# Bayesian Binary Logistic Generalized Linear Mixed Models of Female Genital Mutilation

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**Abstract**

**Background:** Female genital mutilation could be a global public unhealthiness, and it's practiced by many communities in Africa, special Ethiopia. In Ethiopia, the factors related to FGM practices are poorly understood. Therefore, this study aimed to assess the prevalence of female genital mutilation and its associated factors with FGM among reproductive age women within the country.

**Method:** A secondary data analysis was disbursed supported the Ethiopia Demographic and Health Survey 2016. Bayesian binary Logistic Regression GLMM, which allows taking into consideration both individual and population variability in model parameter estimate was employed.

**Results:** The general prevalence of female genital mutilation among participants (15-49 years old) in Ethiopia was found to be 69.6%. From Bayesian random intercept binary logistic analysis it had been found that rural, Muslim, middle Wealth index, rich Wealth index people, Secondary and above were statistically significant with Female genital mutilation.

**Conclusion:** Rural residence, Muslim religion, middle wealth index , rich wealth index, people 25-34 years old, the people 35-49 years old, ever heard of female genital mutilation, occupation of girls were positively related to female genital mutilation practice. On the opposite hand, husband/partner's primary education level, husband/partner's secondary and above educational level, husband/partner occupation (merchant and others) were negatively related to female genital mutilation. Despite the presence of various interventions, the prevalence of female genital mutilation continues to be very high within the country.

**Keywords**: Bayesian, Ethiopia, Factors, Female Genital Mutilation, Women, Binary

## Background

Female genital mutilation refers to all or any procedures that include partial or total removal of the external female genital or other injury to the feminine genital organs whether for cultural or other non –medical reasons, usually without the consent of the individual[1].

FGM is worldwide public unhealthiness affecting most ethnic groups [2]. Globally, in 2016, there are an estimated that quite 200 million women and girls who undergone FGM. The practice is primarily performed in Africa where 30 countries and quite 3 million girls are in peril of experiencing FGM[2, 3] . In East Africa; Ethiopia (74%) have the foremost effective female genital mutilation prevalence[3].

Currently, the globe Health Organization joint statement classified female genital mutilation into four types keep with the type of tissue removed: Type1 (Clitoridectomy): partial or total removal of the clitoris, Type2 (Excision): partial or total removal of the clitoris and labium, Type3 (Infundibulations): narrowing of the vaginal opening through the creation of a covering seal, and Type4 (other): all other injurious procedures to genitals for non-medical purpose that is cauterizing, incising, pricking, piercing, scraping, stretching and the genital area[4].

All sorts of FGM have immediate (short-term) and long-term health complications counting on the type performed and also the hygienic conditions[5]. Immediate health complications include severe pain, anemia thanks to excessive bleeding, genital tissue swelling, shock, and death. Long-term health complications include urinary problems, infection, menstrual problems, sexual problems, psychological problems, increased risk of childbirth complications, and newborn deaths [6]. In Ethiopia, FGM is widespread across the majority of regions and ethnic groups, with Type I and II having the foremost effective national prevalence[7]. The national prevalence of female genital mutilation among girls (age 15–49 years) is 74.3% [8].

FGM has varying sociology-cultural meanings, degrees of practice and support for its continuation or discontinuation. The practice of FGM is maintained due to social and family pressure to stay to tradition and also the meaning passed from generation to generation. Even women support the continuation of FGM for these reasons, leaving other girls and girls to indefensibly suffer the results[9, 10]. Relying on the kind, FGM poses complex socio-cultural and heavy sexual and reproductive health risks for girls and girls. Cultural and social factors for performing has huge problem of FGM. The reasons why female genital mutilations are performed vary from one region to a certain similarly as over time, and include a mixture of sociocultural factors within families and communities[11].

FGM threatens the health and wellbeing of ladies, causing hemorrhage, infection, prolonged labor and pain during gender. It'll be linked to increased future complications and maternal deaths. Understanding the socioeconomic and health consequences of female genital mutilation, the Ethiopian government has shown high levels of political promise to finish FGM. The govt. has been implementing various interventions and FGM has been declining across Ethiopia [12]. However, there has been lack of evidence the factors associated to FGM. This lack of evidence is detrimental to designing interventions for the areas with highest FGM prevalence and indicates a requirement to test the regional variation of FGM and socio-economic factors. Hence, identifying region with higher prevalence is additionally a big turning point for the rapid reduction and elimination of FGM through better targeted population interventions. Therefore, this study identifies the random intercept variation and socio-economic and demographic factors associated with FGM in Ethiopia.

## Methods

The analysis used data from women aged 15-49 years from Ethiopia Demographic and Health Survey (EDHS) 2016. The women data has a hierarchical structure. Because, this structure often yields data that are correlated and thus can be assumed dependencies[13]. Taking into account the hierarchical structure of the dataset and the possible correlation that may exist within and between clusters, we used a two-level random intercept binary logistic regression model. The independent variables included in the data analysis were age, place of residence, religion, wealth index, current marital status, husband/partner education, husband/occupations, and respondent occupation and ever heard of female circumcision. The dependent variable is given that $Y_{ij}= 1$ if female i in region j was female genital mutilation and $Y_{ij}= 0$ if female i in region j was not female genital mutilation. Let $\pi_{ij}$ be the probability of female i in region j being used female genital mutilation. We begin with a random intercept or variance components model that allows the overall probability of female genital mutilation to vary across regions. For the complex hierarchical model, parameter estimation using the classical approach becomes very difficult. Instead, the Bayesian binary logistic GLMMs modeling provide a better solution in the case of complex hierarchical models.

## Bayesian Binary Logistic GLMMs

The generalized linear mixed model (GLMM) to include random effects and fixed effects. The random effect. The random effect was heterogeneity among regions and very widely used in analyzing correlated data. Although, there is often interest in identifying the subset of predictors that have random effects, random effects selection can be complex, especially when outcome distributions are binary[2]. Bayesian inference assumes that the observed data are fixed and the unknown parameters are random, then considered to be drawn from some probability distribution. If we consider a given parameter $\theta$ and a set of observed data, the Bayesian approach will be interested in the probability of the parameter $\theta$ given the set of data available $y$, mathematically this can be written as: $\pi(\theta \mid y)$ [14]. The main interest is in computing the posterior distribution of the unknown parameter $\theta$ given that the observed data $y$. This is obtained by multiplying the prior distributions with the likelihood function and is given as[14]:

$$\pi(\theta \mid y) \propto l(y \mid \theta)\, \pi(\theta)$$

Here, $\pi(\theta)$ is the prior density function of $\theta$, $\pi(\theta \mid y)$ is the posterior density function, and $l(y \mid \theta)$ is the sample likelihood function. The prior and posterior distributions are important constituents of the Bayesian statistical model. The main points for the Bayesian evaluation method are to identify prior distribution according to historical information and select proper methods to determine the posterior distribution. In this case, the model is used for within-unit analysis, dealing with internal heterogeneity, and another model for a cross-unit analysis, dealing with external heterogeneity [15]. Hierarchical model associated with parameter variations between groups when there is a model for these parameters. Occurrence of hierarchy exists when the model parameters are located ‘on’ the model of data.

## Bayesian Variance Components Model

The variance component model estimate the variability accounted for by each level of the hierarchy. We are able to therefore begin by estimating no predictor's model to look at the extent of variability of the dichotomous outcome across level-2 units (regions). The variance component model for individual i in region j. This can be expressed, for a general link function Logit ($p_{ij}$), by the formula [16]:

Logit ($p_{ij}$) =$\beta_0 + +U_{oj}$ . . . (1)

Where $\beta_0$ is fixed intercept and $U_{0j}$ represents the random intercept effect for region j. ICC represents the proportion of the total variance that is attributable to between-group differences and it provides an assessment of whether or not significant between-groups variation exists. Then the intra class correlation coefficient (ICC) at regions level is given by $ICC = \rho = \frac{\sigma_u^2}{\sigma_u^2+\sigma_e^2}$ Where $\sigma_u^2$ is the between-groups variance which can be estimated by $U_{0j}$ and $\sigma_e^2$ is within-group variance [17]. There is no covariate information and the effects are split into terms accounting for regional variation and terms trying to explain region by Female genital mutilation variation. A Bayesian formulation the Variance Components model takes form $y_{ij} \sim Bern(p_{ij})$, logit($p_{ij}$) = $\beta_0 + U_{oj}$ , $\beta_0 \sim$ N($\mu_{\beta,}\sigma_\beta^2$), $U_{oj}/\sigma_j^2 \sim$ N(0, $\sigma_j^2$), $\sigma_j^2 \sim$ inv-gamma($\alpha = 0.001, \beta = 0.001$). The variance component $\sigma_j^2$ (variance of the random effect) measure the variability between the region while $\sigma_e^2 = \frac{\pi^2}{3}$ measure variability of within regions.

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Algorithm 1: Variance Components Model

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1. Set initial values: $\beta_0^{(0)}$,$u_{0j}^{(0)}$ $and\ \sigma_u^{2(0)}$
2. Sampling from the full conational distribution according to i = 0, 1, 2,…, n-1
3. Simulate : $\beta_0^{(i+1)} \sim \pi(\beta_0^{(i)}/\text{Y}, u_{0j}^{(i)}, \sigma_u^{2(i)})$
4. Simulate : $u_{0j}^{(i+1)} \sim \pi(u_{0j}^{i}/\text{Y}, \beta_0^{(i+1)}, \sigma_u^{2(i)})$
5. Simulate: $\sigma_u^{2(i+1)} \sim \pi(\sigma_u^{2(i)} / Y, u_{0j}^{(i+1)}, \beta_0^{(i+1),})$
6. Continue required number of iterations

7. Stop

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## Bayesian Random Intercept Binary Logistic Model

A random intercepts model is vary across the cluster, and therefore, the scores on the dependent variable for each individual observation are predicted by the intercept that varies across groups, but the relation between explanatory and response variables cannot differ between groups. If we have explanatory variable, $x_{ij}$, measured at the female level, then extended two-level random intercept model is as follows:

$$\text{Logit}(\text{p}_{\text{ij}}) = \beta_{0j} + \beta_{1j}\text{x}_{1ij} + \cdots \beta_{kj}\text{x}_{kij}$$

Where the intercept term is assumed to vary randomly across region and is given by the sum of an average intercept βo and group-dependent deviations $U_{oj}$, that is $\beta_{oj}=\beta_o+U_{oj}$. And $u_{0j} \sim N(0,\sigma^2_u)$. For a random intercept model consists of two terms: a fixed component $\beta_0$ and a region specific component, the random effect u0j. Here, it is assumed that the $u_{0j}$ track a normal distribution with mean zero and variance $\sigma^2_{u0}$. Each individual subjects in the group are assumed to be independent of each other, the likelihood function over the data sets of n subjects in the m regions :

$$L(y\backslash\beta,\sigma_u^2) = \prod_{i=1}^{n}\prod_{j=1}^{m}\left(\frac{e^{X_i{}^T\beta+U_{oj}}}{1+e^{e^{X_i{}^T\beta+U_{oj}}}}\right)^{y_{ij}}\left(1-\frac{e^{X_i{}^T\beta+U_{oj}}}{1+e^{e^{X_i{}^T\beta+U_{oj}}}}\right)^{1-y_{ij}}$$

The most available in Bayesian approach is to choice a proper prior distribution to include in the model. The following method is employed in the selection of prior for the Bayesian approach with non-informative since it has not previews evidence.

The prior distribution is using a normal distribution with a large variance with large variance ($\sigma^2_\beta$ = 1000) and mean ($\mu_\beta$= 1). $\beta_d \sim N(\mu_\beta, \sigma^2_\beta)$ where d=1,2,3,…,k

The variance $\sigma^2_\beta$ is transformed to $\tau = 0$.. The region-level random effect $U_{0j} \sim N(0,\sigma^2_u)$ is assumed to be normally distributed (0, $\sigma^2_u$), and $\sigma^2_u$ follows an inverse Gamma distribution (0.001, 0.001). The vague prior is inverse gamma distribution with $\alpha$ = 0.001 and $\beta$ = 0.001[18]. The joint posterior density function will be the product of the priors' distribution and likelihood distribution.

$$p(\beta,\sigma_u^2/y) \ \propto\ L(y\backslash\beta,\sigma_u^2)\times \mathrm{p}(\beta,\sigma_u^2)$$

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Algorithm 2: Bayesian random intercept model with covariates

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1. Set initial values: $\beta_0^{(0)}\ \beta_1^{(0)}\ \ldots.\ \beta_k^{(0)}\ ,u_{0j}^{(0)},\ \sigma_u^{2\,(0)}$
2. Sampling from the full conational distribution according to i = 0, 1, 2,…, n-1
3. Simulate: $\beta_0^{(i+1)}\sim\pi(\beta_0^{(i)}\ /\beta_1^{(i)}\ \ldots.\ \beta_k^{(i)},u_{0j}^{(i)},\sigma_u^{2\,(i)}$,Y,X)

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4. Simulate: $\sigma_u^{2\,(i+1)}\ \sim\pi(\sigma_u^{2\,(i+1)}\ /u_{0j}^{(i+1)},\beta_0^{(i+1)}\ \ldots.\ \beta_k^{(i+1)}$,Y,X)
5. Continue required number of iterations
6. Stop

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**Bayesian Random Coefficient model**

The multilevel random coefficient logistic regression is based on linear models for the log-odds that include random effects for the groups or other higher-level units. Suppose that there are k-level explanatory variables $X_1$, $X_2$…, Xk, and consider the model where all predictor variables have varying slopes and random intercept. That is

$$\mathrm{logit}(p_{ij})=\beta_0+\sum_{h=1}^{k}\beta_h X_{ij}+U_{oj}+\sum_{h=1}^{k}U_{hj}X_{hij}$$

he first part $\beta_0+\sum_{h=1}^{k}\beta_h X_{hij}$ is called the fixed part of the model, and the second parameter $U_{oj}+\sum_{h=1}^{k}U_{hj}X_{hij}$ is called the random part of the model. The random variables or effects, 1 ,…, k are assumed to be independent between groups but may be correlated within groups. So the components of the vector (1 ,…, $k_{)}$ are independently distributed as a multivariate normal distribution with zero mean vector and variances and co-variances matrix[7]. The key ingredients to a Bayesian analysis are the likelihood function, which reflects information about the parameters contained in the data. Bayesian multilevel logistic analysis specifies a dichotomous dependent variable as a function of a set of explanatory variables. The likelihood contribution from the n subject in the $j^{th}$ region and the prior distribution is probability that represents the prior information associated with parameter interest. For the prior distribution, the fuzzy prior or non-informative priors is used, since no information is known about the priors, ie by taking the large variance. Therefore, the normal and inverse gamma is used as a prior distribution. The prior distribution $\beta$ ~ N(0,0.001) , $u_{0j}$, $u_{1j}$ ,..., $u_{kj}$ ~ N(0, $\sigma_u^2$), $\sigma_u^2 = (\sigma_{u_{0j}}^2, \sigma_{u_{1j}}^2, \ldots, \sigma_{u_{kj}}^2)$ ~ inverse gamma (0.001, 0.001).

The posterior probability of a random event is the conditional probability that is assigned after the relevant evidence is taken into account. The posterior probability distribution of one random variable given the value of another can be multiplying the prior probability distribution and the likelihood function[19].

**Markov chain Monte Carlo**

The Markov chain Monte Carlo method is a general method that generates the estimates of θ (unknown parameters) from appropriate distribution and then corrects the values generated to have a better estimate of the desired posterior distribution p(θ|y). To check convergence diagnostic using time series, Autocorrelation, density and Gelman-Rubin convergence diagnostic. With the multiple chains generated simultaneously, the diagnostic test is applied by computing and comparing within-sample variability and between-sample variability. The model was computed via the Gibbs sampler, a MCMC technique[20], which was implemented using Win BUGS software[21]. The 95% Bayesian credible interval (95% BCI) was used to examine the significance of covariates, which provides probability interpretations with normality assumption on unknowns and confidence interval estimations. Specifically, those coefficient estimations were identified as significant, whose 95% BCIs does not cover zero.

**Model comparison using Deviance information criterion (DIC)**

The deviance information criterion is a measure of model comparison and adequacy; it assumes that we can use the posterior mean as good estimate of central location for explaining the posterior distribution. The parameters are considered random variables. Thus, the parameters in the second layer are used just to describe the probability distributions of the parameters in the first layer.

Models with large number of parameters should be penalized in the same way the Akaike information criterion does for regression or log-linear models. The effective number of parameters $P_D$ is a measure of complexity of the model and is defined by

$$P_D = \overline{D} - D(\bar{\theta})$$

Which means the posterior expectation of the Bayesian deviance minus the Bayesian deviance calculated by replacing θ with their posterior expectations $\bar{\theta}$. The Deviance Information Criterion puts these two measures together

$$DIC = \overline{D} + P_D$$

And this new measure allows the cornparison of arbitrarily complex models. DIC is a measure of fit together with a measure of the effective number of Parameters, based on the posterior distribution of the log-likelihood under each model. This criterion is a natural generalization of Akanke's Information Criterion. Another advantage of using this tool is that $\overline{D}$ and $P_D$ are easy to compute from a MCMC output analysis. DIC over other criteria in the case of Bayesian model selection is that the DIC is easily calculated from the samples generated by a Markov chain Monte Carlo simulation. The idea is that models with smaller DIC should be preferred to models with larger DIC[22].

## Results

In this study, a total of 7163 women and girls had been included in the analysis. The overall prevalence of female genital mutilation was found to be 69.6%. The prevalence of female genital mutilation among the 15–24, 25-34 and 35–49 years old women was 59.6%, 74.7% and 77.9% respectively. About three-fourth of rural participants had female genital mutilation. The prevalence of female circumcision is highest in Somali region (98.4%) and lowest in Tigray region (27.6%). More than three-fourth (77.1%) of participants with poor wealth index had reported female genital mutilation practice. The prevalence of female genital mutilation among never married women was 53.5%. The practice of female genital mutilation decreased from 83.9% to 61% with non-educated and secondary and above educational level of husband/partner respectively. The majority of Muslim women (89.9%) reported that FGM (**Table-1**).

Table- 1: Percentage of female genital mutilation during their life time, according to background characteristics, Ethiopia EDHS 2016

| | | Female genital mutation practices | |
|---|---|---|---|
| **Variables** | **Categories** | **No(%)** | **Yes(%)** |
| Age in 5-year groups | 15-24 | 1154(40.4) | 1764(59.6) |
| | 25-34 | 587(25.3) | 1737(74.7) |
| | 35-49 | 438(22.1) | 1543(77.9) |
| Type of place of residence | Urban | 1046(40.7) | 1524(59.3) |
| | Rural | 1133(24.7) | 3460(75.3) |
| Religion | Chirstian | 1857(44.9) | 2275(55.1) |
| | Muslim | 302(10.1) | 2691(89.9) |
| | Other | 20(52.6) | 18(47.4) |
| Wealth index combined | Poor | 586(22.9) | 1975(77.1) |
| | Middle | 240(25.9) | 687(74.1) |
| | Rich | 1353(36.8) | 2322(63.2) |
| Current marital status | Never Married | 914(46.5) | 1055(53.5) |
| | Married or living with partner | 1057(23.7) | 3405(76.3) |
| | Windowed or divorced or Separted | 208(28.3) | 526(71.7) |
| Husband/partner's education level | No education | 337(16.1) | 1754(83.9) |
| | Primary | 318(23.7) | 1021(76.3) |
| | Secondary and above | 402(39) | 630(61) |
| Husband/partner's occupation (grouped) | Not working | 49(11.9) | 364(88.1) |
| | Employed(Salary paid) | 591(22.4) | 2044(77.6) |
| | Merchant | 96(25.6) | 279(74.4) |
| | Other | 321(30.9) | 718(69.1) |
| Respondent's occupation (grouped) | Not working | 927(25.9) | 2655(74.1) |
| | Employed(Salary paid) | 562(36.7) | 969(63.3) |
| | Merchant | 360(30.2) | 831(69.8) |
| | Others | 330(38.4) | 529(61.6) |
| Ever heard of female circumcision | No | 52(74.3) | 18(25.7) |
| | Yes | 2127(30) | 4966(70) |
| Respondent circumcised | No | 2179(30.4) | |
| | Yes | 4984(69.6) | |

Time series plot: it's one in every of the tests accustomed diagnose the convergence of Bayesian analysis. Statistic plot indicates an honest convergence three independent generated chains will mix together or overlapped (Fig-1). Here, the diagnostic graphs conclude the simulation draws are reasonably converged and then, we are going to be more confident about the accuracy of posterior inference.

Density plot: it's another technique for identifying convergence. The plots for all statistically significant covariates have bimodal density, and hence the simulated parameter values were converging (Fig-2).

Autocorrelation plot: it is a test used for convergence of Bayesian analysis. From fig-3, we observe that the autocorrelation for all parameters become low only after considering a lag up to 50. If the 50 lags of three independently parameters generated chains confirmed, then better convergence indicated. The plots show that independent chains were mixed or overlapped to each other.

From Table-2: For empty model parameters the HPD didn't contain zero, which demonstrates the "statistical significance" of the parameters. The variation between regions of the common is 0.544. A model was taken because the beginning line within the statistical analysis, which only includes the intercept. The Deviance Information Criterion (DIC), which could be accustomed compare different Bayesian models for the identical data. the entire correlation as a measure of the variability between the region of FGM to the complete variability because the sum of the variances between and within regions of FGM amounts to 0.142.

Table-2 : Model summary for empty Bayesian multilevel model

| Variables | Parameter | Mean | SD | 95% BCI for EXP(β) | |
|---|---|---|---|---|---|
| | | | | Lower | Upper |
| Fixed effect | | | | | |
| Intercept | $\beta_0$ | 1.089 ** | 0.450 | 1.226 | 7.228 |
| Random effect | | | | | |
| $U_{0j}$ | $\sigma_u^2$ | 0.544 ** | 0.250 | 1.186 | 3.177 |
| ICC | | 0.142 | | | |
| DIC | | 7399.9 | | | |

Significant **

From **Table -3** after checking the MCMC convergence diagnostic and accepting the Monte Carlo error diagnostic for all three models, in the Study Stage, we compare the model with the three DIC values. After comparing the DIC values, we selected the Bayesian Random intercept model as the most suitable one using by DIC value. The best model was determined based on the smallest DIC. Based on this results the best model was Bayesian random intercept models.

Table-3 Results of model comparison using DIC

| Model | $\bar{D}$ | $D(\bar{\theta})$ | $P_D$ | DIC |
|---|---|---|---|---|
| Bayesian Empty-model | 7389 | 7378.7 | 10.6 | 7399.9 |
| Bayesian Random intercept model | 6567 | 6538.8 | 28.2 | 6595.2 |
| Bayesian Random slope | 6683.9 | 6646.6 | 37.3 | 6721.2 |

As shown in **Table- 4**, the variance of $\sigma^2_{u_{0j}}$, indicating the magnitude of the between- region variance, is 0.857. Hence, the ICC is 20.67%. This means that 20.67% of unexplained variance in individual Female genital mutilation were resulted from between-region variance, which strongly suggests the usefulness of the model specification of hierarchical structure. If a binomial regression model was implemented without considering the random effects between regions, the results will be biased and inaccurate. The variance of the random component related to intercept term is found to be significant. Indicating that, female genital mutilation variations among regional states of Ethiopia were non-zero. Parents of rural residence were 1.805 times more likely to have FGM practices on the daughters than parents from urban areas. Similarly, parents who ever heard of female circumcision showed more FGM practices on the daughters than their counterparts (OR=9.189).

According to the model output with respect to educational status, it was observed that those participants whose husband's/partner's education at primary level were 0.747 times less likely to be circumcised than those with mothers with no education. Similarly, participants whose husband's/partner's education at secondary and above education level were 0.482 times less likely to support for the FGM practice than those with no education. Girls from Muslim mothers were 3.216 times more likely to have undergone the FGM practice than those from Christian. Married or living with a partner and widowed or divorced or separated were 1.643, 1.757 times more likely to support the FGM practices compared to those with never married respectively.

Wealth index has also statistical relationship with an FGM practice. Accordingly, middle and rich household women were 1.449, 1.514 times more likely to undergo FGM practice compared to those with poor household women respectively. Similarly, merchant respondents showed more FGM practices on their daughters than those women who were not working (OR=1. 375).
Regarding to husband/ partner's occupation, it was observed that those respondents whose husband/partner employed (salary paid) and merchant were 0.745, 0.684 times less likely to support for FGM practices compared to those with not working respectively.
Female genital mutilation was increased by 72.2 % for FGM practices in the age group 25-34 years compared to the daughters or women in the age group 15-24 years controlling for the other variables in the model. Similarly, age group 35-49 years showed more FGM practices on daughters or women than the age group 15.24 years (OR=2. 125) (Table-4).

**Table -4: Bayesian estimates for random intercept model**

| Variable categories | | Posterior Point Estimate | | | | 95% BCI for EXP(β) | |
|---|---|---|---|---|---|---|---|
| | Parameters | Mean | SD | OR | MC error | 2.50% | 97.50% |
| Intercept | α: | - 2.239** | 0.538 | 0.107 | 0.02616 | 0.0360 | 0.3097 |
| Ever heard of female circumcision(ref=No) | | | | | | | |
| Yes | $\beta_{1}$: | 2.218** | 0.3414 | 9.189 | 0.01518 | 4.7636 | 18.2835 |
| Age in 5-year groups(ref=15-24) | | | | | | | |
| 25-34 | $\beta_{2}$: | 0.5434** | 0.08267 | 1.722 | 8.337E-4 | 1.4642 | 2.0269 |
| 35-49 | $\beta_{3}$: | 0.7539** | 0.09236 | 2.125 | 9.516E-4 | 1.7739 | 2.5462 |
| Residence(ref=urban) | | | | | | | |
| Rural | $\beta_{4}$: | 0.5906** | 0.1103 | 1.805 | 0.002193 | 1.4554 | 2.2470 |
| Religion(ref=Christian) | | | | | | | |
| Muslim | $\beta_{5}$: | 1.168** | 0.08573 | 3.216 | 7.557E-4 | 2.7183 | 3.8076 |
| Other | $\beta_{6}$: | -1.054** | 0.366 | 0.3485 | 0.001824 | 0.1686 | 0.7109 |
| Wealth index(ref=poor) | | | | | | | |
| Middle | $\beta_{7}$: | 0.3709** | 0.1071 | 1.449 | 9.488E-4 | 1.1748 | 1.7830 |
| Rich | $\beta_{8}$: | 0.4149** | 0.09791 | 1.514 | 0.001656 | 1.2493 | 1.8325 |
| Current marital status(ref=Never Married ) | | | | | | | |
| Married or living with partner | $\beta_{9}$: | 0.4964** | 0.08213 | 1.643 | 9.418E-4 | 1.3981 | 1.9276 |
| Windowed or divorced or separated | $\beta_{10}$: | 0.5638** | 0.1224 | 1.757 | 0.001097 | 1.3813 | 2.2331 |
| Husband/partner's education level(ref=No education) | | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Primary | $\beta_{11}$: | -0.2913** | 0.08347 | 0.747 | 9.202E-4 | 0.6346 | 0.8793 |
| Secondary and above | $\beta_{12}$: | -0.7306** | 0.09553 | 0.482 | 0.001325 | 0.4000 | 0.5815 |
| Husband/partner's occupation (ref= Not working) | | | | | | | |
| Employed(Salary paid) | $\beta_{13}$: | -0.2942** | 0.1331 | 0.745 | 0.002963 | 0.5745 | 0.9683 |
| Merchant | $\beta_{14}$: | -0.3803** | 0.1602 | 0.684 | 0.003039 | 0.4995 | 0.9343 |
| Other | $\beta_{15}$: | -0.4666** | 0.1378 | 0.627 | 0.003059 | 0.4791 | 0.8211 |
| Respondent's occupation( ref=Not working) | | | | | | | |
| Employed(Salary paid) | $\beta_{16}$: | -0.145 | 0.08298 | 0.865 | 6.48E-4 | 0.7361 | 1.0172 |
| Merchant | $\beta_{17}$: | 0.3184** | 0.09131 | 1.375 | 6.78E-4 | 1.1508 | 1.6458 |
| Other | $\beta_{18}$: | 0.1181** | 0.0977 | 1.125 | 7.058E-4 | 0.9285 | 1.4726 |
| | Random effects | | | | | | |
| Between region | $\sigma^2_{u_{0j}}$ | 0.857** | 0.4042 | - | 0.005339 | 1.3084 | 6.1349 |
| | ICC | 0.2067 | - | - | - | - | - |

MC Error < 0.05, Significant **

## Discussion

In this study, we used the fourth nationally representative population based survey from Ethiopia. the prevalence of female genital mutilation found 69.6% among the respondents. The findings also showed a decreasing trend of FGM prevalence over time and significant variation across the regions. The prevalence of female genital mutilation was highest in Somali region (98.4%) and lowest in Tigray region (27.6%). This study used a Bayesian hierarchical modeling approach to analyze the variation within the risk and intention to the practice of FGM in Ethiopia. As opposition a more standard Mark of chain town approach, we employed an Integrated Gibbes algorithm within the R library. The study has proved heterogeneity within the practice, and support for the practice of FGM in Ethiopia. Those Rural respondents were having higher odds of FGM practice as compared to their counterparts. It’s in line with previous studies conducted in Ethiopia [23-25].

The possible reasons may include cultural variability, gaps in knowledge, lack of access to relevant information, increased availability of traditional practitioners, inadequate health education and dominated higher cognitive process by husbands. Reasons may include cultural variability, gaps in knowledge, lack of access to relevant information, increased availability of traditional practitioners, in- adequate health education and dominant decision making by husbands, Muslim women were more likely to possess undergone the FGM practice than women with the religion, which is in agreement with previous evidences[25, 26]. The possible reason may be a perception that uncircumcised woman isn't pure and clean within the eyes of God. This practice could even be performed from the perspectives of marriage ability of a woman and her desire control. Husband/partner no education were more likely to undergo female genital mutilation than primary, secondary and above education level. Previous studies corroborate the finding that primary and better education achieved by women and girls could reduce extirpation [27, 28].

This may be thanks to the very fact that those educated parents have an honest understanding about the effect of female genital mutilation on women's health. Women of the rich and middle wealth quantity were more likely to be female genital mutilation than those of the poor. It's contradicted by different study in[27, 29, 30] . The results also revealed that women's age may be a strong determinant of circumcision. The women, aged 35–49 and 25-34 years old were more likely to be circumcised compared with their younger counterparts. These findings corroborate results by[27]. Married or living a partner were more likely to support FGM practice compared to those with never married respectively it's also in line with a study conducted in Kersa district of Ethiopia[28].

## Conclusions

This paper applies a hierarchical Bayesian logistic model with binary responses to investigate the impacts of FGM variables to taking into account between-region variance and within-region correlation. Analysis results indicate that the total variance is induced by the between-region variance, showing the appropriateness of the utilized hierarchical modeling approach. The study finding showed Female Genital mutation varies across regions in Ethiopia. Wealth index, age of women, residence, religion, education, marital status, husband's/ partner's occupation, and Ever heard of FGM were found to be significant determinants of Female Genital mutation. The government's effort towards elimination of FGM should be well strengthened by addressing FGM disparity in Ethiopian regions and also taking into account identified factors of FGM by this study.

**Abbreviations**

BCI: Bayesian Credible Interval; CI: Confidence Interval; DIC: Deviance Information Criteria; EDHS: Ethiopia Demography and Health Survey; FGM: Female Genital Mutilation; ICC: Intra Correlation Coefficient; MLE: Maximum Likelihood Estimation; OR: Odds Ratio; WHO: World Health Organization

## Declarations

### Availability of data and materials

The data that support the findings of this study are available from Measure DHS website (www.measuredhs.com) but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Measure DHS.

### Competing interests

The authors declare that they have no competing interests.


### Funding

No funding was received for this study


**Consent for publication:** Not applicable.

**Ethics approval and consent to participate:** Not applicable.

### Authors' contributions

MSW conceived, designed the study and performed the data analysis and interpretation. assisted in designing the study and interpretation. MSW drafted the manuscript, read and approved the final manuscript.


### Acknowledgements

The authors would like to acknowledge Measure Demographic and Health Survey for providing online permission to use the Ethiopia Demographic and Health Survey 2016 data set.


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**Appendix**

Fig-1: Time series for convergence of coefficients for the predictors

Fig-2: Density plot for convergence of coefficients for the predictors

Fig-3: Auto correlation plot for convergence of coefficients for the predictor