Bayesian Modeling of Incidence of Pregnancy among Women under ART Follow-up at Adare Hospital, Hawassa, Ethiopia

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Abstract

Background: HIV/AIDS is the most serious disease 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 giving birth to a healthy (HIV-free) baby could be significantly improved with increased access to antiretroviral therapy (ART). Despite this fact, HIV infected women largely shun pregnancy in fear of mother to child transmission of HIV.

Objective: The objective of this study was to investigate the likelihood of pregnancy among HIV/AIDS patient women under ART follow-up.

Methods: A retrospective cohort study was conducted based on secondary data obtained from the medical chart of HIV/AIDS patient women aged 15-49 years under ART follow-up from April 2008 to February 2015. Out of all women under ART follow-up in Adare Hospital, Hawassa, a sample size of 328 was selected by using simple random sampling. Bayesian binary logistic regression analysis was used to identify the significant factors of likelihood of pregnancy.

Results and conclusions: The results of this study revealed that 21.3% of women got pregnant during the follow-up period. Bayesian logistic regression analysis indicated that younger age, lower levels of education and advanced WHO clinical stages were associated with decreased likelihood of pregnancy among women under ART follow-up. On the other hand, longer time on ART and higher CD4 cell counts were positively related with the incidence of pregnancy. The predictors identified in this study could be used to care for those HIV/AIDS patient women who want to bear children.

Keywords: *HIV/AIDS, antiretroviral therapy, Bayesian logistic regression, likelihood of pregnancy*

1. Background

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 (Cooper et al., 2007). HIV/AIDS compromises their immunity which further aggravates their chances of conception and supporting pregnancy to term. AIDS epidemic has now spanned more than three decades and was first recognized by the United States Center for Disease Control and Prevention in 1981. An estimated 35.3 million people were living with HIV worldwide in 2012. The number of new infections has declined by 33% from 2001 (3.4 million) to 2012 (2.3 million). Due to improved access to antiretroviral therapy (ART), the number of AIDS deaths has declined from 2.3 million in 2005 to 1.6 million in 2012 (UNAIDS, 2013).

The massive global expansion of access to antiretroviral treatment (ART) has transformed not only the HIV epidemic but the entire public health landscape, demonstrating that the right to health can be realized even in the most trying of circumstances. In low and middle income countries, about 1.6 million more people were receiving ART at the end of 2012 compared with a year earlier, with the greatest contribution coming from the WHO African Region. The 300000 people who were receiving ART in low and middle income countries in 2002 increased to 9.7 million in 2012. This figure represented 61% of all people who were eligible. The scaling up of ART averted an estimated 4.2 million deaths in these countries between 2002 and 2012. In the WHO African Region, which continues to bear the brunt of the HIV epidemic, more than 7.5 million people were receiving treatment at the end of 2012 compared to 50000 people a decade earlier (WHO, 2013).

In 2012, over 900000 pregnant women living with HIV received treatment for prevention of mother-to-child transmission (PMTCT) – one third more than in 2009. Expanding programs for PMTCT and the use of more effective ARV regimens helped prevent more than 800000 children from becoming newly infected between 2005 and the end of 2012. In the 21 African priority countries in the Global Plan, which account for about 90% of all pregnant women living with HIV and new infections among children globally, mother-to-child transmission rates declined overall from an estimated 26% [24-30%] in 2009 to 17% [15-20%] in 2012 due to increased access to ART (WHO, 2013).

The global roll-out of ART has contributed to a greater awareness of issues related to fertility and childbearing among HIV-infected women and men, particularly in sub-Saharan Africa where a large proportion of HIV-infected individuals are women in their reproductive years and the prevention of mother-to-child transmission of HIV is an ongoing challenge (WHO, 2008). Few qualitative studies from Africa suggest that HIV might modify but does not eliminate broader desires to have children and that ART use may be associated with increased fertility desires among HIV-infected women, possibly through increased hopes and planning for the future (Maier, 2008).

Based on EHNRI (2012) and EDHS (2011) estimates, about 760, 000 people were living with HIV in Ethiopia in 2012. The country has recorded some modest progress with respect to access to ART for its population. For instance, the ART coverage has increased from 55% in 2011 to 60% in 2012. In the country, approximately 38,000 pregnant women were living with HIV and 15,828 (about 41%) of these have received a full course of effective ARV treatment to prevent mother to child transmission in 2012. This coverage was remarkably higher compared to a year earlier (24%).

A number of studies have been conducted in Sub-Saharan Africa focusing on the incidence of pregnancy among women under ART follow-up. However, as to the authors' knowledge, there were no studies on pregnancy status as well as pregnancy rate of women under ART follow-up in Ethiopia. This is particularly essential since there is broad access to ART with extremely large at-risk population of reproductive-age women in the country. To fill this gap, this study attempted to explore the likelihood of pregnancy and its potential predictors among HIV/AIDS patient women under ART follow-up at Adare Hospital, Hawassa, Ethiopia.

Therefore, the objective of this study is to investigate the likelihood of pregnancy among HIV/AIDS patient women under ART follow-up using Bayesian logistic regression analysis. The specific objectives of the study are:

1. To identify the major predictor variables of likelihood of pregnancy among women under ART follow-up.
2. To explore the pregnancy status of HIV/AIDS patient women under ART follow-up
3. To provide information to health workers, governmental & non-governmental organization and researchers.

2. Literature Review

With the advent of antiretroviral therapy (ART) and heightened global support for HIV/AIDS treatment, HIV positive women are living healthier and longer lives (WHO, 2010). ART use is associated with significantly higher pregnancy rates among HIV-infected women in sub-Saharan Africa. While the possible behavioral or biomedical mechanisms that may underlie this association require further investigation, these data highlight the importance of pregnancy planning and management as a critical but neglected component of HIV care and treatment services. Such services are in a unique position to address the childbearing desires of HIV-infected individuals as well as to ensure safe pregnancy and delivery (Myer et al., 2010).

A study in Uganda by Makumbi et al. (2011) reported that the use of ART was associated with increased pregnancy rates in HIV positive women, while older age and use of family planning were associated with lower pregnancy prevalence. Moreover, the prevalence of pregnancy during ART use was higher among women with CD4 count of 100–250 compared to those with CD4<100, and women aged 35–45 years compared to those aged 15–24 years.

According to a study in urban Malawi (Tweya et al., 2013), the incidence of pregnancy was significantly and negatively associated with current age and WHO clinical stage at ART initiation. On the other hand, longer time on ART was associated with increased probability of becoming pregnant. A retrospective clinical cohort study in South Africa reported that rates of pregnancy were highest in women with CD4 cell counts in the range 350 – 500 and much higher in younger women compared to older women (Westreich et al., 2012).

A study by Myer et al. (2010) utilizing proportional hazards models revealed that the factors that were significantly associated with an increased risk of pregnancy of women under ART follow-up included younger age, increased duration of follow-up, lower levels of education, being married or cohabiting, nonuse of contraception, and higher current CD4 cell counts. On the other hand, more advanced HIV disease (as indicated by higher WHO staging) was strongly associated with reduced incidence of pregnancy.

According to a study by Kabami et al. (2014) in western Uganda, younger women, women who have fewer children and women who did not know their spouse's HIV status were more likely to get pregnant. The study found no significant association between pregnancy and religion, WHO disease stage and CD4 cell count at enrollment. A study conducted in southeastern Brazil has shown that age, level of education, marital status, use of ART and CD4 cell count were associated with the risk of pregnancy. However, the number of living children and HIV-related conditions did not show a clear association with pregnancy (Ruth et al., 2010).

As discussed above, studies have been conducted in Sub-Saharan Africa focusing on the incidence of pregnancy among women under ART follow-up. However, as to the authors' knowledge, there were no studies on pregnancy status as well as pregnancy rate of women under ART follow-up in Ethiopia. To fill this gap, this study attempted to explore the likelihood of pregnancy and its potential predictors among HIV/AIDS patient women in the country.

3. Materials and Methods

3.1 Study design, data source and sample size

A retrospective cohort study was conducted based on secondary data obtained from medical charts of HIV infected women from ART clinic of Adare Hospital, Hawassa, Ethiopia. All HIV/AIDS patient women aged between 15 and 49 years who were under ART follow-up for at least three months between April 2008 and February 2015 comprise the population under consideration. A random sample of 328 women under ART follow-up was selected using single population proportion formula with degree of precision 4%. The data were collected by data experts from the ART clinic of the hospital using a structured questionnaire prepared to explore the factors that are associated with likelihood of pregnancy**.** The questionnaire was pre-tested to assess its clarity, flow and consistency.

3.2 Variables in the study

a) **Dependent variable**

The dependent (outcome) variable of the study was pregnancy status of HIV/AIDS patient women under ART follow-up. For logistic regression analysis, those women who were pregnant at the time of the survey were coded as 1 and those who were not as 0.

b) **Explanatory variables**

Based on the literature reviewed, the independent variables that are used to explore the likelihood of pregnancy of HIV/AIDS patient women under ART follow up were age, level of education, occupation, marital status, religion, place of residence, number of children alive before ART follow-up, contraception use, WHO clinical stage, illness due to co-infection, body weight, time under ART follow-up, CD4 cell count and spouse's HIV status.

3.3 Logistic regression model

Logistic regression analysis extends the techniques of multiple regression analysis to research situations in which the dependent variable is categorical. Logistic regression allows one to predict a discrete outcome, such as group membership, from a set of independent variables that may be continuous, discrete, dichotomous, or a mix of any of these. It is much more relaxed and flexible in its assumptions than multiple regression analysis. Unlike multiple linear regression analysis, for instance, logistic regression does not have the requirements of the dependent variable to be normally distributed, linearly related, nor equal variance within each group (Hosmer & Lemeshow, 2000). Logistic regression has a peculiar property of easiness to estimate logit differences for data collected both retrospectively and

prospectively (Mc Cullagh and Nelder, 1983) and this has contributed a lot to its importance in application areas.

Binary logistic regression is a type of logistic regression that is used when the dependent variable is dichotomous and the predictor variables are of any type. It estimates the probability that a certain characteristic is present (in our case, the probability that a woman under ART follow-up is pregnant) given the values of explanatory variables. Suppose $X_i = (x_{1i}, x_{2i}, \ldots, x_{ki})'$ denotes the vector of predictor variables for the i^{th} individual, $i = 1, 2, \ldots, n$. The probability of success of the i^{th} individual (that is, the probability that i^{th} woman under ART follow-up is pregnant) given her background characteristics X_i is given by:

$$P_i = \Pr ob(Y_i = 1 | X_i) = \frac{e^{X_i'\beta}}{1 + e^{X_i'\beta}} \quad \ldots\ldots (1)$$

where $\beta = (\beta_1, \beta_2, \ldots, \beta_k)'$ is a vector of unknown parameters. The logit transformation of P_i is a linear function of the explanatory variables:

$$\log it(P_i) = \ln\left[\frac{P_i}{1 - P_i}\right] = X_i'\beta = x_{1i}\beta_1 + x_{2i}\beta_2 + \ldots + x_{ki}\beta_k \quad \ldots\ldots (2)$$

This transformation has certainly helped the popularity of the logit model.

3.4 Bayesian logistic regression

Bayesian analysis is a statistical procedure that answers research questions by expressing uncertainty about unknown parameters using probabilities. It is based on the fundamental assumption that not only the outcome of interest but also all the unknown parameters in a statistical model are essentially random and are subject to prior beliefs.

Bayesian analysis starts with the specification of a posterior model. The posterior model describes the probability distribution of all model parameters conditional on the observed data and some prior knowledge. The posterior distribution has two components–a likelihood, which includes information about model parameters based on the observed data, and a prior, which includes prior information (before observing the data) about model parameters. The likelihood and prior models are combined using the Bayes rule to produce the posterior distribution: Posterior $\propto$ Likelihood x Prior

3.4.1 Likelihood function

Each response Y_i may be treated as a single draw from a Bernoulli distribution with probability of success equal to P_i, $i = 1, 2, \ldots, n$. Since the responses $Y_1, Y_2, \ldots, Y_n$ are assumed to be independent, their joint density is simply the product of Bernoulli probabilities. Thus, using equation (1), the likelihood function is given by:

$$L(\beta \mid Y_1, Y_2, \ldots, Y_n; X) = \prod_{i=1}^{n} P_i^{y_i}(1-P_i)^{1-y_i}$$

$$= \prod_{i=1}^{n}\left[\left(\frac{e^{X_i'\beta}}{1+e^{X_i'\beta}}\right)^{y_i}\left(1-\frac{e^{X_i'\beta}}{1+e^{X_i'\beta}}\right)^{1-y_i}\right] \ldots\ldots (3)$$

3.4.2 Prior distribution

To progress with the Bayesian analysis, it is necessary to specify a joint prior distribution over the parameter space. If no prior information on the model parameters exists or it is difficult to elicit or formalize, then initial uncertainty about the parameters can be quantified with a non-informative prior distribution. This is equivalent to utilizing just the information provided by the data in the analysis. Souza and Migon (2004) and Migon and Tachibana (1997) proposed independent normal priors for the components of β with extremely small precisions. These priors are equivalent to non-informative priors on these parameters, with all parameter values treated as equally plausible, and are given by:

$$f(\beta_j) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left\{\frac{-1}{2}\left(\frac{\beta_j-\mu_j}{\sigma_j}\right)^2\right\} \qquad j = 1, 2, \ldots, k \ \ldots\ldots (4)$$

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 $\sigma_j = 10$ to $\sigma_j = 100$ (Rashwan et al., 2012).

3.4.3 Posterior distribution

The posterior distribution is obtained by multiplying the prior distribution over all parameters by the full likelihood function, and is given by:

$$p(\beta \mid Y; X) = \prod_{i=1}^{n}\left[\left(\frac{e^{X_i'\beta}}{1+e^{X_i'\beta}}\right)^{y_i}\left(1-\frac{e^{X_i'\beta}}{1+e^{X_i'\beta}}\right)^{1-y_i}\right] \mathrm{x} \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left\{\frac{-1}{2}\left(\frac{\beta_j-\mu_j}{\sigma_j}\right)^2\right\} \ldots (5)$$

3.4.4 Markov chain Monte Carlo

Posterior distributions are rarely available in analytical forms and often involve multidimensional integrals. They are commonly estimated via simulation. Markov chain Monte Carlo (MCMC) sampling is often used to simulate potentially very complex high-dimensional posterior distributions. MCMC is a simulation-based method of estimating posterior distributions. It produces a sequence or a chain of simulated values (MCMC estimates) of model parameters from the estimated posterior distribution. If the chain "converges", the sequence represents a sample from the desired posterior distribution. There are different MCMC methods to estimate the chains of simulated values. Two more commonly used MCMC methods are Metropolis-Hastings (MH) algorithm and Gibbs algorithm.

3.4.5 The Gibbs sampling algorithm

Gibbs sampling (Gibbs sampler) introduced by Geman and Geman (1984) is an MCMC algorithm for obtaining a sequence of observations which are approximated from a specified multivariate probability distribution when direct sampling is difficult. This sequence can be used to approximate the joint distribution of a set of random variables or the marginal distribution of one of the variables or some subset of the variables. As with other MCMC algorithms, Gibbs sampling generates a Markov chain of samples, each of which is correlated with nearby samples. As a result, care must be taken if independent samples are desired. Generally, samples from the beginning of the chain (the burn-in period) may not accurately represent the desired distribution and are usually discarded. For this reason, MCMC algorithms are typically run for a large number of iterations in the hope that convergence to the target posterior will be achieved (Gelfand and Smith, 1990). In this study, the Gibbs sampler algorithm was used to estimate the marginal posterior distribution for each of the parameters by WinBUGS software.

3.4.6 Assessment of convergence of MCMC algorithm

The basic idea on an MCMC algorithm is to create a Markov process that has a stationary distribution which is the same as the posterior distribution of interest. Thus, technically speaking, convergence occurs when the generated Markov chain converges in distribution to the posterior distribution of interest. In an attempt to perform some kind of statistical analysis to assess the convergence of MCMC algorithms, a number of convergence diagnostics have been suggested (e.g., Brooks and Gelman, 1998; Cowles & Carlin, 1996; Brooks & Roberts, 1998). These include trace (time series) plots, autocorrelation plots, Gelman-Rubin statistics and density plots. For instance, a trace plot illustrates the values of the simulated parameters against the iteration number and connects consecutive values with a line. For a well-mixing parameter, the range of the parameter is traversed rapidly by the MCMC chain, which makes the drawn lines look almost vertical and dense. Sparseness and trends in the trace plot of a parameter suggest

convergence problems. For a given parameter, the Gelman-Rubin statistic compares the within-chain and between-chain variabilities. The model is judged to have converged if the ratio of between to within variability is close to one.

Once we confirm that convergence has been achieved, further iterations are needed to obtain samples for posterior inference. To assess the accuracy of the posterior estimates, we can use the Monte Carlo error for each of the parameters. As a rule of thumb, if the MC error is less than 5% of its posterior standard deviation, then we can conclude that the posterior density is estimated with accuracy.

4. Results and Discussion

The objective of the study was to identify factors that affect the likelihood of pregnancy of HIV/AIDS patient women under ART follow-up. Among the 328 women included in the analysis, 21.3% had pregnancy during the study period. The Chi-square test of association was employed to examine the association between the response variable (whether a woman under ART follow-up is pregnant or not) and predictor variables. The results revealed that pregnancy of women under ART follow-up is significantly associated with WHO clinical stage, spouse's HIV status, marital status, educational level, occupation, contraceptive use, number of children before ART follow-up, age, CD4 cell count and time under ART follow-up. The percentage distribution reveals that the likelihood of pregnancy increases with the level of education and CD4 cell counts of women under ART follow-up, and decreases with increases in age and WHO clinical stages.

Bayesian analysis was utilized to estimate the parameters of the binary logistic regression model. The Gibbs sampler algorithm was implemented with 20000 iterations in three different chains, and 5000 burn-in terms were discarded from each so as to get 45000 samples from the posterior distribution. Table 1 presents the Bayesian logistic regression results based on the sample obtained from the joint posterior distribution.

The results indicate that WHO clinical stage, marital status, spouse's HIV status, educational level, contraception use, number of children before ART follow-up, occupation, CD4 cell count, time under ART follow-up and age were significant predictor variables of likelihood of pregnancy among women under ART follow-up (since the 95% credible intervals do not contain zero for at least one category of predictor variables). From the posterior means we can see that the likelihood of pregnancy was positively associated with time under ART follow-up, educational level and CD4 cell count. In contrast, WHO clinical stage, age and number of children alive at ART initiation were negatively associated with likelihood of pregnancy.

Table 1: Summary statistics of the posterior distribution of the model parameters

					95% Credible Interval	
Predictor	Category	Mean ($\hat{\beta}$)	S.E.	MC Error	Lower	Upper
Constant		-3.383	0.181	0.102	-10.230	2.693
Time under ART follow-up	25-48 month	4.542*	0.067	0.012	2.288	7.080
	> 48 months	3.935*	0.072	0.013	1.455	6.565
	≤ 24 months (ref.)					
WHO clinical stage	Stage II	-2.118*	0.067	0.013	-4.204	-0.151
	Stage III	-7.611*	0.103	0.023	-11.490	-4.180
	Stage IV	-6.779*	0.142	0.021	-12.120	-1.965
	Stage I (ref.)					
Spouse HIV status	Positive	2.644*	0.062	0.013	0.490	4.912
	Unknown	-1.072	0.060	0.008	-3.226	1.038
	Negative (ref.)					
Marital status	Unmarried	-6.626*	0.091	0.015	-10.060	-3.595
	Divorced	-7.185*	0.091	0.016	-10.640	-4.199
	Widowed	-6.702*	0.106	0.017	-10.770	-3.237
	Married (ref.)					
Educational level	Primary	1.515	0.071	0.019	-0.936	4.104
	Secondary	1.438	0.081	0.028	-1.365	4.417
	College and above	2.913*	0.083	0.024	0.048	5.944
	No education (ref.)					
Contraception uses	Rarely	-1.708	0.081	0.009	-4.604	1.131
	Mostly	-5.610*	0.082	0.015	-8.692	-2.904
	Always	-5.463*	0.091	0.015	-9.009	-2.530
	Never use (ref.)					
Number of children alive	1-2 child	-3.834*	0.059	0.011	-6.051	-1.854
	3 or more children	-2.728*	0.074	0.012	-5.445	-0.194
	No child (ref.)					
CD4 Count	250-350	-4.547*	0.099	0.027	-8.150	-1.088
	351-500	2.491	0.085	0.032	-0.389	5.693
	>500	3.699*	0.079	0.026	1.110	6.704
	<250 (ref.)					
Occupation	Employed	4.018*	0.069	0.017	1.664	6.636
	Housewife	0.936	0.065	0.011	-1.345	3.273
	Student	-3.240	0.159	0.012	-9.124	2.232
	Unemployed (ref.)					
Age	25-29	0.633	0.065	0.015	-1.633	2.985
	30-34	-3.661*	0.087	0.019	-6.909	-0.727
	35-39	-6.398*	0.105	0.018	-10.330	-2.899
	40-49	-4.836*	0.142	0.018	-10.190	-0.047
	15-24 (ref.)					

ref. = reference category, * = significant at the 5% level

4.1 Assessment of convergence and accuracy of the fitted model

The convergence of the parameter estimates was assessed using the trace, autocorrelation and density plots as well as Gelman-Rubin statistics.

The trace plots of all parameter estimates under consideration look like a horizontal band (the three independently generated chains appear to be overlapping on one another), with no long upward or downward trends. Thus, we are reasonably confident that convergence has been achieved for the estimated parameters (that is, the Markov chain has converged to its stationary distribution for each of the parameter estimates). The time series plots for time under ART follow-up (25-48 months) and WHO clinical stage II are shown in Figure 1 for illustration.

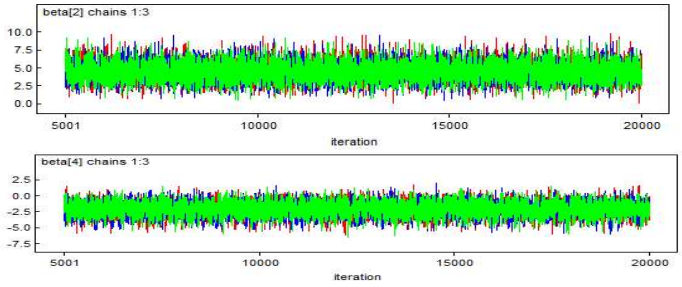

Figure 1: Trace plots of selected regression coefficient estimates

The realized values during MCMC are not independent of each other. The autocorrelation plot is a popular measure of this dependence. High autocorrelations indicate slow mixing within a chain, and hence, slow convergence to the posterior distribution. In this study, we observe quick drop-off in the autocorrelation functions of all parameter estimates as the number of lags increases. This is an indication that the sampler explored the posterior distribution much quicker. For illustration, the autocorrelation plots of time under ART follow-up (25-48) and WHO clinical Stage II are displayed in Figure 2.

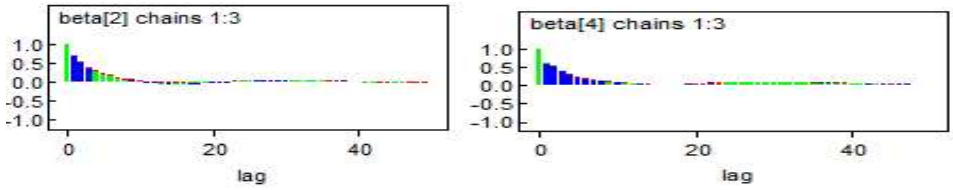

Figure 2: Autocorrelation plots of selected regression coefficient estimates

The Gelman-Rubin statistics which compare the within-chain and between-chain variabilities are alternative measures of convergence. This ratio converged to approximately one for each of the parameter estimates considered in this study. Thus, we can safely conclude that convergence of chains has been achieved. The Gelman-Rubin statistics for time under ART (25-48 months) and WHO clinical stage II are shown below.

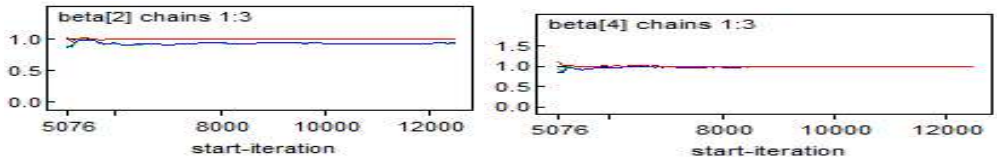

Figure 3: Gelman-Rubin diagnostics for selected regression coefficient estimates

The density plots (marginal posterior distributions) for beta parameters obtained from the joint distribution were found to be symmetric, unimodal and approximately normally distributed. This is an indication that the Markov chain has attained its posterior distribution. Figure 4 displays the density plots for time under ART (25-48 months) and WHO clinical stage II.

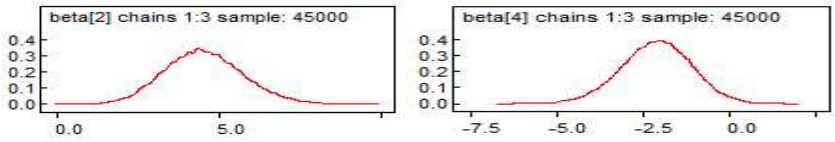

Figure 4: Density plots of selected regression coefficient estimates

The accuracy of posterior estimates can be assessed by comparing the Monte Carlo error for each of the parameters with the posterior standard deviation. In this study, the MC error for each of the significant parameters was less than 5% of its posterior standard deviation. This indicates that the posterior density is estimated with accuracy and that the fitted model is adequate for posterior inference.

4.2 Discussion

The duration of time under ART follow-up was found to be a significant predictor of likelihood of pregnancy. Women with ART follow-up period of greater than 24 months were more likely to become pregnant compared to those who were under ART follow-up for less than 24 months. This indicates that longer time on ART was associated with increased probability of becoming pregnant. This result is supported by the findings of Tweya et al. (2013) and Myer et al. (2010) in which the risk of pregnancy appeared to increase continuously with increasing duration of follow-up in women on ART.

The study has shown that WHO clinical stage was a significant predictor of likelihood of pregnancy among women under ART follow-up. Women in advanced WHO clinical stages were less likely to become pregnant as compared to those in stage I. This is result is similar with that reported by Tweya et al. (2013) and Myer et al. (2010). Our result also revealed that lower CD4 cell counts during follow-up were associated with lower incidence of pregnancy. For instance, women with CD4 cell counts less than 250

were less likely to be pregnant compared to those whose CD4 cell counts were in excess of 500. Various studies have reported similar findings (Westreich et al., 2012; Makumbi et al, 2011; Ruth et al., 2010; Myer et al., 2010).

The other significant predictor was level of education. The results revealed that educational level was positively associated with the likelihood of pregnancy. In particular, women under ART follow-up with college and above educational level were more likely to become pregnant compared to non-educated women. This result is consistent with those of Myer et al. (2010) who reported that lower levels of education are significantly associated with an increased risk of pregnancy of women under ART follow-up. Marital status was found to be significantly associated with the likelihood of pregnancy among AIDS patient women under ART follow up. Our result indicated that women who were married or cohabiting at enrollment were more likely to become pregnant. This finding is also supported by similarly studies (Makumbi et al, 2011; Kabami et al., 2014; Ruth et al., 2010). Contraception use was another significant predictor of likelihood of pregnancy. The likelihood of pregnancy was highest for women under ART follow-up who never used contraception, and lowest for women who used contraception (mostly or always). This result is consistent with the studies of Kabami et al. (2014) and Myer et al. (2010) in which women who reported any contraceptive use during follow-up had lower pregnancy rates than those who did not.

The results of this study indicated that the number of children alive before ART follow-up had a significant influence on likelihood of pregnancy, that is, women who had at least one child at ART initiation were less likely to be pregnant compared to those who had no children. The result is consistent with the findings of Kabami et al. (2014). Occupation of women was also a significant factor of likelihood of pregnancy. Employed women were more likely to become pregnant compared to unemployed women, whereas there was no significant difference in the likelihood of pregnancy among students and housewives compared to unemployed women. This result is inconsistent with that reported by Tweya et al. (2013) in Malawi.

Age was significantly and negatively related with the likelihood of pregnancy among women under ART follow-up. The likelihood of pregnancy was significantly higher for women in the age groups 15-24 and 25-29 compared to those in older age groups. In general, when age of women increased, the probability of becoming pregnant decreased. This finding is supported by similar studies (Westreich et al., 2012; Tweya et al. 2013; Makumbi et al, 2011; Kabami et al., 2014; Ruth et al., 2010).

5. Conclusion and Recommendations

The main purpose of this study was to identify the factors that are associated with the likelihood of pregnancy among HIV/AIDS patient women of reproductive ages (15-49 years) under ART follow-up. From the descriptive analysis, the proportion of women under ART follow-up who became pregnant during the study period was 21.3%. In Bayesian analysis, the posterior inference was implemented by Gibbs sampler algorithm. MCMC diagnostic measures (trace, posterior density & autocorrelation plots and Gelman-Rubin statistics) suggested that each of the parameter estimates has converged to its posterior distribution.

The factors that were significantly associated with an increased risk of pregnancy included younger age, lower levels of education, being married, non-use of contraception, longer time on ART follow-up and higher CD4 cell counts. On the other hand, having live children before initiation of ART and advanced WHO clinical stages were negatively associated with the incidence of pregnancy of mothers under ART follow-up.

Recommendations

Based on the results of this study, the following recommendations are forwarded:

- Our results revealed that the likelihood of pregnancy among HIV/AIDS patient women has increased with an increase in duration of ART follow-up. This demands the inclusion of pregnancy planning and management strategy as a critical component of HIV care and treatment services.

- Women in advanced WHO clinical stage and low CD4 cell counts were found less likely to be pregnant. This might probably be attributed to their apprehensions towards their health and that of the child. Appropriate planning prior to pregnancy and administration of effective interventions during pregnancy will help to address the childbearing desires of HIV-infected women as well as to ensure safe pregnancy and delivery.

- Among the women under ART follow-up in this study, an overwhelming majority (64%) had never used contraceptives. Low prevalence of contraceptive use underscores the importance of addressing fertility-related issues within HIV care and treatment programs.

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