaths from 2.3 (2.1–2.6) million in 2005, because the number of people that take antiretroviral therapy was increased to save life as well as to reduce AIDS related deaths. In low and middle income country, women cover 52% of all people living with HIV/AIDS and men cover 48% globally [2]. However, women account approximately 57% of all people in sub-Saharan Africa which is the center of the global epidemic by 2012. In the same year, in low and middle-income countries 9.7 million people received antiretroviral therapy, which represent 61% of all people who were eligible. According to December 2012, more than 900000 pregnant women living with HIV received antiretroviral treatment worldwide and the coverage of antiretroviral treatment is increased from 57% in 2011 to 62%. Antiretroviral Therapy (ART) prevents AIDS-related illness as well as death and it has significant power to decrease the risk of HIV transmission of mother-to-child. Ethiopia has recorded some modest progress in the prevention of mother to child transmission [3]. HIV epidemic has remained a major public health problem, mainly affecting people of prime productive and reproductive age in Ethiopia [4]. In the country, approximately 38,401 pregnant women were living with HIV and 15, 924 (41.5 %) of these women received a full course of effective antiretroviral drugs (ARV) treatment to prevent mother to child transmission in 2012. HIV can be transmitted through breastfeeding, but it is possible to decrease the transmission by taking drugs throughout pregnancy. For HIV infected women, the chance to be pregnant and having healthy (HIV free) baby could be significantly improved by increasing the availability of antiretroviral therapy (ART), because it has high potential to prevent HIV/AIDS-related illness as well as death. In addition ART decrease the risk of HIV transmission of mother-to-child [5]. Even though, ART treatment has shown significant result clinical importance to decrease the risk of mother to child transmission of HIV/AIDS, patient women remain poorly understood or they fear to be become pregnant and having HIV negative child. Thus, to know the patterns and risk factors of incidence of pregnancy in ART follow-up is significant concern to planning and management for women in treatment of HIV/AIDS. In particular, it is true in Ethiopia, since there is broad access of ART with extremely large at-risk population of reproductive-age women. Hence, it is important to study factors which affect incidence of pregnancy of HIV/AIDS patients women under ART follow up. In addition, Bayesian analysis is a powerful statistical method in medical researches and it has been very scarcely applied in the country. This study has been motivated to address the following research questions:

1. What are the factors that have significant impact on incidence of pregnancy among AIDS patient women under ART follow up?

2. Which predictor variable has positive effect on incidence of pregnancy of HIV/AIDS infected Women?

Therefore, the objective of this study is to investigate the incidence of pregnancy among AIDS patient women under ART follow-up. Specifically:-

1. To identify the major predictor variables of incidence of pregnancy among AIDS patient women under ART follow up.

2. To determine the level of incidence pregnancy of patient women under ART follow up.

3. To provide information to health workers, governmental and non-governmental organization and researchers.

The previous study in Uganda, reported the use of ART was associated with increased pregnancy rates in HIV positive women, and factors associated with lower pregnancy prevalence were older age, those using medication to prevent pregnancy (use of family planning). Being currently married have higher incidence of pregnancy, and incidence pregnancy increase when both women and their spouses desired more children. The prevalence of pregnancy during ART use was higher among women with CD4 of 100–250 compared to those with CD4<100 and older women aged 35–45 years compared to the younger women aged 15–24 years [6]. The study in Urban Malawi reported, incidence of pregnancy was significantly associated with current age, WHO clinical stage at ART initiation and time on ART. That is, incidence of pregnancy was negatively associated with both increasing age and WHO clinical stage at ART initiation. Longer time on ART follow up was associated with increased probability of becoming pregnant [7]. A retrospective clinical cohort study in South Africa conclude that, rates of pregnancy were highest in women with CD4 counts between 350 and 500 cells/mm^3 and much higher in younger women compared with older women [8]. The study in western Uganda, suggest that factors that were not significant predictors of pregnancy include religion, WHO disease stage and CD4 cell count at enrollment. Based on this study, factors that were associated with incidence of pregnancy in the cohort were young age, marital status, lack of knowledge of spouse HIV status, number of child alive, body weight and use of family planning. Younger women were more likely to get pregnant compared to the older women. Moreover, widowed or separated women were less likely to become pregnant compared to those who were single or married and women who did not know their spouse's HIV status were more likely to become pregnant compared to those who knew. And also, Women who have fewer children were more likely to become pregnant compared to women who had more children [9]. The study conducted in southeastern Brazil, shown that, Age, level of education, marital status, use of antiretroviral and CD4 cell count were associated with the risk of pregnancy ($p<0.25$). That is, younger age, less educated, and women living with their spouses/partners were more likely to become pregnant. However, in the study the number of living children and HIV-related condition did not show a clear association with pregnancy [10]. The research conducted on comparison of Bayesian and maximum likelihood estimation, suggested that Bayesian logistic regression was more stable than classical logistic regression in non-informative prior. The maximum likelihood estimation has significant bias for small samples [11]. Another research was conducted on comparisons of maximum likelihood and

Bayesian estimation methods on prostate cancer data. The research recommended Bayesian approach for making statistical inference about application of the logistic regression model because Bayesian approach allows for probabilistic interpretations to logistic coefficients and its results more accurate than the maximum likelihood method under non-informative prior [12]. Bayesian binary regression model was used to predict death of patients after acute myocardial infarction using Markov Chain Monte Carlo (MCMC) methods. Bayesian analysis of the binary regression model using Gibbs sampler and the new developments of stochastic simulation almost eliminate the difficulties associated to the Bayesian analysis of non-linear models, including binary regression models [13]. Previous studies were conducted in sub Saharan Africa, focusing on pregnancy rate, but as authors' knowledge, there is no studies conducted on incidence of pregnancy as well as pregnancy rate under ART follow up in Ethiopia. Hence, in response we would conduct study to explore the incidence and potential predictors of pregnancy among HIV/AIDS patient women under ART follow up.

2. Data and Methodology

Study Design and Data Source

A retrospective cohort study was conducted based on secondary data that reviews or visits of medical charts of HIV infected Women from ART clinic of Adare Hospital, Hawassa, Ethiopia. The data include all HIV/AIDS Patient women under the follow up of ART those who are aged between 15 and 49 years and had at least three month on ART follow-up between April 2008 and February 2015.

Sampling and Data collection

In this study, simple random sampling method was applied and the required sample size was calculated using single population proportion formula with proportion 50% and degree of precision 4%. The representative sample size of 328 was selected from 720 HIV /AIDS patient women. The data were collected by the data experts in ART clinic at the Hospital using structured administered questionnaire. One day training was given for two data collectors about the objectives and procedures of the data collection by the investigators. Questionnaire was pre-tested to assess clarity, understand ability, flow and consistency.

Dependent Variable

Dependent (outcome) variable of the study is incidence of pregnancy of HIV/AIDS patients' women under ART follow-up.

Explanatory Variables

Explanatory variables of the study were age of women, education level, women's occupation, marital status, religion, place of residence, number of child alive before ART follow-up, contraception use, WHO clinical stage, illness due to co-infection, body weight, CD4 cell count, time of ART follow-up and spouse's HIV status.

2.1. Logistic Regression Model

Logistic regression is a statistical technique for predicting the probability of an event, given a set of predictor variables. The logistic model, as a non-linear regression model, is a type of generalized linear model, where the assumptions of normality and constant variance of residuals are not satisfied [14]. Logistic regression uses the logit transformation to linearize the non-linear relationship between independent variable and the probability of dependent variable. Binary logistic regression is a type of logistic regression that used when the dependent variable is a dichotomous and the predictor variables are of any type. This model has another application of combining the dependent variables to estimate the probability that particular event will occur. The statistical model preferred for analysis of such binary (dichotomous) response is binary logistic regression model developed primarily by research named Cox during the late 1950. Based on the binary outcome variable, we use the logistic distribution [15, 16]. Let$X$'s are independent variables and Y is dependent variable, with probability of success (pregnancy occurred) Pi and probability of failure (pregnancy not occurred) 1-Pi.

$$P_i = \frac{e^{\beta_o+\beta_1X_1+\cdots+\beta_kX_k}}{1+e^{\beta_o+\beta_1X_1+\cdots+\beta_kX_k}} = \frac{e^{X'\beta}}{1+e^{X'\beta}} \quad (1)$$

Where, P_i = is the probability that i^{th} HIV infected women is being pregnant (probability of success).

X= design matrix of independent variables

β= is a vector of unknown parameters

In logistic regression model, there are different link function such as logistic (logit), normal (probit) and extreme value (complementary log - log). But in this research, the link function is logit, because logistic regression model has an influential investigative tool for medical research to estimate the regression coefficients using logit link function of probability of success [14]. Hence, the logit transformation of P_i given as follows:

$$logit(P_i) = log\left(\frac{P_i}{1-P_i}\right) = \beta_o + \beta_1X_1 + \cdots + \beta_kX_k \quad (2)$$

2.2. Bayesian Logistic Regression Model

Bayesian approach considers that the parameters of the model as random variable and data are considered as fixed, and also Bayesian model require the prior distributions. Bayesian approach is used to make inference about the parameters of logistic regression model. Bayesian inference for logistic regression analysis follows the common pattern for all Bayesian analysis. The basic steps and concepts that should be considered in Bayesian inference should be the likelihood function of the data, the prior distribution for all unknown parameters and the posterior distribution of the model parameters, given data.

Likelihood Function

Since the trials are independent, the joint distribution of dependent variable $Y_1, Y_2 \ldots Y_n$ is the product of Bernoulli

probabilities. As usual, the likelihood function used by Bayesian approach matches from frequently approach. The likelihood function of probability of success in logistic regression has binomial distribution. That is y_i has binomial distribution, then the likelihood function is given as:

$$L(y_i/\beta) = \prod_{i=1}^{n}[(P_i)^{y_i}(1-P_i)^{1-y_i}]\, L(y_i/\beta) = \prod_{i=1}^{n}\left[\left(\frac{e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}{1+e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}\right)^{y_i}\left(1-\frac{e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}{1+e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}\right)^{1-y_i}\right] \quad (3)$$

Prior Distribution

Bayesian estimation of the model parameters requires a prior distribution for all parameters, thus this is main important feature of any Bayesian estimation. With small sample size this choice can be critical, but with larger samples the choice is less crucial, since information in a data is more important than prior information. If the posterior distribution is highly depending on the prior information (distribution), the data (likelihood function) may have no enough information. Yet, if the posterior distribution is somewhat stable over a choice of prior information (distribution), the data contains significant information. In general, there are two types of prior distribution depends on the available of prior information. That is informative prior distribution if something is known about the possible values of the parameters and non-informative prior distribution, if there is little information about the values of parameters. The results of Bayesian estimation is more accurate than maximum likelihood estimation under non-informative prior on logistic regression model [13]. The maximum likelihood estimation has significant bias for small samples. Bayesian logistic regression model was more stable than classical logistic regression model in non-informative prior, especially for small samples [12]. In this research, prior information is important since the sample size is small and there is little information about the values of parameters then, the prior distribution is non-informative. Based on literatures, the most common prior distribution for binary logistic regression model parameters is normal distribution. The prior distribution of logistic regression coefficient is given as:

$$P(\beta_j) = \frac{1}{\sqrt{2\pi\sigma_j^2}}\, exp\left\{\frac{-1}{2}\left(\frac{\beta_j-\mu_j}{\sigma_j}\right)^2\right\} \quad (4)$$

In Bayesian analysis the precision is often specified instead of variance. The most common choice for μ_j is zero, and σ_j is usually chosen to be large enough to be considered as non-informative, common choices being in the range from $\sigma_j = 10^2$ to $\sigma_j = 10^6$ [13].

Posterior Distribution

Posterior distribution is proportional to the product of likelihood function from data and prior distribution from prior information, that is:

$$P(\beta/data) \propto \prod_{i=1}^{n}\left[\left(\frac{e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}{1+e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}\right)^{y_i}\left(1-\frac{e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}{1+e^{\beta_0+\beta_1X_{i1}+\cdots+\beta_kX_{ik}}}\right)^{1-y_i}\right] \mathrm{x} \prod_{j=1}^{k}\frac{1}{\sqrt{2\pi\sigma_j^2}}\, exp\left\{\frac{-1}{2}\left(\frac{\beta_j-\mu_j}{\sigma_j}\right)^2\right\} \quad (5)$$

This posterior distribution recognized as normal distributions for the βj parameters. Of course, the equation has no closed form and even if it did, so to get the marginal distribution of the parameters, it needs multiple integrations to obtain the marginal distribution for each coefficient. Hence, the Gibbs sampler algorithm was used to estimate the marginal posterior distribution for each parameter by WinBUGS software, because the distribution of posterior is known.

2.2.1. The Gibbs Sampling Algorithm

In Bayesian statistical estimation is based on the posterior distributions of the model parameters. To simplify the problem of Bayesian inference, Markov Chain Monte Carlo (MCMC) simulation was implemented, especially the Gibbs sampling algorithm was used through the WinBUGS14 software to simulate realizations from the joint posterior density. The Gibbs sampler is a special case of Metropolis Hasting algorithm where the random value is always accepted (that is $\alpha = 1$), therefore, the proposed move is accepted in all iterations [17]. Finally the data set obtained by applying Gibbs sampling to the model converges to the joint posterior distribution of the parameters.

The Gibbs sampling algorithm can be present as follows:

Step1: Start the MC with the initial values ofβ_j, given $\beta^o = \beta_0^o, \beta_1^o, \ldots, \beta_k^o$

Step2: Sample for i=0, 1, 2, ... ,N-1

Generate $\beta_0^{(i+1)}\ from\ P(\beta_0/\beta_1^{(i)}, \beta_2^{(i)} \ldots, \beta_k^{(i)}, Y, X)$

Generate $\beta_1^{(i+1)}\ from\ P(\beta_1/\beta_0^{(i+1)}, \beta_2^{(i)} \ldots, \beta_k^{(i)}, Y, X)$

Generate $\beta_k^{(i+1)}\ from\ P(\beta_k/\beta_0^{(i+1)}, \beta_1^{(i+1)} \ldots, \beta_{k-1}^{(i+1)}, Y, X)$

Step3: Repeat step 2 until convergence

Step4: Return $\beta^{(b)}, \beta^{(b+1)}, \beta^{(b+2)}, \ldots, \beta^{(N)}$

2.2.2. Assessment of Convergence of the Algorithm and Accuracy of the Model

The word convergence of a Markov chain Monte Carlo (MCMC) algorithm refers to whether the algorithm has attained its equilibrium (target) distribution. The Gibbs sampling algorithm is one of the simplest Markov chain Monte Carlo algorithms that converge to the target density as the number of iterations become large. The simulation should be run until the Monte Carlo error for each parameter of interest is less than about 5% of the sample standard deviation [18]. In addition, there are different methods to check the convergence of algorithm of Bayesian analyses. Time series plots are commonly used to assess convergence [19]. Autocorrelation plot and Gelman-Rubin statistic are another method to assess convergence in Bayesian analysis. For a given parameter, this statistic assesses the variability within parallel chains as compared to variability between parallel

chains [20]. Density plot is also used to check the convergence of algorithm, if the coefficients of the independent variables are normally distributed implies that the Markov chain has attained its posterior distribution. To assess the accuracy of Bayesian logistic regression model, Monte Carlo error for each parameter was used. If the MC error value is less than 5% its posterior standard deviation, indicates that the posterior density is estimated with accuracy.

3. Results

3.1. Results of Chi-square Tests of Association

The objective of the study was to identify factors that mainly affect the incidence of pregnancy of HIV/AIDS patient women under ART follow-up. Among 328 women, 21.3% had pregnancy during the given year and 78.7% of women have no pregnancy. The Chi-square test of association was employed to examine the association between independent variables and dependent variable at the beginning of the analysis. Then, Bayesian estimation was used for binary logistic regression model to identify the significant factors of incidence of pregnancy. The data were analyzed using SPSS 16 for chi-square test and winBUGS Software for Bayesian analysis. From Chi-square output given in **Table 1**, incidence of pregnancy was associated with illness due to co-infection, Spouse's HIV status, marital status, educational level, place of residence, contraception use, number of child before ART follow-up, CD4 cell count, WHO clinical stage, body weight, occupation, and age at 5% level of significance.

Table 1. *Frequencies, percentages and Chi-square Tests of association of categorical variables of pregnancy status.*

Variables	Categories	Pregnancy not occurred		Pregnancy occurred		Total		df	Pearson Chi-squar (Sig.)	LR (Sig.)
		Count	%	Count	%	N	%			
WHO clinical stage	Stage I	38	46.3	44	53.7	82	25.00	3	73.224 (0.000)	70.532 (0.000)
	Stage II	100	83.3	20	16.7	120	36.59			
	Stage III	85	95.5	4	4.5	89	27.13			
	Stage IV	35	94.6	2	5.4	37	11.28			
Spouse's HIV status	Negative	65	75.6	21	24.4	86	26.22	2	28.924 (0.000)	27.560 (0.000)
	Positive	39	57.4	29	42.6	68	20.73			
	Unknown	154	88.5	20	11.5	174	53.05			
Marital status	Unmarried	37	94.9	2	5.1	39	11.89	3	52.303 (0.000)	58.480 (0.000)
	Married	103	62.4	62	37.6	165	50.31			
	Divorced	59	93.7	4	6.3	63	19.21			
	Windowed	59	96.7	2	3.3	61	18.59			
Educational level	No education	66	88.0	9	12.0	75	22.87	3	16.191 (0.001)	15.290 (0.002)
	Primary	102	82.9	21	17.1	123	37.50			
	Secondary	64	74.4	22	25.6	86	26.22			
	College& above	26	59.1	18	40.9	44	13.41			
Occupation	Unemployed	107	91.5	10	8.5	117	35.67	3	32.559 (0.000)	32.202 (0.000)
	Employed	56	59.6	38	40.4	94	28.66			
	Housewife	82	80.4	20	19.6	102	31.10			
	Student	13	86.7	2	13.3	15	4.57			
Contraceptive use	Never	158	75.2	52	24.8	210	64.02	3	12.736 (0.005)	14.883 (0.002)
	Rarely	20	66.7	10	33.3	30	9.15			
	Mostly	31	86.1	5	13.9	36	10.98			
	Always	49	94.2	3	5.8	52	15.85			
Number of child alive before ART	No child	76	63.3	44	36.7	120	36.59	2	27.347 (0.000)	26.923 (0.000)
	1-2 child	132	89.2	16	10.8	148	45.12			
	>2 child	50	83.3	10	16.7	60	18.29			
Age	15-24	37	64.9	20	35.1	57	17.38	4	16.456 (0.002)	17.413 (0.002)
	25-29	80	73.4	29	26.6	109	33.23			
	30-34	67	83.8	13	16.2	80	24.39			
	35-39	43	87.8	6	12.2	49	14.94			
	40-49	31	93.9	2	6.1	33	10.06			
Last CD4 cell count	<250	96	97.0	3	3.0	99	30.18	3	51.623 (0.000)	58.344 (0.000)
	250-350	56	91.8	5	8.2	61	18.60			
	351-500	51	67.1	25	32.9	76	23.17			
	>500	55	59.8	37	40.2	92	28.05			
Time of ART follow-up	≤24 months	152	87.9	21	12.1	173	52.74	2	20.206 (0.000)	20.144 (0.000)
	25-48 months	61	64.9	33	35.1	94	28.66			
	>48 months	45	73.8	16	26.2	61	18.60			

3.2. Bayesian Logistic Regression Analysis

Bayesian logistic regression analysis was used to estimate the parameters of a logistic regression model. The Gibbs sampler algorithm was implemented with 20000 iterations in three different chains and 5001 burn-in terms discarded, as to get 45000 samples from the posterior distribution. The Gibbs sampler with more than one chain simultaneously provide

autocorrelation and time series plots of each chain in different colors that help us to check convergence. Based on the sample obtained from posterior distribution, summary statistics of all parameters for joint posterior distribution are given in Table 2. From the table, the variables like WHO clinical stage, marital status, spouse's HIV status, educational level, contraception use, number of child before ART follow-up, occupation, CD4 cell count, time of ART follow-up and age were significant predictor variables of incidence of pregnancy at α=5% level of significance, because the 95% credible interval of these variables does not include zero (at least one category). From the result of posterior mean, the values 4.542, 2.644, 2.913, 3.699 and 4.018 were the mean of women with time of ART follow-up 25-48 months, HIV positive spouse, college and above educational level, CD4 count greater than 500 cell count and employed women respectively. This implies that incidence of pregnancy had significant positive association with time of ART follow-up, educational level, CD4 count and occupation of women. While, the values of -6.779, -6.626, -5.463, -2.728 and -4.836 were the posterior means of women belong to WHO clinical stage IV, unmarried, contraception use always, had greater than two child alive and age group 40-49 respectively. Thus variables such as WHO clinical stage, age and number of child alive were negatively associated with incidence of pregnancy.

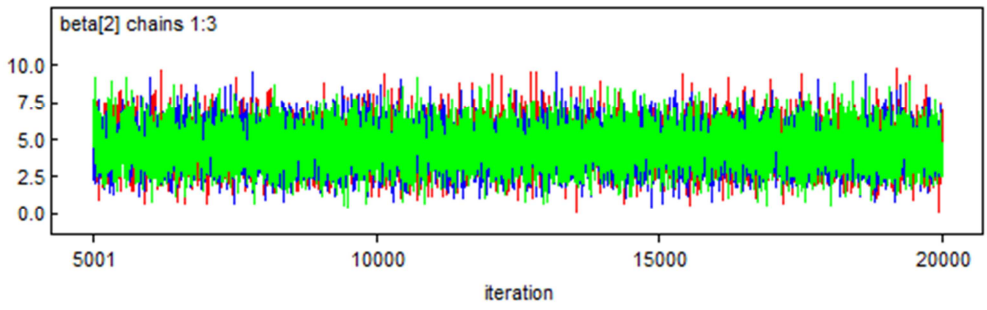
Table 2. *Summary statistic of the posterior distribution of the model parameters.*

Node	Category	B Mean($\hat{\beta}$)	S.E.($\hat{\beta}$)	MC Error	95% Credible Interval ($\hat{\beta}$)	
					Lower	Upper
Constant	beta[1]	-3.383	0.181	0.1022	-10.23	2.693
Time of ART follow up ≤24 months (ref.)	25-48 month	4.542	0.067	0.01199	2.288	7.08*
	.>48 months	3.935	0.072	0.01258	1.455	6.565*
WHO clinical stage Stage I (ref.)	Stage II	-2.118	0.067	0.0134	-4.204	-0.1511*
	Stage III	-7.611	0.103	0.0233	-11.49	-4.18*
	Stage IV	-6.779	0.142	0.02075	-12.12	-1.965*
Spouse HIV status Negative (ref.)	Positive	2.644	0.062	0.01293	0.4898	4.912*
	Unknown	-1.072	0.060	0.008483	-3.226	1.038
Marital status Married (ref.)	Unmarried	-6.626	0.091	0.01472	-10.06	-3.595*
	Divorced	-7.185	0.091	0.01644	-10.64	-4.199*
	Widowed	-6.702	0.106	0.01657	-10.77	-3.237*
Educational level No education (ref.)	Primary	1.515	0.071	0.01899	-0.9355	4.104
	Secondary	1.438	0.081	0.02817	-1.365	4.417
	College and above	2.913	0.083	0.02352	0.04799	5.944*
Contraception uses Never use (ref.)	Rarely	-1.708	0.081	0.008923	-4.604	1.131
	Mostly	-5.61	0.082	0.01549	-8.692	-2.904*
	Always	-5.463	0.091	0.01527	-9.009	-2.53*
Number of child alive No child (ref.)	1-2 child	-3.834	0.059	0.01097	-6.051	-1.854*
	≥3 child	-2.728	0.074	0.01214	-5.445	-0.1938*
CD4 Count <250 (ref.)	250-350	-4.547	0.099	0.02672	-8.15	-1.088*
	351-500	2.491	0.085	0.032	-0.3893	5.693
	>500	3.699	0.079	0.02636	1.11	6.704*
Occupation Unemployed (ref.)	Employed	4.018	0.069	0.01669	1.664	6.636*
	Housewife	0.936	0.065	0.01067	-1.345	3.273
	Student	-3.24	0.159	0.01223	-9.124	2.232
Age 15-24 (ref.)	25-29	0.633	0.065	0.01471	-1.633	2.985
	30-34	-3.661	0.087	0.01925	-6.909	-0.7271*
	35-39	-6.398	0.105	0.01837	-10.33	-2.899*
	40-49	-4.836	0.142	0.01817	-10.19	-0.04729*

ref. = Reference category, * = significant at 5% level of significance.

3.3. Assessment of Convergence and Accuracy of Model

Time series plots**:** the plot looks like a horizontal band, with no long upward or downward trends, then we have evidence that the chain has converged. Time series plot indicates a good convergence of parameters since three independent generated chains are mix together or over lapped. For instance, time series plot for time of ART follow-up (25-48 months), WHO clinical stage II are given below.



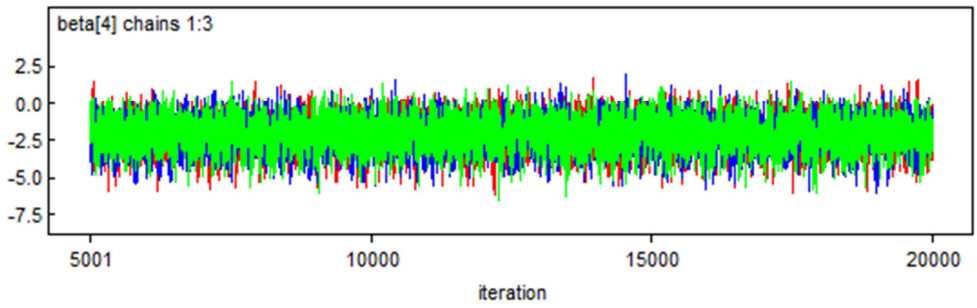


Figure 1. *Time series plot of time of ART follow up (25-48 months) and WHO clinical stage II.*

Autocorrelation plot: For all simulated parameters, the plot of the first 50 lags of three independently generated chains demonstrated good chain mixture indication of convergence. The autocorrelation plot of time of ART follow-up (25-48) and WHO clinical Stage II also given here below.

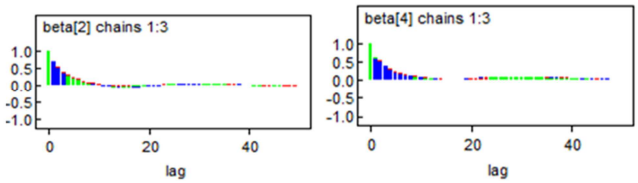


Figure 2. *Autocorrelation plot of time of ART follow up (25-48 months) and WHO clinical stage II.*

Gelman-Rubin Statistics: The model is judged to have converged if the ratio of between to within variability is close to 1. Hence, the Gelman-Rubin statistic of this study emphasis that one should be concerned convergence of ratio close to one. Here below given Gelman-Rubin statistic for time of ART (25-48 months), WHO clinical stage II.

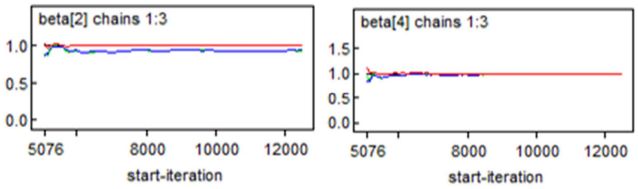


Figure 3. *Gelman-Rubin Statistics plot of time of ART follow up (25-48 months) and WHO clinical stage II.*

Density Plot: The density plots given below for time of ART of 25-48 months and WHO clinical stage II were normally distributed. Thus, this indicates that the Markov chain has attained its posterior distribution.

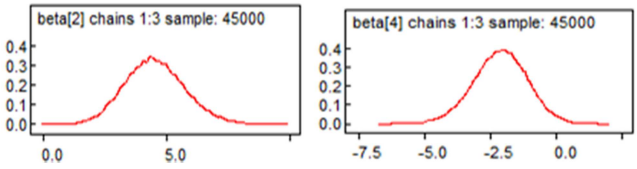


Figure 4. *Density plot of time of ART follow up (25-48 months) and WHO clinical stage II.*

To assess the accuracy of Bayesian logistic regression, we can use Monte Carlo error for each parameter. In this study, MC error for each significant variable is less than 5% of its standard deviation (in Table 2). This indicates that convergence and accuracy of posterior estimates are attained and the model is appropriate to estimate posterior statistics.

4. Discussions

According to the result of the analysis, the proportion of women become pregnancy was 0.213. From Chi-square test of association, all predictor variables except functional status and religion had significant association with the incidence of pregnancy. In Bayesian analysis, the posterior inference was implemented by Gibbs sampler algorithm with 20000 iterations in three independent different chains and 5001 burn in terms discarded. The result of this study shown that time series plot of parameters of the three independent generated chains were mixed together or over lapped. For the given parameters, the red line (ratio) of Gelman-Rubin statistic was also close to one, both indicates there is a good convergence of algorithm. Autocorrelation plots of the parameters shown that, the correlation were small, indicates that the samples obtained appear to be independent. Posterior density gives uni-model distribution which is nearly symmetric and closes to normal, this indicate that the posterior mean as a good measure of central location. In general, based on those four criteria, there was no evidence of convergence problem for significant variables. The posterior estimate of Bayesian analysis was accurate and precise, since MC error was less than 5% of the related posterior standard deviation. The result of posterior mean indicated that age and WHO clinical stage were negatively related with incidence of pregnancy whereas CD4 count, time of ART follow-up and educational level were positively associated with incidence of pregnancy. That is, women with college and above educational level were more likely to become pregnant compared to non-educated women. Women who had HIV positive spouse were more likely to become pregnant compared to those who had HIV negative spouse. The study has shown that WHO clinical stage was strong predictor variable of incidence of pregnancy. Advanced WHO clinical stage was associated with decreasing the probability of women becoming pregnant, that means when WHO clinical stage increase, incidence of pregnancy become decrease. This implies that women who have WHO clinical stage IV had less chance to be pregnant than stage I. This is result is similar with the result done by [8]. The study shown

that, marital status was significant factor for incidence of pregnancy of AIDS patient women on ART follow up. That is, currently married women were more likely to become pregnant as compared with never married women and this result is supported by similar findings of [7, 10, 11]. Contraception use of women was significant predictor of incidence of pregnancy, the incidence of pregnancy was highest for women who never used contraception, and lowest for women who used contraception always. In general, women who ever-used contraception (mostly, always) was less likely to became pregnant. This is similar with the study of [10] in Uganda. The number of child alive before ART follow-up was important significant variable for incidence of pregnancy. Women who had child alive have less chance to be pregnant compared with women who had no child alive and this result was consistent with the finding of [10]. As shown in the result, occupation of women also the significant factor of incidence of pregnancy. Employed women were more likely to become pregnant compared to unemployed women, whereas students and housewife women have no significant difference to become pregnant compared with unemployed women. This implies that incidence of pregnancy was higher in employed women than other groups; this idea is inconsistent with the study by [8] in Malawi. Age of women was significantly and negatively related with incidence of pregnancy on ART follow-up. The highest incidence of pregnancy was occurred in the age group of 15-24 and 25-29 than older women, but there was no significance difference of incidence of pregnancy between age group of 15-24 and 25-29. In general, when age of women increased, the probability of becoming pregnant decreased. This is similar with studies of [7-11]. The result also showed that incidence of pregnancy was positively related with CD4 count of the patient women under ART follow up. Incidence of pregnancy of women was increased with increased of CD4 cell count. The incidence of pregnancy during ART follow-up was highest among women with CD4 count greater than 500 cell counts. This result is similar with findings of [7, 9, 11]. The duration of time of ART follow-up of women was found an important predictor of incidence of pregnancy. That is, time of ART follow-up was positively related with incidence of pregnancy since the posterior mean of time on ART for 25-48 and greater than 48 months were positive. In general, women with time on ART greater than 24 months were more likely to become pregnancy than women on ART less than 24 months. This indicate that longer time on ART follow-up were associated with increasing the probability of becoming pregnant and this idea is similar with the study of [8].

5. Conclusions

The main purpose of this study was to identify the significant factors of incidence of pregnancy among HIV/AIDS patient women under ART follow-up of reproductive ages (15-49 years). Bayesian logistic regression analysis was adopted to meet the objective of the study. Out of 328 sample women, 21.3% were pregnant during the follow-up. The major factors that have a significant effect on incidence of pregnancy were WHO clinical stage, marital status, number of child alive before ART follow-up, use of contraception, occupation, educational level, CD4 count, time of ART follow-up, spouse's HIV status and age. Moreover, there was a decreasing incidence of pregnancy with increasing age and advanced WHO clinical stage were associated with decreased incidence of pregnancy. Time on ART was a strong predictor of becoming pregnant: longer time on ART was associated with increased probability of becoming pregnant. Educational level of Women was positively related with incidence of pregnancy that is, Women who had college and above educational level was more likely to become pregnancy. At the same time, when CD4 count increased, incidence of pregnancy also increased and married women had more chance to become pregnancy. The predictors identified in this study can be used to care for those HIV/AIDS patient women who want to have baby. Clinician should consult women to take ART properly when the patients have faced advanced WHO clinical stage and low CD4 count. Health service organizations should promote the awareness of the advantages of ATR during the follow-up for patient women to have HIV free baby. Health workers should promote patient women to marry HIV positive husband to support and encourage pregnancy. Further research is needed to identify other factors of incidence of pregnancy especially on longitudinal aspects.

References

[1] Cooper, D., Harries J., Myer, L., Orner, P., Bracken, H. (2007). ""Life is Still Going on": Reproductive Intentions among HIV-Positive Women and Men in South Africa," Social Science and Medicine, vol. 65, no. 2, pp. 274–283.

[2] UNAIDS (2013). Report on the Global AIDS Epidemic.

[3] UNICEF (2013). Prevention of Mother to Child Transmission, Thematic Briefing Note , Media and External Relations Section UNICEF Ethiopia, July 2013

[4] Godana, W., Atta, A. (2013). Prevalence of HIV/AIDS and its Associated Factors among Prevention of Mother-to-Child Transmission (PMTCT) Service Users in Jinka Town Health Institutions, South Omo Zone, South Ethiopia, Vol. 1, No. 3, 2013, pp. 125-130.

[5] Siegfried, N., Merwe, V., Brocklehurst, P., Sint, T. T. (2011). Antiretrovirals for Reducing the Risk of Mother-to-Child Transmission of HIV Infection. Cochrane Database Syst Rev 2011, CD003510.

[6] Makumbi, F. E, Nakigozi, G., Reynolds, S. J., Ndyanabo, A., Tom L., Serwada, D. Nalugoda, F., Wawer, M., and Gray, R. (2010). Associations between HIV Antiretroviral Therapy and the Prevalence and Incidence of Pregnancy in Rakai, Uganda, Vol. 2011.

[7] Tweya, H., Feldacker, C., Breeze, E., Jahn, A., Haddad, L. B., Ben-Smith, A., Chaweza, T., Phiri, S. (2012). Incidence of Pregnancy among Women Accessing Antiretroviral Therapy in Urban Malawi: A Retrospective Cohort Study, AIDS Behav (2013) 17:471–478.

[8] Westreich, D., Maskew, M., Rubel, D., Mac, P. D., Jaffray, I., Majuba, P. (2012). Incidence of Pregnancy after Initiation of Antiretroviral Therapy in South Africa: A Retrospective Clinical Cohort Analysis, Volume 2012, Article ID 917059, 7pages.

[9] Kabami, J., Turyakira, E., Biraro, S., Bajunirwe, F. (2014). Increasing Incidence of Pregnancy among Women Receiving HIV Care and Treatment at a Large Urban Facility in Western Uganda, 11:81 doi: 10.1186/1742-4755-11-81.

[10] Ruth, K. F., Francisco, I. B. (2010). Pregnancy Rates and Predictors in Women with HIV/AIDS in Rio de Janeiro, Southeastern Brazil, Rev Saúde Pública 2011;45(2):373-81.

[11] Henry D. (2013).Bayesian Logistic Regression Modelling via Markov Chain Monte Carlo Algorithm. Journal of Social and Development Sciences**,** Vol. 4, No. 4, pp. 193-197, Apr 2013 (ISSN 2221-1152).

[12] Rashwan, N. I., Eldereny, M. (2012). The Comparison between Results of Application Bayesian and Maximum Likelihood Approaches on Logistic Regression Model for Prostate Cancer Data. Journal of Applied Mathematical Sciences, Vol. 6, no. 23, p.1143 – 1158.

[13] Aparecida, D. P., Helio S. M. (2004). Bayesian Binary Regression Model: An Application to In-Hospital Death after AMI Prediction. Pesquisa Operacional, v.24, n.2, p.253-267.

[14] McCullagh, P., Nelder, J. A. (1989). Generalized Linear Models. 2nd Edition. Chapman and Hall, New York, USA.

[15] Cox, D. R., and Snell, E. J. (1989). Analysis of Binary Data. London: Chapman and Hall.

[16] Hosmer, D. and Lemeshow, S. (2000). Applied Logistic Regression, Second Edition, John Wiley & Sons Inc., New York.

[17] Gelman, A., Carlin, J. C., Stern, H. and Rubin, D. B. (1984). Bayesian Data Analysis. Chapman and Hall, New York.

[18] Muluneh, S., Emmanuel, G., (2011). Factors Influencing the Intention Not to Use Contraceptives among Sexually Active Women in Ethiopia, vol. 20.

[19] Merkle, E., Zandt, T. V. (2005). WinBUGS Tutorial Outline.

[20] Brooks, S. P. and Gelman, A. (1998). Alternative Methods for Monitoring Convergence of Iterative Simulations. Journal of Computational and Graphical Statistics.7, 434-455.