Health and Prevention Journal, 2025, 2(1), 74-91
https://www.hillpublisher.com/Journals/hpj/
ISSN Online: 3066-1021

Impact and Consequences of Early Marriage in Bangladesh Using BDHS Data

Md Abdul Alim Sarkar*, **Abdullah Al Mahmud, Md Fazle Rabbi Sujan, Abul Hossain**

Department of Statistics, Comilla University, Cumilla 3506, Bangladesh.

How to cite this paper: Md Abdul Alim Sarkar, Abdullah Al Mahmud, Md Fazle Rabbi Sujan, Abul Hossain. (2025) Impact and Consequences of Early Marriage in Bangladesh Using BDHS Data. *Health and Prevention Journal*, 2(1), 74-91.
DOI: 10.26855/hpj.2025.12.007

Received: September 2, 2025
Accepted: October 23, 2025
Published: December 16, 2025

***Corresponding author:** Md Abdul Alim Sarkar. Department of Statistics, Comilla University, Cumilla 3506, Bangladesh.

Abstract

In Bangladesh, early marriage is still a major problem that has a big impact on socioeconomic development and maternal health. This study uses data from the 2014 Bangladesh Demographic and Health Survey (BDHS) to examine the factors linked to early marriage among Bangladeshi women. We examined a sample of 1,750 women using both binary logistic regression and bivariate analysis (chi-square tests). According to the findings, 77.5% of the sample's women were married before turning 18. Significant protective variables against early marriage were the woman's education level (OR=0.485, p<0.001) and her husband's education level (OR=0.867, p=0.039). The study comes to the conclusion that improving boys' and girls' educational attainment is a crucial tactic for lowering Bangladesh's high rate of early marriage.

Keywords

Early Marriage; Child Marriage; Logistic Regression; Women's Education; Socio-economic Factors; Adolescent Marriage

1. Introduction

1.1 Introduction

Marriage or nuptiality is crucial turning point for both man and woman. But it's a privilege for low or developing countries to marry adolescent aged persons-specially for women. Early marriage or premature nuptial relationship is like an epidemic form in poor countries. Lack of education, poverty, rapid growth and also lack of rights to upright one's honor- are most common in our country. In addition, social consequences of early marriage, including higher population growth, more rapid spread of disease, and a higher incidence of orphans (see for example, Jensen and Thornton, 2003). Proponents of age of consent laws argue that forcing parents to delay marriage will increase female schooling attainment and reproductive control and decrease the incidence of domestic violence, and social programs increasingly contain program rules designed to discourage the practice. For instance, a prominent micro-finance program in India excludes parents who marry daughters before 17, and national education vouchers in Bangladesh exclude married girls. However, while statistics indicate that women who marry young fare worse, it is difficult to assess the extent to which these outcomes are driven by the timing of marriage as opposed to common factors related to poverty and traditional gender views that also hinder female advancement. Given that child marriage is most common in impoverished and culturally traditional surroundings, the observation that women who married young- have on average less education does not imply that forcing girls to postpone wedlock would improve their outcomes. This paper attempts to shed light on the issue by studying the schooling consequences of early marriage for girls in rural Bangladesh, an area with one of the highest rates of child marriage worldwide. Since it is also an environment of rapidly expanding schooling opportunities and returns to education for girls, adolescent marriage is frequently blamed for the persistent gender gap in schooling attainment (see for example, Jensen and Thornton 2003).

The idea behind the early marriage strategy is the following: While there are frequently incentives to marry daughters as young as possible, in Bangladesh as in many parts of the world, girls are typically held from the marriage market until the onset of puberty. This institutional feature in the context of high rates of very early marriage presents a binding constraint on exposure to adolescent marriage opportunities. In particular, natural variation in the timing of first menstruation within the age range of 11 to 16 generates quasi-random differences in the earliest age at which girls are at risk of marrying. Our estimates indicate that each additional year that menarche is delayed postpones marriage

0.74 year. This physical barrier to younger marriages, in so far as it is independent schooling investment, presents a unique opportunity to assess the effects of child marriage on female education outcomes (see for example, Palmert and Boepple, 2001).

1.2 Background

Marriage is often followed by pregnancy, even if a girl is not yet physically or mentally ready. In developing countries, nine out of 10 births to adolescent girls occur within a marriage or a union. In these countries, complications from pregnancy and childbirth are among the leading causes of death among adolescent girls aged 15 to 19 (see for example, Susheela Singh and Renee Samara, 1996).

Girls who are married may also be exposed to sexually transmitted infections, including HIV. When girls marry, they are often forced to drop out of school so they can assume household responsibilities. This is a defiance of their right to an education. Early marriage also confines their opportunities like as future employment prospects, and has long-term effects on their families. Girls who leave school have worse health and economic outcomes than those who stay in school, and eventually their children fare worse as well.

The relationship between marriage before 16 years and pregnancy outcome throughout the childbearing period was examined. Most of the early married women were illiterate and unconscious about their first marriage. The association between infant morbidity and mortality and young age pregnancy has been a public health concern (see for example, S. Shawky and W. Milaat). Early marriage and early childbearing are still strongly related to each other. In fact, early marriage interferes with economic success for families. The strong inverse relationship between age at marriage and durability of marriage has alsobeen demonstrated in repeated investigation (see for example, Jacobsen 1950, Monahan, 1953; burchinal 1965, Schoen,1975).

Research has given a great deal of attention to the many variables that lead to marital unhappiness and dissolution. Of this body of research, a substantial literature has shown hostile conflict to be one of the strongest predictors of marital unhappiness (see for example, Gottman, 1994; Mathews, Wickrama, and Conger, 1996). In fact, several studies have found that the presence of hostile conflict may predict marital dissolution with 80% accuracy (see for example, Gottman, 1994; Gottman and Levenson, 1992; Mathews et al., 1996). Gottman (1994) denned hostile conflict as a pattern of negative couple interaction including; hot and frequent arguments, insults, name calling, unwillingness to listen, lack of emotional involvement, and a ratio of more negative behaviors than positive behaviors.

Multi-generational family theory suggests that individual acquire a foundation for interpersonal relationships in their families of origin (see for example, Framo, 1981; Hoopes, 1987; Kerr, 1981). Current marital and family difficulties are seen as extensions of relationship problems in the spouses' original families (see for example, Framo, 1976; Hoopes, 1987). Relationship issues such as conflict stemming from family-of-origin influences, may emerge with different meaning and increased intensity when individuals experience courtship or when they marry and begin to develop their own nuclear family. For this reason, when couples are preparing for marriage, they may begin to experience these family-of-origin influences in a way and with an intensity that they have not previously experienced. This influence may be conscious or unconscious (see for example, Hoopes, 1987) and remains strong even when individuals may not have continuing contact with their families of origin (see for example, Bartle-Haring and Sabatelli, 1998). These multi-generational influences may govern beliefs, attitudes, behaviors, self-esteem, and interactional patterns; whether they are functional or dysfunctional within the merging systems (see for example, Hoopes, 1987).

In a research problem, there were 399 men in total in the sample and 94 of those men had data at all three remaining assessments and were physically aggressive at pre-marriage. Of these 94 men, 22 (23.40) were physically aggressive at only the pre-marriage assessment; 15 (15.96 percent) were physically aggressive at one of the three remainingassessments; 18 of the men (19.15 percent) were physically aggressive at two of the remaining assessments; and 39 (41.45 percent) of them were aggressive at all three additional assessments (see for example, Michael F. Lorber and

.

K. Daniel O Leary).

The degree of premarital physical aggression and child abuse in the family of origin emerged as unique predictors of aggression persistence. Higher levels of physical aggression were independently associated with the persistence of aggression. However, with all of the other predictors statistically controlled, higher levels of child abuse appear to have contributed to less, rather than more, persistent aggression. This counter intuitive relation was contrary to our hypotheses. The predicted consequence of child abuse victimization would be risk for the development of antisocial-spectrum behavior (see for example, Moffit, 1993). However, child abuse is also associated with the development of anxiety disorders, such as PTSD (see for example, Boney-McCoy and Finkelhor, 1996).

1.3 Objectives

To identify the factors that influence early marriage in Bangladesh.

To find out long run relationship between early marriage of a women and their education level.

To investigate the association among factors that influence early marriage and the socio-economic structure of the society.

To examine the simultaneous effect of all the explanatory variable (Highest education level, Husband/Partner education level etc.) on the use of early marriage.

2. Literature review

This chapter will review the literature available concerning the general relationship between perception of early marriage and level of educational attainment or goals. Prior to the examination of current research information regarding the relationship of the variables, the literature review will briefly cover the operational definition of early marriage; general and ethnic issues related to early marriage; and information regarding the factors relating to early marriage. To understand factors related to early marriage it is important to consider the Hmong's marital traditions and family unit. Lastly, the literature on the effects of early marriage have on education will be included.

A marriage is a legally recognized union between a man and a woman in which they are united sexually; cooperate economically, and may have children through birth or adoption (see for details, Strong, DeVault and Sayad, 1998). Throughout the literature reviews, early marriage is either one or both of the married couple being under the age of 18 years old or in high school (see for example, Hutchinson and McNall, 1994, Lindsay, 1985, Walker-Moffat, 1995).

According to Erickson's identity vs. role diffusion, the years of puberty (12 years old to 18 years old) may be a time for confusion because adolescents are trying new roles as they transition into adulthood (for more details, Strong and DeVault, 1992). To make a successful transition, they need to have a sense of self. As with every marriage, there will be stresses and strains but because adolescents have not established their individuality, education, and career they are more prone to the problems of marriage. Teti, Lamb, and Elster (1987) suggest that the high marital instability in teen marriages may be a result of multiple stresses from marriage, parenthood, and adolescent stage. Lind-say (1985) found that young couples, married or not, face many difficulties including financial hardship, communication problems, three generational living, sexual adjustment, and transitioning into parenthood before the couples have a chance to strengthen their relationship with each other. Premarital births are related to subsequent marital dissolution (see for example, Teachman, 1992).

Marriage or living with a partner brings many changes into an adolescent's life such as communication, arguments, and financial issues (see for example, Lindsey, 1985). There is also a loss of individual freedom because for a marriage to work both partners have to be fully committed. It is likely that couples whom array as adolescents have had less experience in developing the maturity and social cognitive skills required to maintain a stable marital union than couples who marry as adults (see for example, Teti, et al., 1987). Developing these skills as married adolescents may be restricted by the coincidence of socio- economic and role transitions. Adolescent marriage is associated not only with a higher rate of dissolution of first marriages by with subsequent marriages as well. Teti, et al. found that blacks and white males who married as adolescents appeared to have experienced similarly high levels of marital disruption.

Adolescent marriages are more likely to end in divorce than are marriages that take place when couples are in their twenties or older for both whites and African Americans because younger partners are less likely to be emotionally mature (see for example, Strong, et al., 1998).

Early marriage is also related to development of self-concept. For Hmong girls who married early there is no concept of self-identity to be developed, there is only the transfer of one’s identity to a new family. For example, Hmong a girl goes from becoming a daughter to a daughter-in-law (see for example, Walker-Moffat, 1995).

3. Description of Data and Variable

An efficient, informative and knowledge-versed project is fulfilled by a loyal, suitable and objective dataset. But its source as well as collection, arrangement and overall information are necessary.

3.1 Data Source

The data used in this study has been taken from the Bangladesh Demographic and Health Survey (BDHS) conducted in 2014.The 2014 Bangladesh Demographic and Health Survey (2014 BDHS) was implemented under the authority of the National Institute of Population Research and Training (NIPORT), Ministry of Health and Family Welfare. The survey was implemented by Mitra and Associates from June to November 2014. The funding for the 2014 BDHS was provided by the United States Agency for International Development (USAID) of Bangladesh. ICF International provided technical assistance as well as funding through The DHS Program, a USAID funded project. The opinions expressed in this report are those of the authors and do not necessarily reflect the views of USAID. Information about the BDHS may be obtained from the National Institute of Population Research and Training (NIPORT), Azimpur, Dhaka, Bangladesh (Telephone: 5861-1206; Internet: http://www.niport.gov.bd) or from Mitra and Associates,2/17 Iqbal Road, Mohammadpur, Dhaka, Bangladesh (Telephone: 911-5503; Fax: 912-6806; Internet: www. mitra.bd.com). Information about The DHS Program may be obtained from: ICF International, 530 Gaither Road, Suite500, Rockville, MD 20850, USA; Telephone: 301-407-6500; Fax: 301-407-6501; Internet: http://www.DHSprogram.com. Suggested citation: National

Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International 2015. Bangladesh Demographic and Health Survey 2014: Key Indicators. Dhaka, Bangladesh, and Rockville, Maryland, USA: NIPORT, Mitra and Associates, and ICF International.

3.2 Dependent Variable

As the purpose of the study to determine the factors affecting early marriage, the dependent variable is "Age at first marriage" which takes the value "1" for early marriage, "0" for not early marriage person.

3.3 Explanatory Variable

Exploratory variables are those variables which are examined, estimated to predict the values of predictors. Our study perceives some crucial variables which are describes below

Table 1. Variable Definitions and Categories for Household Survey

Variables	Definition	Categories
Household	Number of households	
Religion	Religion	Islam Hinduism Buddhism Christianity Other
Region	Respondent Region	Chittagong
Residence	Types of residence	Urban Rural
Education	Highest education level	No education Primary Secondary Higher
Daughter at home	Daughter at home	-
Partner Occupation	Husband/Partner's occupation	Agricultural Worker Non-Agricultural Worker Good Job Others
Partner's Education	Husband/Partner's Education	No education Primary Secondary Higher Don't know
Respondent's occupation	Respondent's occupation	Agricultural worker Non-Agricultural Worker Good Job Others

Data source*: Bangladesh Demographic and Health Survey (BDHS), 2014.*

4. Methodology

4.1 Introduction

The present study aims to determine the factors affecting the use of early marriage. As a starting tool for the analysis provides a preliminary idea of how two variables are associated but does not provide an indicator of causal relationship between them. Therefore, regression analysis is required to explore the form of their relationship. Available regression methods for analyzing binary data are linear probability, logistic regression model and probit model. Logistic regression, the most popular method of fitting binary data, requires the assumption of independence of the observations. However, data considered in the following study in hierarchical in the nature which violates this assumption. To settle down this problem one of the best possible solutions is to use multi-level logistic regression instead of traditional logistic regression.

4.2 Bivariate analysis

Bivariate analysis allows looking at the associations among two variables. These measures of association relate how well one variable relates to other and help to understand this relationship. This is done by tabulating them in a two-way format known as contingency table. Contingency tables are used to visually assess whether the variables might be related but it is not sufficient to test a hypothesis about the relationship between two variables. An additional statistic, chi-square, is needed to perform a hypothesis testing about two variables.

4.3 Chi-square test

The Chi-square test statistic is used to determine whether there is a significant association between two categorical variables. The hypotheses of the chi-square test is,

H_0: There is no association between two variables.

H_1: There is association between two variables.

The test statistic is defined as,

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

where O_{ij} (i= 1,2,3..., r and j= 1, 2, ..., c) denotes the observed frequencies and, E_{ij} (i= 1,2,3..., r and j= 1, 2, ..., c) denotes the expected frequencies. The test statistic follows Chi-square distribution with (r-1)(c-1) degree of freedom under null hypothesis.

The P-value for test statistic is defined as the probability of observing more extreme data under null hypothesis. Before performing a test level of significance (i.e., probability of incorrect rejection of null hypothesis) is chosen. If p-value is smaller or equal to the significance level, the null hypothesis is rejected. For the test of independence, p-value is calculated from chi-square distribution.

4.4 Models for binary Logistic Regression Model

4.4.1 Logit model

Many categorical response variables have only two categories. The observation for each subject might be classified as a "Success" or a "Failure". Represent these outcomes by 1 and 0. The Bernoulli distribution for binary random variables specifies probabilities

$p(Y=1)=\pi$ and $p(Y=0)=1-\pi$ for the two outcomes, for which $\pi = E(Y)$. When *Yi* has Bernoulli distribution with parameter π_i, the probability mass function is,

$$\begin{aligned} f(y_i;\pi_i) &= \pi_i^{y_i}(1-\pi_i)^{1-y_i} \\ &= (1-\pi_i)\left(\frac{\pi_i}{1-\pi_i}\right)^{y_i} \\ &= (1-\pi_i)\exp\left[y_i \log\left(\frac{\pi_i}{1-\pi_i}\right)\right] \end{aligned}$$

This distribution is in the natural exponential family. The natural parameter $Q(\pi)=\log\left[\frac{\pi}{1-\pi}\right]$, the log odds of response 1, is called the logit of π. GLMs that use the logit link is called logit models.

4.4.2 Logistic regression model

Because of the structural problems with the linear probability model, it is more fruitful to study models implying a curvilinear relationship between x and $\pi(x)$. When we expect a monotonic relationship, the S-shaped curves are natural shapes for regression curves a function having this shape,

$$\pi(x) = \frac{exp(\alpha + \beta x)}{1 + (\alpha + \beta x)}$$

is called the logistic regression function. When the model holds with $\beta = 0$, the binary response is independent of X.

The logistic regression curve has,

$$\frac{\delta\pi(x)}{\delta x} = \beta\pi(x)\left[1-\pi(x)\right].$$

For model, the odds of making response 1 are,

$$\frac{\pi(x)}{1-\pi(x)} = \exp(\alpha + \beta x) = e^{\alpha}\left(e^{\beta}\right)^{x}$$

This formula provides a basic interpretation for β. The odds increase multiplicatively by
e for every unit increase in x. The log odds have the linear relationship is,

$$\log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta x$$

4.4.3 Inference for logistic regression

From Wald"s general asymptotic results for ML estimators, it follows that parameter estimators in logistic models have large sample normal distribution.

Let $\gamma = (\gamma_1, \gamma_2, ..., \gamma_q)'$ denote a subset of model parameters. Suppose we want to test

$H_0: \gamma = 0$.

Let M_1 denote the fitted model and M_2 denote the simpler model with 0. Large sample tests can use Wilk's likelihood ratio approach, with test statistic based on twice the log of the ratio of maximized likelihoods for M_1 and M_2. Let L_1 denote the maximized log likelihood for M_1 *and* L_2 denote the maximized log likelihood for M_2 under H_0, the statistic,

$$-2(L_2 - L_1)$$

Has a large sample chi-squared distribution with degrees of freedom q. Alternatively, by the large sample normality of parameter estimators, the statistic,

$$\hat{\gamma}'\left[\hat{cov}(\hat{\gamma})\right]^{-1}\hat{\gamma}$$

has the same limiting null distribution.

4.4.4 Odds Ratio and Coefficient of Linear Logistic Regression

When the independent variables are dichotomous or polychotomous, the logistic regression coefficients can be linked with odds ratios. In the linear logistic model, the dependence of the probability of success on independent variables is assumed to be-

$$\pi_i = \frac{exp(\sum_{j=0}^{p} \beta_i x_{ij})}{1 + exp(\sum_{j=0}^{p} \beta_i x_{ij})}$$

and

$$1-\pi_i = \frac{1}{1+\exp\left(\sum_{j=0}^{p} \beta_i x_{ij}\right)}$$

.

Consider the simplest case, where there is one independent variable, x_1 which is either 0 or 1. The linear regression model has become,

$$p(y=1|x_1)=\frac{e^{\beta_0+\beta_1 x_1}}{1+e^{\beta_0+\beta_1 x_1}} \quad \text{and} \quad p(y=0|x_1)=\frac{1}{1+e^{\beta_0+\beta_1 x_1}}$$

Values of the model, when $x_1 = 0$ and 1, are

$$p(y=1|x_1=0)=\frac{e^{\beta_0}}{1+e^{\beta_0}} \qquad p(y=1|x_1=1)=\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}$$

$$p(y=0|x_1=0)=\frac{1}{1+e^{\beta_0}} \qquad p(y=0|x_1=1)=\frac{1}{1+e^{\beta_0+\beta_1}}$$

Thus, we get the odds Ratio as

$$OR=\frac{\frac{p(y=1|x=1)}{p(y=0|x=1)}}{\frac{p(y=1|x=0)}{p(y=0|x=0)}}=\frac{\frac{\frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}}{\frac{1}{1+e^{\beta_0+\beta_1}}}}{\frac{\frac{e^{\beta_0}}{1+e^{\beta_0}}}{\frac{1}{1+e^{\beta_0}}}}=\frac{e^{\beta_0+\beta_1}}{e^{\beta_0}}=e^{\beta_1}$$

$$\therefore \hat{OR}=e^{\beta_1}$$

and the log odds ratio is $\log(\hat{OR})=e^{\beta_1}$. Thus, the estimated logistic regression coefficient also provides an estimate of the odds ratio i.e., $\hat{OR}=e^{\hat{\beta}_1}$. If the confidence interval for β *is* $x\pm\mu$ then the confidence interval for e^{β} is $e^{x\pm\mu}$.

4.4.5 Logit model for categorical data

Logit model for I×2 table

Suppose there is a single explanatory factor, having I categories. In row i of the $I\times 2$ table, the two response probabilities are $\pi_{1|i}$ and $\pi_{2|i}$,, with $\pi_{1|i}+\pi_{2|i}=1$. In the logit model,

$$\log\left(\frac{\pi_{1|i}}{\pi_{2|i}}\right)=\alpha+\beta_i$$

Where $\{\beta_i\}$ describes the effects of the factor on the response.

Let $\{n_{ij}\}$ denote the number of times response *j* occurs when the factor is at level *i*. It is usual to treat as fixed the total counts $\{n_{i+}=n_{i1}+n_{i2}\}$ at the *I* factor levels. When binary responses are independent Bernoulli ransom variables, $\{n_{i1}\}$ are independent binomial random variables with parameters $\{\pi_{1|i}\}$.

For any set $\{\pi_{1|i}>0\}$, there exist $\{\beta_i\}$ such that model holds that model has as many parameters as binomial observations, and it is said to be saturated. When a factor has no effect on the response variables the simpler model,

$$\log\left(\frac{\pi_{1|i}}{\pi_{2|i}}\right)=\alpha$$

hold. This is the special case in which $\beta_1=\beta_2=...=\beta_I$. Since it is equivalent to $\pi_{1|1}=\pi_{1|2}=...=\pi_{1|I}$, is the model of statistical independence of the response and factor.

4.4.6 Goodness of fit as a likelihood ratio test

For a given logit model, we can use model parameter estimates to calculate predicted logits and hence predicted probabilities and estimated expected frequencies

$$\hat{m}_{ij} = n_{i+}\hat{\pi}_{j|i}$$

When expected frequencies are relatively large, we can test goodness of fit with a Pearson or Likelihood ratio chi-squared statistic. For a model symbolized by *M*, we denote this statistics by $\chi^2(M)$ and $G^2(M)$. For instance,

$$G^2(M) = 2\sum_i\sum_j n_{ij} \log\left(\frac{n_{ij}}{\hat{m}_{ij}}\right)$$

The degrees of freedom equal the number of logits minus the number of linearly independent parameters in the model.

We used the likelihood ratio principle to construct a statistic,

$$-2(L_2 - L_1)$$

That tests whether certain model parameters are zero by comparing the fitted model M_1 with a simpler model M_2. When explanatory variables are categorical, we denote this statistic for testing M_2, given that M_1 holds, by $G^2(M_2 \mid M_1)$. Let L_s denote the maximized log-likelihood for the saturated model. The likelihood-ratio statistic for comparing models *M*1 and *M* 2 is,

$$G^2(M_2 \mid M_1) = -2(L_2 - L_1)$$

$$= -2(L_2 - L_s) - \lfloor\lceil -2(L_2 - L_s)\rceil\rfloor$$

$$= G^2(M_2) - G^2(M_1)$$

That is, the test statistic for comparing two models is identical to the difference in G^2 goodness of fit statistics for the two models.

4.4.7 Model diagnostics Residuals

Let *yi* denote the number of successes for *ni* trials at the ith level of *I* settings of the explanatory variables. For a binary response model, residuals for the fits provided by the *I* binomial distributions are,

$$e_i = \frac{y_i - n_i\hat{\pi}_{1|i}}{[n_i\hat{\pi}_{1|}(1-n_i\hat{\pi}_{1|i})]^{1/2}} \quad , \text{i}= 1,2, \ldots, 1$$

If $\hat{\pi}_{1|i}$ were replaced by the true value $\hat{\pi}_{1|i}$ in e_i would be the difference between a binomial random variable and its expectation, divided by its estimated standard deviation, if *ni* were large, *ei* would have an approximate standard normal distribution.

The $\{\pi_{1|i}\}$ is unknown, however, so replaces them by their estimates for the model.

Because the estimates depend on $\{y_i\}$, $\{y_i - n_i\hat{\pi}_{1|i}\}$ tend to be smaller than $\{y_i - n_i\pi_{1|i}\}$. Thus, $\{e_i\}$ tend to show less variation than standard normal random variables. In fact, the

Pearson statistic for testing the fit of the model is related to $\{e_i\}$ by $\chi^2 = \quad e^2.\sum\ _i$

If χ^2 has df *v*, it follows that the sum of squared residuals is asymptotically comparable to the sum of squares of *v* (rather than *I*) standard normal random variables. Despite this, residuals are often treated like standard normal deviates with absolute values larger than 2 indicating possible lack of fit.

4.5 Hypothesis testing

4.5.1 Wald test

In multiple regressions, the common *t*-test for testing the significance of a particular regression coefficient is a Wald test. In logistic regression, the Wald test is calculated in the same manner. The formula for the Wald statistic is

$$z_j = \frac{b_j}{s_{b_j}}$$

Where s_bj is an estimate of the standard error of b_j provided by the square root of the corresponding diagonal element of the covariance matrix, (β).

With large sample sizes, the distribution of z_j is closely approximated by the normal distribution. With small and moderate sample sizes, the normal approximation is described as adequate. " The Wald test is used in *NCSS* to test the statistical significance of individual regression coefficients.

4.5.2 Lagrange multiplier test

The Lagrange multiplier, or LM, test is the third of the three classical tests. Instead, they are usually based on the gradient vector, or score vector, of the unrestricted log likelihood function, evaluated at the restricted estimates. In fact, as we will see, some of the GNR- based tests that we encountered are essentially Lagrange multiplier tests. In such cases, the *r* restrictions can be written as $\theta_2 = \mathbf{0}$, where the parameter vector θ is partitioned as

$\theta = [\theta_1 \; \vdots \; \theta_2]$ possibly after some reordering of the elements. The vector $\tilde{\theta}$ of restricted estimates can then be expressed as $\tilde{\theta} = [\tilde{\theta}_1 \; \vdots \; 0]$ The vector $\tilde{\theta}_1$ maximize the restricted log likelihood function $l(\theta_1, \mathbf{0})$, and so it satisfies the restricted likelihood equation

$$g_1(\theta_1, 0) = 0$$

where $g_1(\cdot)$ is the vector whose components are the $k - r$ partial derivatives of $l(\cdot)$ with respect to the elements of θ_1.

The formula which gives the asymptotic form of an MLE, can be applied to the estimator $\tilde{\theta}$ when $\theta_2 = \mathbf{0}$. If we partition the true parameter vector θ_0 as $[\theta_1^0 \; \vdots \; \mathbf{0}]$, we find that

$$n^{\frac{1}{2}}(\theta_1 - \theta_1^0) = (\mathcal{J}_{11}(\theta_0))^{-1} n^{-1/2} g_1(\theta)$$

Where $\mathcal{J}_{11}$ is the $(k-r) \times (k-r)$ top left block of the asymptotic information matrix $\mathcal{J}(.)$ of the full unrestricted model. This block is, of course, just the asymptotic information matrix for the restricted model.

4.5.3 Likelihood ratio test

Let $f(x; \theta)$ be either a probability density function or a probability distribution where θ is a real valued parameter taking values in an interval Θ that could be the whole real line. We call Θ the parameter space. An alternative hypothesis H_1 will restrict the parameter θ to some subset Θ_1 of the parameter space Θ. The null hypothesis H_0 is then the complement of Θ_0 with respect to Θ. For instance, if $f(x; \theta)$ is the negative exponential distribution with pdf-

$$f(x;\theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}} \text{ for } x > 0$$

the alternative hypothesis that specifies that the mean is not equal to 3 has $\Theta = \{\theta: 0 < \theta < \infty\}$ and $\Theta_1 = \{\theta: \theta \neq 3\}$ so $\Theta_0 = \{\theta: \theta = 3\}$.

Initially, we will confine our discussion to cases where the parameter is completely specified under the null hypothesis so H_0: $\theta = \theta_0$ for some value θ_0 in the parameter space. That is, the null hypothesis is simple so $\Theta_0 = \{\theta: \theta = \theta_0\}$ consists of a single point.

We will test H_0 versus H_1 on the basis of random sample $X_1, X_2, \ldots, X_n$ from $f(x; \theta)$. If the null hypothesis holds, we would expect the likelihood

$$L(\theta) = \mathbf{G}_{i=1}^{n} f(x_i; \theta)$$

to be relatively large, when evaluated at the prevailing value θ_0. The reference for judging this comparison is taken to be the maximum of the likelihood over the whole parameter space

$$(\theta) = max_{\theta \epsilon \Theta} \mathbf{G}_{i=1}^{n} (x_i; \theta)$$

This will always be at least as large as the likelihood $L(\theta_0)$, evaluated at the particular value θ_0. However, we cannot discredit the null hypothesis unless $L(\theta_0)$ is much smaller than $L(\theta)$. The likelihood ratio test is actually based on the likelihood ratio

$$\lambda = \frac{L(\theta_0)}{L(\theta)} = \frac{\prod_{i=1}^{n} (x_i;\theta_0)}{max_{\theta\epsilon\Theta} \prod_{i=1}^{n} f(x_i;\theta)}$$

and the null hypothesis H_0: $\theta = \theta_0$ is rejected if λ is small.

5. Result and Analysis

5.1 Introduction

The exploratory data analysis has been performed to get a visual understanding of the distribution of occurring early marriage across different categories of the explanatory variables. Then a bivariate analysis has been performed to evaluate cell-wise percentage and also association with occurring early marriage. Nevertheless, we examine the simultaneous effect of all the explanatory variables on the use of early marriage.

5.2 Explanatory data analysis

Explanatory data analysis is necessary for summarizing the characteristics of the data. This analysis helps to figure out the relationship between the dependent and independent variables. To determine the distribution of the early marriage over different categories of the explanatory variables bar diagram has been used. These figures indicate that the distribution of the early marriage. For example, the percentage of occurring early marriage is high among the uneducated women. And also, graphical presentation shows that the categories of the explanatory variables may have an influence on the use of antenatal care.

5.3 Univariate analysis

Univariate analysis is the simplest analyzing data. “Uni” means “one”, so in other words our data has only one variable. In this section, the univariate analysis of the early marriage is discussed in a table. Mean, variance and standard deviation are the three pivots of basic statistics.

Table 2. Frequency distribution of highest education level

Highest education level			
	Frequency	Percent	Cumulative Percent
No education	344	19.7	19.7
Primary	455	26.0	45.7
Secondary	838	47.9	93.5
Higher	113	6.5	100.0
Total	1750	100.0	

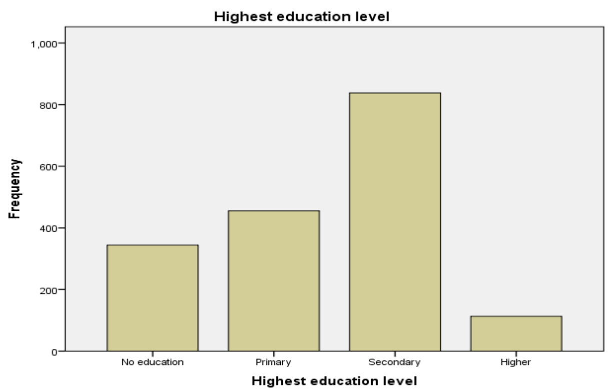

Figure 1. Bar chart of highest education level of respondents.

In this analysis, almost half of the population 47.9% acquires secondary education level. Whereas 26.0% gets primary education, 19.7% have no educational qualification and 6.5% get higher education. So, education level of womenfolk is passing the stage of Secondary level on half of the study people.

Table 3. Frequency distribution of husband/partners education level.

Husband/partners education level			
	Frequency	Percent	Cumulative Percent
No education	456	26.1	26.1
Primary	508	29.0	55.1
Secondary	549		86.5
Higher	235		99.9
9	2		100.0
Total	1750		

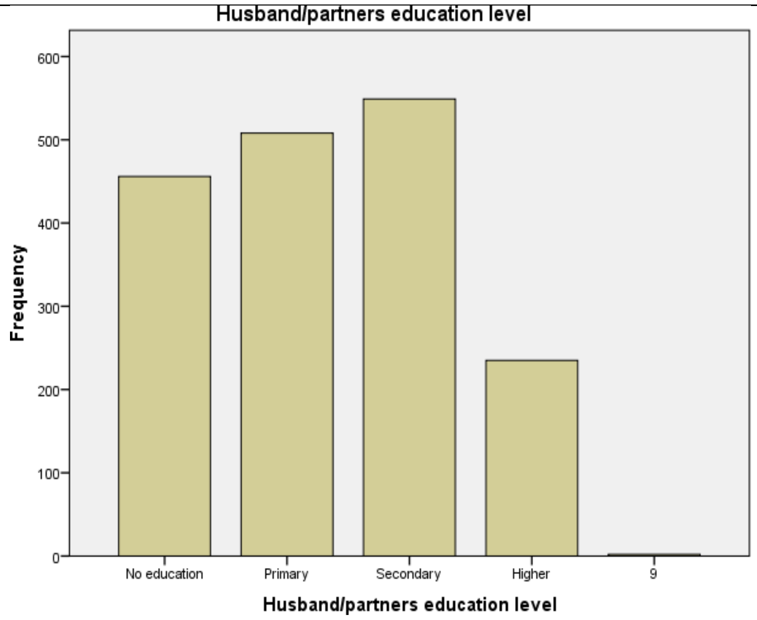

Figure 2. Bar chart of husband/partners education level of respondents.

For performing a life, educational qualification of spouse is also crucial. 31.4% Husband/partners education level, Secondary 29.0% peoples Husband/partners education level gets crossed primary level. So, educational qualification for spouse is also quite satisfactory level.

Table 4. Frequency distribution of religion

Religion			
	Frequency	Percent	Cumulative Percent
Islam	1608	91.9	91.9
Hinduism	125	7.1	99.0
Buddhism	16	.9	99.9
Christianity	1	.1	100.0
Total	1750	100.0	

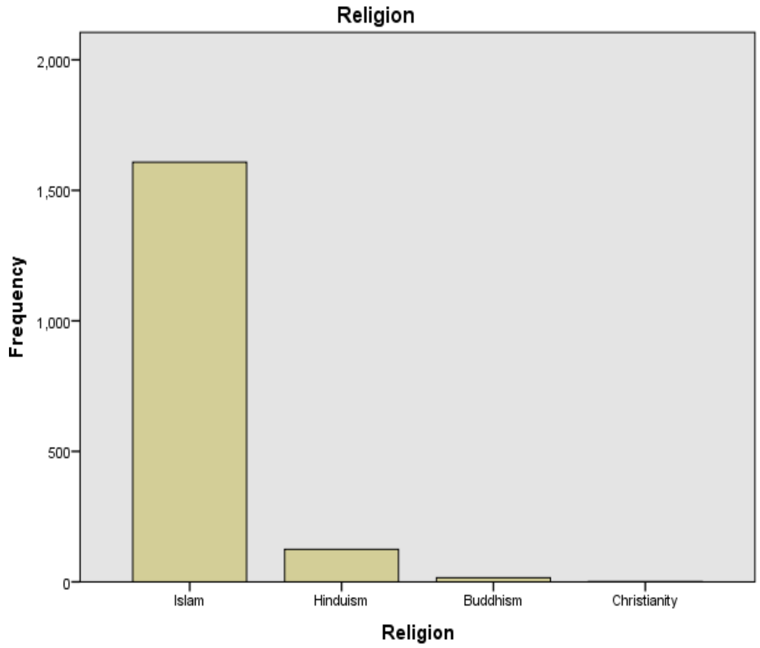

Figure 3. Bar chart of religion of respondents.

In our study, 91.9% peoples Religion are Islam and 7.1% peoples Religion are Hinduism. i.e., Maximum people are Muslim.

Table 5. Frequency distribution of Husband/partners occupation

Husband/partners occupation			
	Frequency	Percent	Cumulative Percent
Agricultural worker	1196	68.3	68.3
Non-Agricultural worker	339	19.4	87.7
Good Job	206	11.8	99.5
Others	9	.5	100.0
Total	1750	100.0	

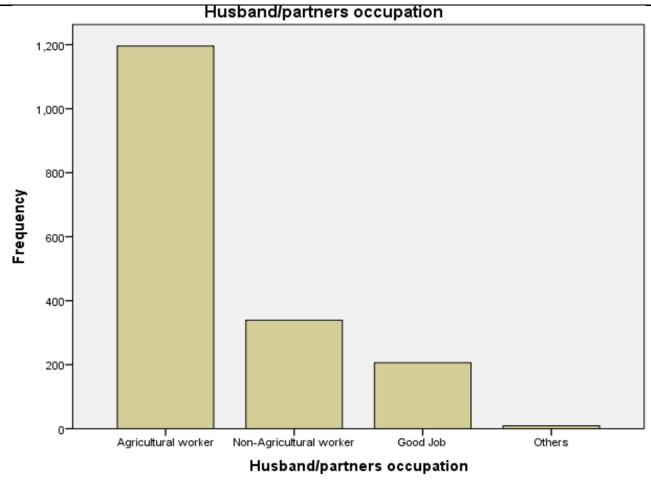

Figure 4. Bar chart of husband/partners occupation of respondents.

In this analysis, 68.3% are engaged in agricultural activities and 19.4% are non-agricultural worker. So, for an agro-based nation, the prevalence of agricultural workers is on lion's share.

Table 6. Frequency distribution of Age at First Marriage

Age at First Marriage			
	Frequency	Percent	Cumulative Percent
not early married	393	22.5	22.5
early married	1357	77.5	100.0
Total	1750	100.0	

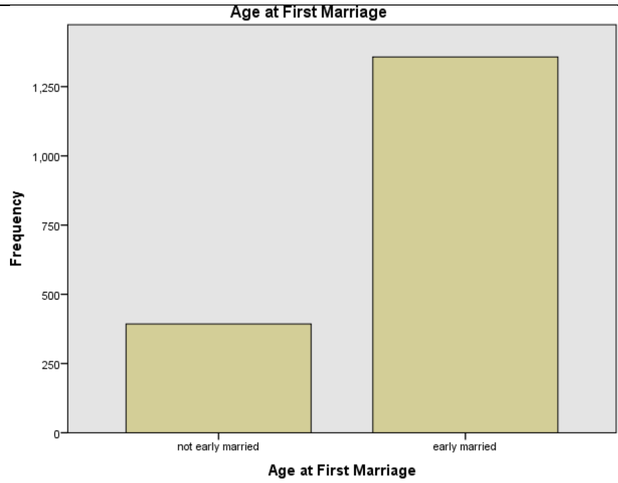

Figure 5. Bar chart of age at first marriage of respondents.

Early marriage and its clutch on our socio-economic life is our prime focus. On our study, 77.5 percent have experienced in early marriage. So, the extremeness of early marriage is on bottom line.

Table 7. Frequency distribution of type of place of residence

Type of place of residence			
	Frequency	Percent	Cumulative Percent
Urban	562	32.1	32.1
Rural	1188	67.9	100.0
Total	1750	100.0	

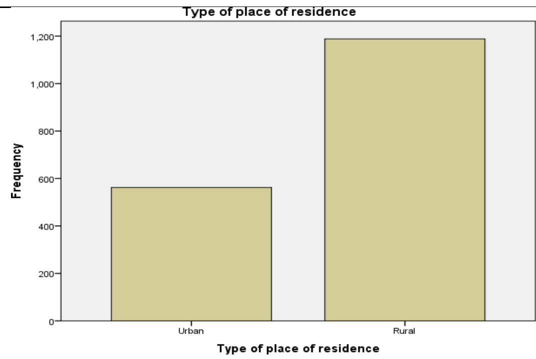

Figure 6. Bar chart of type of place of residence of respondents.

Like as agro-based country, its norm and fact to live and lead a life in pastoral society. Around 68 percent people live on rural place.

5.4 Bivariate analysis

Bivariate analysis means the analysis of bivariate data. It is one of the simplest forms of statistical analysis, used to find out if there is a relationship between two sets of value. An additional statistic, chi-square, is needed to perform a hypothesis testing about two variables.

Table. Bivariate analysis for Age at First Marriage and Highest education level.

Table 8. Age at First Marriage by Highest education level Cross tabulation

	Highest education level					Total
		No education	Primary	Secondary	Higher	
Age at First Marriage	not early married	39	71	198	85	393
	early married	305	384	640	28	1357
Total		344	455	838	113	1750

From Table 8, there is a positive association between age at marriage and educational qualification. On our study, the proportions of married women have assured 47.2 percent Secondary level.

Table 9. Chi-Square Test of age at first marriage and highest education level

Chi-Square Test			
	Value	**df**	**P-value**
Pearson Chi-Square	218.015	3	.000
Likelihood Ratio	184.038	3	.000
Linear-by-Linear Association	120.091	1	.000
N of Valid Cases	1750		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 25.38.

A highly significant chi-square test ($p<0.001$) shows a considerable correlation between education and early marriage. The nature and degree of this link are measured using odds ratios from the following logistic regression model.

5.5 Binary Logistic Regression

In binary logistic regression, we estimate regression coefficient with the presence or absence of dependent variables. The binary logistic regression model is

$Y\iota = \alpha + \beta 1 X1 + \beta 2 X2 \ldots \ldots \ldots . . (1)$

Where Y= Age at first marriage, X_1 = Highest education level, X_2 = Husband/partner education level.

Table. Logistic Regression Analysis of age at first marriage with highest education level and husband/partner education level.

Table 10. Dependent variable encoding for model (1)

Dependent Variable Encoding	
Original Value	Internal Value
not early married	0
early married	1

The dependent variable encoding table above shows the dependent variable, age at first marriage, is coded with the reference category, 1="early marriage", and the not-early marriage category is coded "0". This conventional for logistic analysis, which here focuses on the probability that age at first marriage=1.

Table 11. Classification table for model (1)

Classification Table				
Observed		Predicted		
		Age at First Marriage		Percentage Correct
		not early married	early married	
Age at First Marriage	not early married	0	393	.0
	early married	0	1357	100.0
Overall Percentage				77.5
a. Constant is included in the model.				
b. The cut value is .500				

The classification table above is a 2 x 2 table which tallies correct and incorrect estimates for the null model with only the constant. The columns are the two predicted values of the dependent, while the rows are the two observed (actual) values of the dependent. In a perfect model, all cases will be on the diagonal and the overall percent correct will be 100%. If the logistic model has homoscedasticity (not a logistic regression assumption) the percent correct will be approximately the same for both rows. Here it is not, with the model predicting non-early married cases but not predicting early married cases. While the overall percent correctly predicted seems moderately good at 77.5%, the researcher must note that blindly estimating the most frequent category (non-early married) for all cases would yield the same percent correct (77.5%).

Table 12. Variables in the equation for model (1)

Variables in the Equation						
	B	S.E.	Wald	Df	P-value	OR
Constant	1.239	.057	467.986	1	.000	3.453

The initial test for the model in which the coefficients for all the independent variables are 0. The finding of significance above indicates this null model should be rejected. So, the necessity of parameters is a must.

Table 13. Omnibus tests of model coefficients for model (1)

Omnibus Tests of Model Coefficients			
	Chi-square	Df	P-value
Step	134.451	2	.000
Block	134.451	2	.000
Model	134.451	2	.000

The chi-square goodness-of-fit test tests the null hypothesis that the step is justified. Here the step is from the constant-only model to the all-independents model. When as here the step was to add a variable or variables, the inclusion is justified if the significance of the step is less than 0.05. If the step is going to drop variables from the equation, then the exclusion would have been justified if the significance of the change was large (ex., over 0.10).

Table 14. Model Summary for model (1)

Model Summary		
-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1729.766	.074	.113
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.		

The Cox-Snell R^2 and Nagelkerke R^2 are attempts to provide a logistic analogy to R^2 in OLS regression. The Nagelkerke measure adapts the Cox-Snell measure so that it varies from 0 to 1, as does R^2 in OLS.

Table 15. Classification table for model (1)

Classification Table				
Observed		**Predicted**		
		Age at First Marriage		Percentage Correct
		not early married	early married	
Age at First Marriage	not early married	60	333	15.3
	early married	22	1335	98.4
Overall Percentage				79.7
a. The cut value is .500				

The classification table above is a 2 x 2 table which tallies correct and incorrect estimates for the full model with the independents as well as the constant. The columns are the two predicted values of the dependent, while the rows are the two observed (actual) values of the dependent. In a perfect model, all cases will be on the diagonal and the overall percent correct will be 100%. If the logistic model has homoscedasticity (not a logistic regression assumption) the percent correct will be approximately the same for both rows. Here it is not, with the model predicting all but 60 non-early married cases but predicting 22 early married cases. While the overall percent correctly predicted seems moderately good at 79.7%, the researcher must note that blindly estimating the most frequent category (non-early married) for all cases would yield an even higher percent correct (75.5%), as noted above. This implies Age at first marriage status cannot be differentiated on the basis of higher education level, husband/partner education level for these data.

Table 16. Variables in the equation for model (1)

Variables in the Equation						
	B	S.E.	Wald	df	P-value	OR
Hi.Ed.L	-.724	.094	58.798	1	.000	.485
HorP.Ed	-.143	.070	4.241	1	.039	.867
Constant	2.592	.151	295.623	1	.000	13.350
a. Variable(s) entered on step 1: Hi.Ed.L, HorP.Ed.						

$Y_\iota = 2.592 - .724X_1 - .143X_2$

On logistic regression, we exhibited relationship of several factors through the occurrences of early marriage. If a marriage occurs, then it will be decrease 0.143 units towards occurring early marriage in the perspective of husband/partners education level. The odds of occurring early marriage in husband/partners education level is 0.867 times less than other highest education level.

6. Summary and Conclusion

6.1 Highlight of the study

On our study, 77.5 percent women are married at early stage (or below 18 years). Whereas 48 percent has accomplished secondary level. Also, 91.9 percent are Muslim in religion.

The educational as well as occupational status is crucial in case of life of a woman in marital stage. 31.4 percent have accomplished Secondary level. Also, 68.3 percent engaged in agricultural sectors.

On bivariate analysis, we assess age at marriage is associated strongly with the educational qualification of husband.

Logit or binary logistic regression model is employed with educational qualification of both husband and wife. Result reveals significant on both estimators. Also, we run regression model with residential status and highest educational level.

Overall scenario depicts us that age of women at marital stage is a matter of discussion. So, we accordance with government will come forward to uphold woman right.

6.2 Conclusion

Practicing child marriage is now stands in a standard stage for city dwellers but not for rural life. 77.5 percent women are married at early stage (or below 18 years). While 48 percent has accomplished secondary level. Also, 91.9 percent are Muslim in religion.

Education, not only backbone of a nation but also for man and even woman also. About 31.4 percent have accomplished Secondary level. Also, 68.3 percent engaged in agricultural sectors.

By and large, the circumstances depict us that age of women at marital stage is a matter of discussion. So, we accordance with government will come forward to uphold woman right.

Empowerment and opportunity to workforce participation is crucial. So, we have to free them not only for the benefits of masculine society, but also for our nation's pride.

For triggering up the situation of women‟s life, awareness needs to be risen all-in a row.

References

[1] Amin S. Reforming marriage practices in Bangladesh. New York: Population Council; 2008. [viewed 2015 Aug 15].

[2] Boyd A, Ashford L, Haub C, Cornelius D. The worlds' youth 2000. Washington, DC: Population Reference Bureau; 2000. [viewed 2015 Sep 14].

[3] Choe MK, Thapa S, Mishra V. Early marriage and early motherhood in Nepal. J Biosoc Sci. 2005;7(2):1-20. [viewed 2015 Aug 25].

[4] Field E, Ambrus A. Early marriage, age of menarche, and female schooling attainment in Bangladesh. J Polit Econ. 2008;116(5):881-30. [viewed 2015 Aug 25].

[5] Fleischer A, LutzJean M, Schmidt O. Population dynamics in Bangladesh: A case study on the causes and effects of demographic change in Bangladesh. Dhaka: Division of Health, Education and Social Protection; 2010. [viewed 2015 Sep 24].

[6] Hirschman C. Premarital socioeconomic roles and the timing of family formation: a comparative study of five Asian societies. Demography. 1985;22(1):35-59. [viewed 2015 Sep 15].

[7] Innocenti Digest. Early marriage: child spouses. Italy: UNICEF; 2001. [viewed 2015 Aug 12].

[8] Jain G, Bisen V, Singh SK, Jain P. Early marriage of girls as a barrier to their education. Int J Adv Eng Technol. 2011;2(3):193-8. [viewed 2016 May 20].

[9] Kumchulesi G, Palamuleni M, Kalule-Sabiti I. Factors affecting age at first marriage in Malawi. In: Sixth African Population Conference; 5-9 Dec 2011; Ouagadougou-Burkina Faso. [viewed 2015 Sep 17].

[10] Nasrin SO, Rahman KM. Factors affecting early marriage and early conception of women: A case of slum areas in Rajshahi City, Bangladesh. Int J Sociol Anthropol. 2012;4(2):54-62.

[11] NIPORT. Bangladesh demographic and health survey 2011. Dhaka: Mitra & Associates; 2013. [viewed 2015 Aug 7].

[12] Rahman M, Hossain M, Islam M. Female age at marriage of rural-urban differentials in Bangladesh. Internet J Biol Anthropol. 2008;3(2):1-7. [viewed 2015 Sep 23].

[13] Raj AD, Bhattarai R, Amudha P, Edwin VT, Glyn C. Factors associated with teenage pregnancy in South Asia: a systematic review. Health Sci J. 2010;4(1):3-14. [viewed 2015 Aug 13].

[14] Sah R, Gaurav K, Baral D, Subedi L, Jha N, Pokharel P. Factors affecting early age marriage in Dhankuta Municipality, Nepal. Nepal J Med Sci. 2014;3(1):26-30.

[15] Singh S, Samara R. Early marriage among women in developing countries. Int Fam Plan Perspect. 1996;22(4). [viewed 2015 Aug 13].

[16] Somerset C. Early marriage: whose right to choose? UK: Forum on Marriage and the Rights of Women and Girls; 2000. [viewed 2015 Sep 7].

[17] Tristam P. Child marriage: facts, causes and consequences. about news. 2014:1. [viewed 2015 Sep 7].

[18] Verma R, Sinha T, Khanna T. Asia child marriage initiative: summary of research in Bangladesh, India and Nepal. Delhi: International Center for Research on Women; 2013. [viewed 2015 Sep 13].

[19] Agresti A. Analysis of ordinal categorical data. New York: Wiley; 1984.

[20] Agresti A. A survey of exact inference for contingency tables. Statis Sci. 1992;7:131-53.

[21] Agresti A. Computing conditional maximum likelihood estimate for generalized Rasch models using simple loglinear models with diagonal parameters. Scand J Statist. 1993;20:63-71.

[22] Agresti A. A model for repeated measurements of a multivariate binary response. J Amer Statist Assoc. 1997;92:315-21.

.