Beyond the Cox Model: A Comparative Parametric Survival Modelling of Time to First Birth Among Married Women

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Abstract: *Background:* Data on time-to-first birth typically involves censoring, as not all individuals in the survey experience their first birth by the survey date. Traditional analyses often rely on the semi-parametric Cox proportional hazards model; however, violations of the proportional hazards (PH) assumption necessitate more flexible modelling approaches.

Objectives: This study aimed to compare the performance of multiple parametric survival models against the Cox model in estimating time-to-first birth among currently married women in Bangladesh and to identify key predictors of time-to-first birth.

Methods: Data were drawn from the 2022 Bangladesh Demographic and Health Survey (BDHS), encompassing 17,146 currently married women aged 15–49 years. Survival analyses were conducted using the Kaplan–Meier estimator, log-rank tests, Cox regression, and five parametric models: Exponential, Weibull, Log-normal, Gompertz, and Generalised Gamma. Model fit was assessed using AIC and BIC, and log-likelihood statistics.

Results: The mean time-to-first birth after marriage was 40.12 ± 0.50 months, with a median of 26 months, indicating a right-skewed distribution caused by some women experiencing notably delayed first births. The Cox model failed PH assumption tests, highlighting its inadequacy. Among parametric models, the Generalized Gamma model provided the best fit, effectively capturing complex hazard structures. Key predictors of the time-to-first birth included age at first marriage, women's and husbands' education, contraceptive use, administrative division, living arrangement with spouse, and media exposure.

Conclusion: This study underscores the importance of using flexible parametric models—such as the Generalised Gamma model—when dealing with time-to-event data where the proportional hazards assumption is violated. This approach provides more reliable effect estimates and improves the interpretability of covariate influences on fertility timing. Findings underscore the importance of the identified predictors in designing reproductive health policies and interventions aimed at delaying early childbearing.

Keywords: Marriage-to-first birth, First birth interval, Survival analysis, Cox model, Parametric model, Bangladesh.

INTRODUCTION

Time to first birth after marriage, often referred to as the first birth interval (FBI), is defined as the duration between marriage and the birth of the first child. It is a critical demographic and public health indicator that has profound implications for reproductive health and maternal and child outcomes. It shapes not only individual life trajectories but also influences national fertility trends and population growth patterns [1-3]. The first birth interval is influenced by various socio-demographic and cultural factors [4-6]. Understanding these factors is essential for developing effective fertility-related policies and interventions.

Time-to-first-birth data, a specific type of time-to-event (TTE) data, is unique because it considers not only whether an event (such as a first birth) has occurred, but also when it occurred. Time-to-event data from any cross-sectional survey typically involves censoring, as not all individuals in the survey experience the event of interest (in this case, the first birth) by the survey date. Researchers face the challenge of analysing event history data as it involves censoring. Analysis that excludes censored observations and includes only complete cases—that is, women who have given birth within the study duration—can lead to misleading results in terms of the average duration of the FBI and its predictors. This is because censored cases are more likely to include women who take a longer time to give birth, and removing them from the analysis tends to underestimate the true average time to first birth in the population. Traditional regression models (logistic or linear) fail to accommodate such censoring, necessitating the use of survival analysis techniques [7]. Survival analysis techniques are specifically designed to handle censoring, making them appropriate for studying time-to-event data [7].

The Cox proportional hazards (PH) model is a widely used survival model applied in demographic research due to its semi-parametric nature and flexibility in handling censored data [8]. However, the validity of the Cox model relies on the PH assumption (the hazard of variables is independent of time), which, when violated, can lead to biased estimates [16]. Parametric survival models—such as the Exponential or Weibull or Log-normal—offer an alternative, allowing for explicit specification of the baseline hazard function and potentially greater efficiency in estimation [9]. Comparative studies have demonstrated that parametric models outperform the Cox model when the PH assumption fails, especially in fertility-related research [10, 11]. Parametric models offer precise

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coefficient estimates and directly evaluate the influence of explanatory variables on survival time, simplifying interpretation through the time ratio (TR). Additionally, fitted parametric models can be used for predictive purposes.

While earlier studies have explored the determinants of the first birth interval using the Cox model or a limited set of parametric approaches, they often overlook a crucial methodological issue: the violation of the proportional hazards (PH) assumption inherent to the Cox model. This assumption, if unmet, can lead to biased hazard ratio estimates and unreliable inferences. Given that violations of the PH assumption are common in socio-demographic datasets [12, 13], there is a need for research that moves “beyond the Cox model” to identify both robust predictors and optimal statistical methods. To address this, we employed a parametric survival modelling approach. We systematically compare a comprehensive set of parametric survival models. By moving beyond the limitations of the Cox model, our study introduces a more robust methodological framework for modelling the time to first birth.

This study extends the scope of modelling time-to-first birth by incorporating two additional parametric survival models—Generalized Gamma and Gompertz—alongside the more commonly used Exponential, Weibull, and Log-normal models, considering marriage to the first birth interval as the outcome variable. The Generalized Gamma distribution is employed in this study due to its remarkable flexibility in modelling various hazard rate forms, including increasing, decreasing, bathtub-shaped, and unimodal patterns—features that are particularly relevant for fertility timing, where risk profiles can shift over time due to biological, behavioural, or societal influences [14]. The Gompertz model is included because its assumption of an exponentially increasing hazard rate aligns with the age-related nature of first birth timing, offering a distinct advantage over models that do not explicitly account for this feature [11].

This study aims to investigate the socio-demographic and economic determinants of time to first birth among currently married women in Bangladesh using data from the 2022 Bangladesh Demographic and Health Survey (BDHS). In Bangladesh, where early marriage remains prevalent and socio-economic disparities influence reproductive behaviour, understanding the determinants of the first birth interval is essential for designing effective policies aimed at improving health outcomes and managing population growth. By employing a comparative parametric survival analysis beyond the traditional Cox model, this research not only ensures methodological robustness but also advances statistical modelling practices in fertility research, offering a more precise identification of predictors of time to first birth.

METHODS AND MATERIALS

Study Design and Data Sources

Data for this study were obtained from the 2022 Bangladesh Demographic and Health Survey (BDHS). The survey was conducted by the National Institute of Population Research and Training (NIPORT) under the Ministry of Health and Family Welfare (MoHFW) with the financial and technical support provided by the Government of Bangladesh and the United States Agency for International Development (USAID). Field data collection took place between 27 June and 12 December 2022. The details of the survey are available in the final report of the 2022 BDHS [15]. The dataset is publicly available through the Demographic and Health Surveys (DHS) Program website: (https://dhsprogram.com/data/dataset/Bangladesh_Standard-DHS_2022.cfm?flag=1).

The 2022 BDHS survey followed a two-stage stratified sampling design. In the first stage, 675 EAs (237 in urban areas and 438 in rural areas) were selected with probability proportional to EA size. EAs are the smallest statistical sample units containing 50 to 160 households, used in the national population and housing census in Bangladesh. The list of EAs is prepared and updated by the Bangladesh Bureau of Statistics (BBS) prior to each census. In the second stage, a systematic sample of 30 households on average was chosen per EA to produce statistically reliable estimates of key demographic and health indicators for the country as a whole, as well as for urban and rural areas separately and for each of the eight divisions: Barishal, Chattogram, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet [15].

The 2022 BDHS dataset contained information on 30,078 ever-married Bangladeshi women aged 15–49 years. For this study, we limited our sample to women who were currently married, as data on some key variables—especially those related to the husband—were missing for widowed, divorced, and separated women. This study also focuses exclusively on the first birth history of each respondent. Births that occurred during biologically implausible durations, such as less than nine months after marriage or before marriage, were excluded. After applying all these exclusion criteria, the final analytic sample consisted of 17,146 currently married women. Among them, 15,250 women had experienced their first birth (status = 1), while the remaining 1,896 were right-censored (status = 0), indicating no first birth had occurred by the survey date.

Outcome Variable

The outcome variable in this study is the time, in months, between marriage and the first birth among currently married women. Women were either at risk of giving birth after marriage or had already given birth by the survey date. For those who had given birth, the survival time was calculated as the period from marriage to the first birth. For those who had not yet given birth, the time was measured from marriage to the survey date, which was labelled as right-censored. Biologically implausible durations, such as negative durations or those less than 9 months, were excluded, in accordance with clinical standards for full-term pregnancies [16].

Explanatory Variables

Depending on the availability of variables in the 2022 BDHS data set, this study considered a total of 13 explanatory variables to examine their association with the outcome variable, time to first birth. These include place of residence, age at first cohabitation or marriage, educational attainment, sex of household head, wealth index, administrative division, religion, ever used anything to avoid or delay pregnancy, husband's education, frequency of watching television, respondent's occupation, husband's occupation, and currently residing with husband.

Survival Analysis

The two key quantitative measures in survival analysis are the survivor function S(t) and the hazard function h(t). In the context of the present study, the survival function gives the probability that a woman "survives" longer than some specified time t without a birth after marriage, while the hazard function gives the instantaneous potential per unit time to have a first childbirth after time t, given that the woman had not had a first childbirth up to time t. Mathematically, the survival function S(t) and hazard function h(t) are defined as follows.

Let the random variable T denote the survival time, and let $f(t)$ denote its probability density function (pdf). Then the probability of failure before a specific time t is given by the cumulative probability distribution

$$F(Y) = P(Y < y) = \int_0^y f(t)dt.$$

Then $S(t) = P(T > t) = 1 - F(t)$ and $h(t) = \frac{f(t)}{S(t)}$.

Unlike the survivor function (S(t)), which indicates the probability of not failing before time t, the hazard function (h(t)) shows the failure rate at time t among those still alive at that moment.

There are three types of models for analysing the survival time. These are: the nonparametric models such as the Kaplan-Meier (K-M) model [17], the semi-parametric Cox Proportional Hazard model [8], and the parametric models. In the K-M method, we assume that we have a sample of n independent observations denoted by (t_i, c_i) (i=1, 2, …., n) of the underlying survival time *T* and the censoring indicator C. Among the n observations, let there be m ≤ n recorded times of the first birth. Let $t_{(1)} \leq t_{(2)} \leq \cdots \leq t_{(m)}$ are the rank-ordered survival times of the first birth. Let n_i be the number of women exposed to have a first birth at $t_{(i)}$ and d_i be the observed number of women with first birth at $t_{(i)}$, then the K-M estimator of the survivorship function at time *t* is obtained from the equation

$$\hat{S}(t) = \prod_{t(i)\leq t} \left(\frac{n_i - d_i}{n_i}\right) \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

with $\hat{S}(t) = 1$ if $t<t_{(1)}$.

In this study, we employed the K-M method to obtain the summary measures (mean and median) of the time to first birth. After obtaining summary statistics of survival time, a comparison of the time to first birth among subgroups of women, defined by the categories of a covariate, was conducted using the log-rank (LR) test.

The widely used semi-parametric model, the Cox proportional hazards (PH) model, was then fitted to examine the association between time to first birth and selected explanatory variables reflecting sociodemographic factors. The model expresses the hazard for an individual as the product of a baseline hazard function and an exponential function of covariates. Formally, the hazard at time t for the i th individual is given by

$$h_i(t) = h_{0i}(t)\, exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta p x p_i),$$
i=0, 1, ……..n

where $h_0(t)$ is the baseline hazard, x_{ji} represent the covariates and β are the corresponding regression coefficients [18]. The model does not require any specific form for the baseline hazard, making it flexible and suitable for a wide range of survival data. Interpretation is often based on hazard ratios (HRs), which are estimated as HRj = $\exp(\beta_j)$, indicating the relative change in hazard for a one-unit change in the covariate x_j, assuming all other variables are held constant. The Cox PH model relies on a strong assumption that the HRs between any two individuals or groups stay constant over time, which may not be true for all situations. Violations of the proportional hazards (PH) assumption can lead to biased estimates and inaccurate p-values, affecting conclusions about statistical significance. We, therefore, also conducted Schoenfeld residual tests to verify the presence of these violations.

Following this, a set of parametric survival models was fitted using different baseline distributions, including Exponential, Weibull, Log-normal, Gompertz, and Generalized gamma. A parametric survival model assumes that survival time follows a specific probability distribution.

Exponential Distribution

Among parametric survival models, the exponential distribution is considered the simplest, and it is defined by a single parameter, λ. It assumes a constant hazard rate over time, indicating that the probability of an individual experiencing the event in a small interval Δt, given survival until time t, remains the same at all time points. The probability density function (PDF) is given by:

$$f(t) = \lambda e^{-\lambda t} \ ; t \geq 0 \text{ and } \lambda > 0,$$

and the cumulative distribution function (CDF) is given by $F(t) = 1 - e^{-\lambda t}$; t ≥ 0.

The corresponding survival function S(t) is:

$$S(t) = e^{-\lambda t}$$

Then by definition, $h(t) = \frac{f(t)}{S(t)}$, the hazard function for the exponential distribution simplifies to: h(t) = λ; t ≥ 0.

Weibull Distribution

The Weibull distribution is a flexible parametric model that generalizes the exponential distribution. It can be used to model survival data when the hazard is monotone—either increasing or decreasing [18]. The two-parameter Weibull distribution includes a shape parameter γ and a scale parameter λ. The probability density function (PDF) is given by:

$$f(t) = \lambda\gamma(\lambda t)^{\gamma-1} e^{-(\lambda t)^{\gamma}} \ ; t \geq 0, \gamma, \lambda > 0$$

when γ = 1, the Weibull distribution simplifies to an exponential distribution.

The cumulative distribution function F(t) is given as: $F(t) = 1 - e^{-(\lambda t)^{\gamma}}$

The survival function S(t) is given by: $S(t) = e^{-(\lambda t)^{\gamma}}$

The hazard function is: $h(t) = \lambda\gamma(t)^{\gamma-1}$

Log-Normal Distribution

The log-normal distribution is defined as the distribution of a variable whose logarithm follows a normal distribution [9]. It is particularly useful for describing nonmonotonic hazard functions, but is recommended only when the survival data contain few censored observations [19]. The two-parameter log-normal distribution includes a location parameter μ and a scale parameter σ. The probability density function (PDF) is given by:

$$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} exp\left\{-\frac{1}{2\sigma^2}(logt - \mu)^2\right) \ ; \ t > 0, \sigma > 0$$

The survival function S(t) is:

$$S(t) = \frac{1}{\sigma\sqrt{2\pi}} \int_t^{\infty} \frac{1}{x} exp\left\{-\frac{1}{2\sigma^2}(log\, x - \mu)^2\right\} dx$$

$$S(t) = 1 - G(log\, \frac{at}{\sigma})$$

where G(y) is the cumulative distribution function of a standard normal variable.

The hazard function is:

$$h(t) = \frac{(1/t\sigma\sqrt{2\pi}) exp[-(log\, at)^2/2\sigma^2]}{1 - G(log\, at/\sigma)}$$

Generalized Gamma Distribution

The generalized gamma distribution (GG) was introduced by Stacy [20] and includes several well-known distributions as special cases, such as the exponential, Weibull, and gamma distributions. It is suitable for modelling data with different forms of hazard rate functions: increasing, decreasing, bathtub-shaped, and unimodal. The cumulative distribution function (CDF) is given by:

$$F(t) = \gamma\{\alpha/p, (\lambda t)^p\}/\Gamma(\alpha/p); t, \lambda, p, \alpha > 0$$

The probability density function (PDF) is given by:

$$f(t) = p\lambda(\lambda t)^{\alpha-1} e^{-(\lambda t)^p}/\Gamma(\alpha/p$$

The hazard function is:

$$h(t) = \frac{p\lambda(\lambda t)^{\alpha-1} e^{-(\lambda t)^p}}{\gamma\{\alpha/p, (\lambda t)^p\}}$$

where $\gamma(s,x) = \int_0^x t^{s-1} e^{-t} dt$ is the incomplete gamma function.

The generalized gamma distribution simplifies to the gamma distribution when $p = 1$. If both $p = \alpha = 1$, it reduces to the exponential distribution. When $\alpha = p$, it simplifies to the Weibull distribution.

Gompertz Distribution

The Gompertz distribution, introduced in 1825 [21], is a parametric model for survival and mortality law.

Gompertz developed his distribution based on empirical mortality data and provided a theoretical foundation for its use in survival analysis. The distribution is defined by a shape parameter $b > 0$ and a scale parameter $\theta > 0$. The probability density function (pdf) of the Gompertz distribution is given by

$$f(t) = b\,exp\,(t/\theta)\,exp\,(b\,\theta\,(1 - exp\,(t/\theta))) \quad , \quad 0 < t < \infty$$

The cumulative distribution function is

$$F(t) = 1 - exp\,(b\,\theta\,(1 - exp\,(t/\theta)))$$

The survival function is given as

$$S(t) = exp\,(b\,\theta\,(1 - exp\,(t/\theta)))$$

The hazard function is

$$h(t) = b\,exp\,(t/\theta)$$

Table **1** presents a comparative analysis of the characteristics of the five parametric models. To compare the performance of these parametric models and determine which model provides the best fit to the data, we use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). All the analysis were done using RStudio (version 4.3.2) with the survival and flexsurv packages.

RESULTS

Characteristics of the Sample Respondents

Among 17,146 currently married women, 64.6% were from rural areas and 35.4% from urban settings. Over half (56.8%) of the women married between the ages of 15 and 19, with around 27.3% marrying at 14 or younger (Table **2**). In education, 11.9% had no formal schooling, 27.3% completed primary education, 47.4% attained secondary education, and 16.0% had higher education. About 12.0% of households were female-headed. The sample included women from all eight divisions of Bangladesh, predominantly Muslim (89.6%) and contraceptive users (84.3%). Husbands' education was mostly at the secondary level (32.7%). Nearly half (49.6%) of women watched TV weekly, and 65.2% were housewives. Regarding husbands' occupations, 62.4% were employed in skilled or unskilled jobs. Most women (84.4%) lived with their husbands, while 7.5% had husbands living elsewhere in Bangladesh and 8.1% had husbands abroad.

Time to First Birth and Its Covariates

Out of 17,146 currently married women, 15,250 (88.94%) had their first childbirth by the survey date, while 1,896 (11.06%) had not and were censored in the survival analysis. The Kaplan-Meier estimates of the time-to-first birth after marriage indicate a mean waiting time of 40.12 ± 0.50 months and a median waiting time of 26 months (Table **2**). This suggests a right-skewed distribution, indicating that some women experienced significantly delayed first births. The log-rank test revealed that the majority of the covariates examined in this study were significantly associated with time to first birth. These included age at first marriage, educational attainment, wealth index, division, religion, contraceptive use, husband's education, respondent occupation, husband's occupation, and whether the respondent was currently residing with her husband or partner.

Urban women had a longer mean time to first birth (40.80 ± 0.89 months) compared to rural women (39.48 ± 0.59 months) (p = 0), though both groups had a median of 26–27 months. Women who were married at age 14 or younger had a median time of 30 months, with similar trends observed across education levels.

Age at first marriage showed a strong association with time to first birth. Those who were married at age ≤14 had the longest mean time to first birth (43.68 ± 0.85 months, median 30), while those aged 15–19 had

Table 1: A Comparative Analysis of the Key Characteristics of the Five Models

Model	Number of Parameters	Shape of Hazard Function	Special Cases
Exponential	1 (rate λ)	Constant hazard over time	Special case of Weibull when γ = 1
Weibull	2 (shape γ, scale λ)	Monotonic: increasing if γ > 1, decreasing if γ < 1	Reduces to the Exponential distribution when γ=1
Log-normal	2 (location μ, scale σ)	Non-monotonic (unimodal); hazard increases to a peak and then decreases	
Gompertz	2 (shape b, scale θ)	Exponentially increasing (or decreasing) over time	Related to Makeham model
Generalized Gamma	3 (α, p, λ)	Very flexible, increasing, decreasing, bathtub-shaped or unimodal	• Gamma distribution when p = 1 • Exponential distribution when p = α =1 • Weibull distribution when α = p

Table 2: Demographic Characteristics of Women and their Kaplan-Meier Estimates for Time to First Birth (Months).

Covariate	Frequency (%)	Time to First Birth		Log Rank Test p-Value
		Mean ± SE	Median	
Total	17146 (100.0)	40.12±0.50	26	
Place of Residence				0.051
Urban	6078 (35.4)	40.80±0.89	27	
Rural	11068 (64.6)	39.48±0.59	26	
Age at first marriage				<.001
≤ 14	4683 (27.3)	43.68±0.85	30	
15-19	9732 (56.8)	36.79±0.57	25	
≥ 20	2731 (15.9)	42.12±1.40	25	
Educational Attainment				<.001
No Education	2038 (11.9)	47.22±1.56	29	
Incomplete Primary	2010 (11.7)	38.46±1.07	26	
Complete Primary	2214 (12.9)	37.21±0.92	25	
Incomplete Secondary	6124 (35.7)	37.33±0.77	25	
Complete Secondary	2011 (11.7)	35.06±0.95	26	
Higher	2749 (16.0)	40.39±0.94	30	
Sex of Household Head				0.644
Male	15032 (87.7)	40.49±0.55	26	
Female	2114 (12.3)	36.72±0.87	26	
Wealth Index				0.001
Poorest	2903 (16.9)	38.97±1.09	26	
Poorer	3312 (19.3)	39.80±1.06	26	
Middle	3404 (19.9)	39.93±1.09	26	
Richer	3608 (21.0)	37.50±0.92	26	
Richest	3919 (22.9)	41.24±1.01	28	
Division				<.001
Barishal	1850 (10.8)	42.05±1.31	30	
Chattogram	2509 (14.6)	32.41±0.90	22	
Dhaka	2620 (15.3)	41.77±1.24	28	
Khulna	2253 (13.1)	39.98±1.18	28	
Mymensingh	1842 (10.7)	40.83±1.38	28	
Rajshahi	2248 (13.1)	43.13±1.62	28	
Rangpur	2075 (12.1)	39.43±1.19	27	
Sylhet	1749 (10.2)	36.43±1.48	21	
Religion				< 0.010
Muslim	15371 (89.6)	40.21±0.53	27	
Non-Muslim	1775 (10.4)	38.46±1.43	25	
Contraceptive use				<.001
No	2688 (15.7)	92.82±3.38	38	
Yes	14458 (84.3)	32.86±0.25	25	
Husband Education				<.001
No Education	3435 (20.0)	41.62±1.05	27	
Primary	4704 (27.4)	36.69±0.77	24	
Secondary	5611 (32.7)	39.14±0.86	26	
Higher	3396 (19.8)	41.74±1.06	30	

Table 2 (contd….)

Covariate	Frequency (%)	Time to First Birth		Log Rank Test p-Value
		Mean ± SE	Median	
Frequency of Watching TV				0.157
Not at all	7361 (42.9)	39.85±0.76	26	
Less than once a week	1277 (7.4)	39.81±1.62	26	
At least once a week	8508 (49.6)	39.66±0.65	27	
Respondent Occupation				<0.001
Housewife	11178 (84.4)	40.21±0.63	26	
Professional	401 (2.3)	42.47±2.11	32	
Agricultural Worker	3368 (19.6)	36.42±0.77	26	
Skilled/Unskilled Woker	2199 (12.8)	42.80±1.57	27	
Husband Occupation				<.001
Not Working	620 (3.6)	43.03±2.30	28	
Professional	1955 (11.4)	38.86±1.00	29	
Agricultural Worker	3876 (22.6)	40.12±0.93	26	
Skilled/Unskilled Woker	10695 (62.4)	39.74±0.67	26	
Residing with Husband				<0.001
Living with her	14478 (84.4)	40.13±0.55	26	
Staying elsewhere within Bangladesh	1279 (7.5)	40.57±1.37	29	
Staying abroad	1389 (8.1)	35.84±1.11	24	

the shortest (36.79 ± 0.57 months). Interestingly, women married at ≥20 had a relatively long mean time to first birth (42.12 ± 1.40) but a similar median of 25 months.

Educational attainment revealed a nonlinear pattern. Women with no education had the longest mean time to first birth (47.22 ± 1.56 months), while those with complete secondary education had the shortest (35.06 ± 0.95). Notably, women with higher education had a longer mean (40.39 ± 0.94) and median (30), implying delayed childbearing possibly due to educational.

The wealth index showed a modest but statistically significant association ($p = 0.001$). Women in the richest quintile had the highest average time to first birth (41.24 ± 1.00 months), indicating delayed childbearing among wealthier groups. Conversely, women in the 'richer' quintile had the shortest average time to first birth (37.50 ± 0.92 months), although all quintiles shared a median of 26 months, except for the richest.

Regional differences (Division) were significant ($p < 0.001$). The longest average time to first birth was recorded in Rajshahi (43.13 ± 1.62 months) and Barishal (42.05 ± 1.31 months), both with a median of 28–30 months. Conversely, Chattogram and Sylhet showed shorter averages (32.41 ± 0.90 and 36.43 ± 1.48 months, respectively), with Sylhet having the lowest median at 21 months, reflecting considerably earlier childbearing in this area.

Religion showed a statistically significant difference ($p = 0.010$). Muslim women had a slightly longer average time to first birth (40.21 ± 0.53 months) compared to non-Muslim women (38.46 ± 1.43 months), although their median time to first birth was higher (27 vs. 25 months), suggesting that religion has a modest impact (Table **2**).

Using contraception to delay or prevent pregnancy had the most significant impact ($p < 0.001$). Women who did not use contraception experienced a much longer average time to first birth (92.82 ± 3.38 months) compared to users (32.86 ± 0.25 months), highlighting a notable behavioural effect on fertility timing.

Husband's education showed a strong association with the time to first birth ($p < 0.001$). Women whose husbands had higher education had the longest average time to first birth (41.74 ± 1.06 months), whereas those with husbands who had primary education had the shortest average (36.69 ± 0.77 months).

Respondent occupation significantly influenced the timing of the first birth after marriage ($p < 0.001$). Professional and skilled/unskilled workers had longer mean time to first birth (42.47 ± 2.11 and 42.80 ± 1.57 months, respectively), with medians of 27–32 months. In contrast, agricultural workers had a shorter mean time to first birth (36.42 ± 0.77 months), possibly reflecting rural, earlier fertility patterns (Table **2**).

Husband's occupation also had a significant impact on time to first birth after marriage ($p < 0.001$). Women with unemployed husbands experienced the longest average time to first birth (43.03 ± 2.30 months), likely due to economic limitations. Other occupational groups showed less variation but generally ranged from 38.9 to 40.1 months.

The current living status with the husband significantly influenced the time to first birth after marriage ($p = 0.001$). Women living with their husbands had an average of 40.13 ± 0.55 months (median 26), while those whose partners were abroad had the shortest duration — 35.84 ± 1.11 months (median 24).

Model Selection

The foregoing bivariate analysis using the K-M method and the LR test identified 10 significant covariates out of 13 explanatory variables considered in this study. However, the bivariate analysis revealed an unadjusted association between the outcome and explanatory variables without controlling for potential confounders. Therefore, to establish an adjusted association between the outcome and the explanatory variables, we initially used the widely employed Cox PH model. The Cox proportional hazards model identified several significant predictors, including age at first marriage, women's education, contraceptive use, administrative division, and living status with husband. However, the test of the PH assumption revealed that the PH assumption was extensively violated for most covariates, as indicated by Schoenfeld residual tests (global test: $\chi^2 = 516.64$, df = 35, $p < 0.001$) (Table **3**), raising concerns about the reliability of the Cox estimates. Out of the 13 covariates included in the model, only three variables—place of residence ($\chi^2 = 1.52$, $p = 0.217$), sex of household head ($\chi^2 = 2.54$, $p = 0.111$), and wealth index ($\chi^2 = 2.71$, $p = 0.608$) —satisfied the PH assumption, while key predictors such as age at first marriage, education, contraceptive use, division, and living arrangement significantly violated it (Table **3**).

The extensive violation of the PH assumption underscores the need to consider parametric survival models that do not rely on this assumption. This study, therefore, extended its analysis beyond the Cox model, fitting multiple parametric alternatives—including the Exponential, Weibull, Log-normal, Gompertz, and Generalized Gamma distributions—to identify a more suitable model for explaining the timing of first birth.

Table **4** presents the results of the Cox PH model alongside five parametric alternatives—Exponential, Weibull, Log-normal, Gompertz, and Generalized Gamma. The results were presented only for the significant variables, by removing those variables that appeared insignificant in all the models. Overall, there was considerable agreement across models in identifying the most influential predictors of time to first birth, though some variables showed inconsistent significance across model specifications.

While both Cox and parametric models identified broadly similar core predictors—age at marriage,

Table 3: Testing the Proportional Hazards Assumptions of Cox Regression

Covariate	χ^2 value	Df	p-Value
Place of Residence	1.52	1	0.217
Age at first cohabitation	139.74	2	<0.001
Educational Attainment	13.20	5	0.022
Sex of Household Head	2.54	1	0.111
Wealth Index	2.71	4	0.608
Division	253.09	7	<0.001
Religion	4.52	1	0.034
Ever used a contraceptive	123.97	1	<0.001
Husband Education	44.28	3	<0.001
Frequency of Watching Television	16.60	2	<0.001
Respondent Occupation	17.34	3	0.001
Husband Occupation	20.46	3	<0.001
Currently Residing with Husband/Partner	56.67	2	<0.001
Global Test	516.64	35	<0.001

Table 4: Results of Fitting the Cox Proportional Hazards Model (PH) and Parametric Models

Covariates	Cox PH Model		Weibull		Exponential AFT Model		Log-Normal AFT Model		Gompertz Model		Generalized Gamma Model	
		p-Value		p-Value	$\hat{\beta}$	p-Value		p-Value	$\hat{\beta}$	p-Value	$\hat{\beta}$	p-Value
Intercept			4.746	0.000	4.669	0.000	4.092	0.000	-4.854	0.000	3.609	0.000
Age at first marriage												
≤ 14 Ref	1		1		1		1		1		1	1
15-19	1.25	<0.001	-0.163	<0.001	0.159	<0.001	-0.168	<0.001	0.170	<0.001	-0.149	<0.001
≥ 20	1.34	<0.001	-0.211	<0.001	0.195	<0.001	-0.227	<0.001	0.213	<0.001	-0.213	<0.001
Educational Attainment												
No Education Ref	1		1		1		1		1		1	
Incomplete Primary	1.12	<0.001	-0.132	<0.001	0.11	0.001	-0.076	<0.001	0.133	<0.001	-0.046	0.017
Complete Primary	1.15	<0.001	-0.137	<0.001	0.125	<0.001	-0.098	<0.001	0.146	<0.001	-0.065	0.001
Incomplete Secondary	1.25	<0.001	-0.220	<0.001	0.178	<0.001	-0.137	<0.001	0.210	<0.001	-0.087	<0.001
Complete Secondary	1.26	<0.001	-0.25	<0.001	0.188	<0.001	-0.132	<0.001	0.227	<0.001	-0.075	0.001
Higher education	1.10	0.026	-0.158	<0.001	0.09	0.033	-0.060	0.025	0.127	0.003	-0.028	0.237
Wealth Index												
Poorest Ref	1		1		1		1		1		1	1
Poorer	0.98	0.474	0.035	0.072	-0.021	0.447	0.003	0.850	-0.028	0.314	-0.004	0.787
Middle	0.97	0.363	0.044	0.027	-0.024	0.395	0.011	0.555	-0.034	0.238	0.001	0.975
Richer	1.02	0.506	0.016	0.458	0.014	0.638	-0.026	0.184	0.005	0.855	-0.029	0.095
Richest	0.96	0.245	0.080	0.001	-0.030	0.372	0.012	0.580	-0.050	0.142	-0.002	0.898
Division												
Barishal Ref	1		1		1		1		1		1	1
Chattogram	1.40	<0.001	-0.229	<0.001	0.247	<0.001	-0.260	<0.001	0.258	<0.001	-0.247	<0.001
Dhaka	1.10	0.003	-0.067	0.004	0.068	0.039	-0.082	<0.001	0.073	0.028	-0.086	<0.001
Khulna	1.09	0.009	-0.024	0.304	0.041	0.224	-0.078	<0.001	0.034	0.314	-0.080	<0.001
Mymensingh	1.11	0.002	-0.067	0.007	0.070	0.048	-0.087	<0.001	0.072	0.043	-0.090	<0.001
Rajshahi	1.09	0.012	-0.043	0.071	0.047	0.173	-0.074	0.001	0.045	0.186	-0.071	<0.001
Rangpur	1.15	<0.001	-0.081	0.001	0.093	0.007	-0.107	<0.001	0.093	0.007	-0.101	<0.001
Sylhet	1.48	<0.001	-0.266	<0.001	0.283	<0.001	-0.289	<0.001	0.298	<0.001	-0.272	<0.001
Contraceptive use												
No Ref	1		1		1		1		1		1	1
Yes	2.28	<0.001	-0.820	<0.001	0.834	<0.001	-0.487	<0.001	0.927	<0.001	-0.262	<0.001
Husband Education												
No Education Ref	1		1		1		1		1		1	1
Primary education	1.03	0.271	-0.010	0.559	0.012	0.639	-0.031	0.059	0.012	0.618	-0.039	0.007
Secondary education	0.95	0.058	0.031	0.094	-0.046	0.087	0.025	0.153	-0.044	0.099	0.015	0.343
Higher education	0.84	<0.001	0.116	<0.001	-0.146	<0.001	0.111	<0.001	-0.147	<0.001	0.087	<0.001
Frequency of Watching TV												
Not at all Ref	1		1		1		1		1		1	1
Less than once a week	0.98	0.500	0.039	0.089	-0.032	0.321	0.020	0.334	-0.041	0.206	0.015	0.429
At least once a week	0.97	0.112	0.018	0.176	-0.021	0.266	0.031	0.010	-0.021	0.264	0.033	0.002
Respondent Occupation												
Housewife Ref	1		1		1		1		1		1	1
Professional	0.88	0.030	0.080	0.045	-0.065	0.254	0.091	0.014	-0.071	0.213	0.074	0.025
Agricultural Worker	1.04	0.069	-0.039	0.009	0.052	0.016	-0.025	0.074	0.055	0.011	-0.015	0.232
Skilled/Unskilled Woker	0.94	0.022	0.050	0.004	-0.040	0.109	0.027	0.095	-0.045	0.071	0.010	0.516
Residing with Husband												
Living with her Ref	1		1		1		1		1		1	1
Staying elsewhere in Bangladesh	0.91	0.015	0.075	0.004	-0.088	0.017	0.044	0.056	-0.09	0.014	0.032	0.114
Staying abroad	1.13	0.001	-0.123	<0.001	0.139	<0.001	-0.142	<0.001	0.155	<0.001	-0.132	<0.001

education, contraceptive use, division, and religion—the parametric models detected additional significant predictors. For example, the husband's education variable was not significant in the Cox model but was significant in all parametric models, particularly at higher education levels. Women's occupation and husband's occupation were inconsistently significant, showing effects in the Weibull, Log-normal, and

Generalized Gamma models but not in the Cox or Exponential models. Media exposure (watching television) reached significance in Cox and most parametric models, though its direction of effect varied slightly. However, the place of residence, wealth index, and sex of the household head were not significant in either the Cox or the parametric models, indicating a limited role in shaping first-birth timing after controlling for other covariates (Table **4**). The results suggest that the parametric approaches provided more nuanced estimates by better capturing non-proportional hazards and complex hazard structures.

Table **5** compares the Cox proportional hazards model to five alternative parametric survival models: Exponential, Weibull, Log-normal, Gompertz, and Generalized Gamma. The results show that the Generalized Gamma model outperformed the others, with the lowest AIC (131,143.5) and BIC (131,438.0), as well as the highest log-likelihood (-65,533.76). The Log-normal model ranked second, showing competitive fit, while the Weibull and Gompertz models provided moderate performance. In contrast, the Exponential model, which assumes a constant hazard over time, performed the poorest, with substantially higher AIC and BIC values. The superior fit of the Generalized Gamma model can be attributed to its flexibility in accommodating different hazard shapes—including increasing, decreasing, and non-monotonic hazard functions—making it well-suited to the heterogeneous first birth incidence patterns observed in the data. Compared to the Cox model, which relies on the proportional hazards assumption that was violated in this study, the parametric approaches—and particularly the Generalized Gamma model—provided more reliable and robust estimates by flexibly capturing the time-varying hazard of first birth, thereby offering a more accurate representation of the underlying fertility dynamics. Given that the Generalized Gamma model provided the best statistical fit, its results were examined in detail to identify the key determinants of time to first birth after marriage in Bangladesh.

Determinants of Time to First Birth

Table **6** presents the adjusted time ratios (TR) and corresponding 95% confidence intervals (CI) for various sociodemographic predictors of the time to first birth, derived from a Generalized Gamma model. A TR value less than one indicates a shorter interval to first birth, while a ratio greater than one indicates a longer time to first birth, relative to the reference category. The analysis revealed several important predictors of delayed first birth. Age at first marriage emerged as a strong predictor of FBI. Compared to women who were married at or before age 14, those who were married at ages 15–19 experienced a 14% shorter time to first birth (TR=0.86, 95% CI: 0.84–0.88), and those aged 20 or above had a 19% shorter time to first birth (TR=0.81, 95% CI: 0.78–0.84; $p < 0.001$ for both).

Educational attainment demonstrated a significant association, with all schooling levels up to complete secondary significantly reducing the time to first birth compared to no education. Incomplete secondary education was linked to an 8% reduction in time to first birth (TR=0.92, 95% CI: 0.89–0.95), while higher education showed no significant difference from the reference group (TR=0.97, 95% CI: 0.93–1.02; p = 0.237). Regional variation was considerable. Women from Sylhet (TR=0.76), Chattogram (TR=0.78), and Rangpur (TR=0.90) experienced significantly shorter time to first births than those in Barishal ($p < 0.001$ for all). Contraceptive users had shorter first birth interval than the noncontraceptive users (TR=0.77, 95% CI: 0.75–0.79; $p < 0.001$), highlighting the impact of fertility preferences and behaviours (Table **6**). Husband's educational level also showed a positive link with delayed childbearing. Women whose husbands had higher education experienced a 9% longer time to first birth compared to those with uneducated husbands (TR=1.09, 95% CI: 1.05–1.14; $p < 0.001$). Media exposure was modestly associated with longer time to first birth, with women who watched television at least once weekly experiencing a 3% longer time to first birth (TR=1.03, 95% CI: 1.01–1.06; p = 0.002). Similarly, being in professional employment was associated with a longer time to first birth (TR=1.08, 95% CI: 1.01–1.15; p = 0.025) compared to housewives. Spousal temporary separation appeared as a significant predictor of time to first birth . Women whose husbands stayed outside Bangladesh at the time of the survey had shorter time to first birth compared to women who

Table 5: Comparison of Five Parametric Models

Model	Log-Likelihood	AIC	BIC
Weibull	-68198.68	136471.4	136758.1
Exponential	-69793.29	139658.6	139937.6
Log Normal	-66037.64	132149.3	132436.0
Gompertz	-69730.61	139535.2	139822.0
Generalized Gamma	-65533.76	131143.5	131438.0

Table 6: Estimates of the Time Ratio (95% CI) and p-Value of the Generalized Gamma Distribution for Time to First Birth Across the Explanatory Variables

Variable	TR (95% CI)	p-Value
Place of Residence		
Urban [Ref]	1.00	
Rural	.99 (0.97-1.01)	0.336
Age at first cohabitation		
≤ 14 [Ref]	1.00	
15-19	0.86 (0.84-0.88)	<0.001
≥ 20	0.81 (0.78-0.84)	<0.001
Educational Attainment		
No Education [Ref]	1.00	
Incomplete Primary	0.95 (0.92-0.99)	0.017
Complete Primary	0.94 (0.90-0.97)	0.001
Incomplete Secondary	0.92 (0.89-0.95)	<0.001
Complete Secondary	0.93 (0.89-0.97)	0.001
Higher	0.97 (0.93-1.02)	0.237
Sex of Household Head		
Male [Ref]	1.00	
Female	1.01 (0.97-1.04)	0.634
Wealth Index		
Poorest [Ref]	1.00	
Poorer	1.00 (0.97-1.03)	0.787
Middle	1.00 (0.97-1.03)	0.975
Richer	0.97 (0.94-1.01)	0.095
Richest	1.00 (0.96-1.04)	0.898
Division		
Barishal [Ref]	1.00	
Chattogram	0.78 (0.75-0.81)	<0.001
Dhaka	0.92 (0.88-0.95)	<0.001
Khulna	0.92 (0.89-0.96)	<0.001
Mymensingh	0.91 (0.88-0.95)	<0.001
Rajshahi	0.93 (0.90-0.97)	<0.001
Rangpur	0.90 (0.87-0.94)	<0.001
Sylhet	0.76 (0.73-0.79)	<0.001
Religion		
Muslim [Ref]	1.00	
Non Muslim	1.00 (0.97-1.03)	0.795
Ever used anything to avoid/delay pregnancy		
No [Ref]	1.00	
Yes	0.77 (0.75-0.79)	<0.001
Husband Education		
No Education [Ref]	1.00	
Primary education	0.96 (0.93-0.99)	0.007
Secondary education	1.01(0.98-1.05)	0.343
Higher education	1.09 (1.05-1.14)	<0.001

Table 6 (contd….)

Variable	TR (95% CI)	p-Value
Frequency of Watching Television		
Not at all Ref	1.00	
Less than once a week	1.02 (0.98-1.05)	0.429
At least once a week	1.03 (1.01-1.06)	0.002
Respondent Occupation		
Housewife Ref	1.00	
Professional	1.08 (1.01-1.15)	0.025
Agricultural Worker	0.98 (0.96-1.01)	0.232
Skilled/Unskilled Woker	1.01 (0.98-1.04)	0.516
Husband Occupation		
Not Working Ref	1.00	
Professional	0.99 (0.93-1.05)	0.638
Agricultural Worker	1.00 (0.94-1.05)	0.872
Skilled/Unskilled Woker	0.98 (0.93 - 1.03)	0.386
Currently Residing with Husband/Partner		
Living with her Ref	1.00	
Staying elsewhere(within Bangladesh)	1.03 (0.99-1.07)	0.114
Staying elsewhere(Outside Bangladesh)	0.88 (0.84-0.91)	<0.001

were continuously living with their husbands (TR=0.88, 98%CI: 0.84-0.91). Variables such as place of residence (urban vs. rural), sex of the household head, wealth index, religion, and most husband occupation categories were not significantly linked to time to first birth ($p > 0.05$).

DISCUSSIONS

This study provides a comprehensive investigation into the timing of first birth after marriage among Bangladeshi women, utilising the recent nationally representative 2022 BDHS data and a rigorous comparative survival analysis framework. By moving beyond the Cox proportional hazards model, which was found to be unsuitable due to violations of the proportional hazards (PH) assumption, the study implemented multiple parametric alternatives and identified the Generalized Gamma model as the best-fitting approach. This methodological decision ensured improved model performance and yielded more reliable estimations of covariate effects.

In this study, the median time to first birth after cohabitation was found to be 26 months, a finding consistent with a previous study conducted in Bangladesh [22]. Another Bangladesh-based study also reported a median duration of 26 months for the first birth interval among ever-married women, further corroborating this result [23]. Studies in many African countries also reported median duration of marriage to first birth ranging from 23 to 30 months [24-26].

To identify the factors influencing the time to first birth, we initially employed the semi-parametric Cox PH model. But it was found to be unsuitable due to violations of the proportional hazards (PH) assumption. The extensive violation of the PH assumption underscores the need to consider parametric survival models that do not rely on this assumption. This study, therefore, extended its analysis beyond the Cox model and examined five parametric survival models to identify a more suitable model for explaining the timing of first birth. While both Cox and parametric models consistently identified some core significant predictors, including age at first marriage, women's education, contraceptive use, administrative division, and living status with husband, the parametric models also detected additional significant predictors.

From a methodological perspective, this study makes a significant methodological contribution by demonstrating that traditional reliance on the Cox model, without testing or adjusting for PH violations, may obscure or distort key predictors. Our findings encourage future fertility studies—especially those using cross-sectional or censored data—to adopt model comparison strategies that include advanced parametric alternatives. Doing so can enhance both the statistical validity and substantive depth of demographic analyses. The study further demonstrates that the advantages of applying flexible parametric survival models—particularly the Generalised Gamma (GG) model—are particularly relevant in time to first birth analysis contexts where the proportional hazards (PH) assumption is violated. The GG model's superior performance, as evidenced by its lowest AIC/BIC and highest log-likelihood, reflects its capacity to capture diverse hazard structures, including non-monotonic, unimodal, and bathtub-shaped risk patterns. Such flexibility is crucial when modeling fertility timing, where biological and socio-cultural factors produce complex temporal dynamics. Similar conclusions were drawn in prior research in Nigeria and Ethiopia, demonstrating that the Generalized Gamma or gamma-based models outperform Cox models in modelling time to first birth and detecting key covariates [2, 27]. These studies, along with more recent evaluations using parametric survival analysis frameworks [28], reaffirm the importance of adopting flexible parametric models in fertility timing research—especially when standard PH assumptions are not met.

Since the Generalized Gamma model demonstrated the best fit in this study, its time ratios were used to assess how key covariates influence the timing of first birth. The best-fitting Generalised Gamma model identified several factors that have a significant association with the marriage-to-first-birth interval. These included age at first marriage, women's level of education, administrative division, contraceptive use, residing with husband, media exposure, women's occupation and husband's education.

Age at first marriage appeared as a significant predictor of time to first birth (TFB), with earlier marriage associated with significantly longer TFB. While seemingly paradoxical, this result aligns with prior findings indicating biological immaturity (i.e., delayed fecundity among younger adolescents, called adolescent sub-fecundity) [29], and social norms that delay cohabitation or fertility immediately after early marriage [30, 31]. In contrast, women married at ages 15–19 or ≥20 exhibited shorter TFB, possibly reflecting greater reproductive readiness. Similar findings were reported by Shayan et al. [10] in Iran and Al-Shanfari and Islam [32] in Jordan.

Educational attainment showed a nonlinear association with time to first birth. Secondary education was linked to shorter time to first birth—suggesting that early marriage despite moderate schooling accelerates fertility onset—whereas higher education was associated with delayed childbirth, likely reflecting women's autonomy, career pursuits, and contraceptive knowledge [33]. Our finding is consistent with the findings of Shayan et al. [10] and Al-Shanfari and Islam [32].

The study found that contraceptive users had a shorter time to first birth compared to women who did not use contraception, indicating that pre-first-birth family planning remains an important yet under-discussed aspect of fertility behaviour. Our findings align with those of the study in Jordan by Al-Shanfari and Islam [32] and another previous study in Bangladesh by Chowdhury & Karim [34]. Although it seems unlikely that contraceptive users have a shorter first birth interval than non-users, this may be because we considered contraceptive use status at the time of the survey, and most contraceptive users probably start using contraception to delay their next birth after having a first child quickly. In a cross-sectional survey data such as the BDHS, contraceptive use is typically reported at the time of interview. Hence, many women classified as "contraceptive users" may have initiated contraception only after their first birth, reflecting postpartum family planning rather than pre-pregnancy avoidance. This misalignment between the timing of contraceptive use and first birth could result in apparent but misleading associations. We also draw attention to socio-cultural dynamics, such as early pressure to conceive and have the first baby and delayed uptake of contraception until after childbirth, that may further contribute to this pattern.

This study observed marked regional disparities in the marriage-to-first-birth interval, with the Sylhet and Chattogram regions showing the shortest delays, and the Rajshahi and Khulna regions exhibiting relatively longer first birth intervals than other regions, suggesting localised cultural or economic factors that encourage earlier fertility. These patterns are consistent with previous BDHS-based analyses, which indicate regional heterogeneity in fertility behaviour due to cultural norms, socioeconomic differences, and service delivery gaps [35]. This finding underscores the need for region-specific reproductive health strategies.

Spousal separation due to the husband's migration outside the country was associated with a significant increase in the marriage-to-first-birth interval. Compared to women living with their husbands, those whose husbands were residing abroad exhibited a significantly shorter delay in having their first child after marriage. The role of husbands' migration in reducing the first birth interval mirrors findings from South Asian migration literature, which highlights how migration reshapes household reproductive strategies [36].

Women whose husbands had only a primary education tended to experience a shorter time to first birth compared to those whose husbands had no formal education. In contrast, women whose husbands attained a higher level of education had longer time to first birth, indicating a negative association at higher levels of male education.

Finally, media exposure and women's employment showed somewhat unexpected results. Women with regular television exposure and those in professional employment tended to have earlier first births, suggesting that modernisation factors may not uniformly delay fertility.

Strengths and Limitations

The main strength of this study lies in its use of a large analytical sample of women, drawn from the most recent and nationally representative dataset, the 2022 BDHSB. This robust sample enables the reliable generalisation of the findings to the Bangladeshi population, provides high statistical power, and facilitates meaningful subgroup analyses. The study employs a comprehensive set of parametric survival models (Exponential, Weibull, Log-normal, Gompertz, Generalised Gamma) in addition to the traditional Cox proportional hazards model. The inclusion of the Gompertz and Generalized Gamma models provides a more thorough analysis, as these models are not commonly used in earlier studies. The study also has some limitations. As the study was based on retrospective data, it does not account for causal inference. The study relies on self-reported survey data for age at marriage and birth, which may be subject to recall bias or social desirability bias—particularly among younger or less educated respondents. In addition, the study was limited to currently married women, excluding never-married, divorced, or widowed individuals who may follow different reproductive trajectories. Although this group is relatively small in the Bangladeshi context, the exclusion may limit generalizability. Future research should aim to include these populations where possible, to capture a more complete picture of fertility behaviour and to align with evolving social norms around marriage and childbearing. Finally, while the BDHS offers rich demographic variables, certain qualitative factors—such as marital quality, family expectations, or fertility intentions—remain unmeasured.

CONCLUSION

This study provides a comprehensive analysis of the socio-demographic and economic factors that influence the timing of the first birth among currently married women in Bangladesh. By systematically comparing traditional and parametric survival models, the research shows that the Generalized Gamma model provides the best fit for the data, outperforming the Cox proportional hazards model, which was found to violate key assumptions in this context.

Key findings indicate that age at marriage, educational attainment (for both the respondent and husband), contraceptive use, regional residence, and living with a spouse significantly influence the timing of first birth. These findings reflect both personal and structural determinants of fertility behaviour.

Policy implications emerging from this study are twofold. First, regions with notably shorter first birth intervals—such as in Sylhet division — should be prioritised for reproductive health programs that aim to delay early childbearing through enhanced access to counselling and contraception. Second, women with no or limited education, who are at higher risk of early first births, would benefit from tailored education and awareness campaigns that integrate reproductive health with broader empowerment initiatives. These targeted strategies could more effectively address the demographic disparities in fertility timing.

From a methodological standpoint, the study underscores the importance of using flexible parametric models—such as the Generalised Gamma model—when dealing with time-to-event data where the proportional hazards assumption is violated. This approach provides more reliable effect estimates and improves the interpretability of covariate influences on fertility timing.

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DATA AVAILABILITY

The study used data from the 2022 Bangladesh Demographic and Health Survey. The data set can be accessed at: https://dhsprogram.com/data/available-datasets.cfm.

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Funding was not provided for this study.

COMPETING INTERESTS

The authors declare no competing interests.

ETHICS STATEMENT

This study used publicly available secondary data obtained from the Demographic and Health Surveys (DHS) Program website (https://dhsprogram.com/data/). As per the DHS data usage policy, no additional ethics approval was required because DHS had already received ethical approval from the Government of Bangladesh before conducting the survey. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

REFERENCES

[1] Goldstein JR. How late can first births be postponed? Some illustrative population-level calculations. Vienna Yearbook of Population Research 2006; 153-165. https://doi.org/10.1553/populationyearbook2006s153

[2] Fagbamigbe AF, Idemudia ES. Survival analysis and prognostic factors of timing of first childbirth among women in Nigeria. BMC Pregnancy and Childbirth 2016; 16(1): 102. https://doi.org/10.1186/s12884-016-0895-y

[3] Safdari-Dehcheshmeh F, Noroozi M, Taleghani F, Memar S. Factors influencing the delay in childbearing: A narrative review. Iranian Journal of Nursing and Midwifery Research 2023; 28(1): 10-19. https://doi.org/10.4103/ijnmr.ijnmr_65_22

[4] Nagdeve DA, Pradhan MR. Determinants of the First Birth Interval Among Women in India. Journal of Family Reproductive Health 2023; 17(4): 229-39.

[5] Candia D, Musoke E, Namugenyi C. Female's preferred birth interval in Uganda: What are the associated factors? Al-Sihah: The Public Health Science Journal 2023; 15(1): 1-11. https://doi.org/10.24252/al-sihah.v15i1.37913

[6] Alam MM. Marriage to first birth interval and its associated factors in Bangladesh. Asian Journal of Social Sciences & Humanities 2015; 4(4): 36-47.

[7] TurksonAJ, Ayiah-Mensah F, Nimoh V. Handling Censoring and Censored Data in Survival Analysis: A Standalone Systematic Literature Review. International Journal of Mathematics and Mathematical Sciences 2021; 2021: 1-16 https://doi.org/10.1155/2021/9307475

[8] Cox DR. Regression models and life-tables. Journal of the Royal Statistical Society. Series B (Methodological) 1972; 34(2): 187-220.

[9] Lee ET, Wang JW. Statistical methods for survival data analysis (3rd ed.). John Wiley and Sons, Hoboken, New Jersey. Wiley 2003. https://doi.org/10.10022012/0471458546

[10] Shayan Z, Ayatollahi SM, Zare N, Moradi F. Prognostic factors of first birth interval using the parametric survival models. Iranian Journal of Reproductive Medicine 2014; 12(2): 125-130.

[11] Moala FA, Dey S. Objective and subjective prior distributions for the Gompertz distribution. Anais Da Academia Brasileira de Ciências 2017; 90(3): 2643-2661. https://doi.org/10.1590/0001-3765201820171040

[12] Therneau TM, Grambsch PM. Modelling survival data: Extending the Cox model. New York: Springer 2000.

[13] Hiller L, Marshall A, Dunn J. Assessing violations of the proportional hazards assumption in Cox regression: does the chosen method matter? Trials 2015; 16(Suppl 2): p. 134.

[14] De Pascoa MAR, Ortega EMM, Cordeiro GM. The Kumaraswamy generalized gamma distribution with application in survival analysis. Statistical Methodology 2011; 8(5): 411-433. https://doi.org/10.1016/j.stamet.2011.04.001

[15] National Institute of Population Research and Training (NIPORT), ICF. Bangladesh Demographic and Health Survey 2022. Dhaka, Bangladesh, and Rockville (MD): NIPORT and ICF 2024.

[16] Pascual ZN, Langaker MD. Physiology, Pregnancy. In StatPearls. StatPearls Publishing,Treasure Island (FL) 2023. http://www.ncbi.nlm.nih.gov/books/NBK559304/

[17] Kaplan EL, Meier P. Nonparametric estimation from incomplete observations. Journal of the American Statistical Association 1958; 53(282): 457-481. https://doi.org/10.2307/2281868

[18] Collett D. Modelling survival data in medical research (3rd ed.). Chapman and Hall/CRC, Taylor and Francis Group, Boca Raton 2014. https://doi.org/10.1201/b18041

[19] Liu X. Survival analysis: Models and applications. John Wiley & Sons and Higher Education Press, Hoboken, New Jersey. https://doi.org/10.1002/9781118307656

[20] Stacy EW. A Generalization of the Gamma Distribution. The Annals of Mathematical Statistics 1962; 33(3): 1187-1192. https://doi.org/10.1214/aoms/1177704481

[21] Gompertz B. On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life 89 contingencies. in a letter to francis baily, esq. frs &c. Philosophical Transactions of the Royal Society of London 1829; (115): 513583.

[22] Setu SP, Kabir R, Islam MA, Alauddin S, Nahar MT. Factors associated with time to first birth interval among ever married Bangladeshi women: A comparative analysis on Cox-PH model and parametric models. PLOS Global Public Health 2024; 4(12): e0004062. https://doi.org/10.1371/journal.pgph.0004062

[23] Ahammed B, Kabir MR, Abedin MM, Ali M, Islam MA. Determinants of different birth intervals of ever married women: Evidence from Bangladesh. Clinical Epidemiology and Global Health 2019; 7: 450-456. https://doi.org/10.1016/j.cegh.2019.01.011

[24] Logubayom IA, Luguterah A. Survival analysis of time to first birth after marriage. Research on Humanities and Social Sciences 2013; 3(12): 117-126.

[25] Chernet AG, Shebeshi DS, Banbeta A. Determinant of time-to-first birth interval after marriage among Ethiopian women. BMC Women's Health 2019; 19: 157. https://doi.org/10.1186/s12905-019-0858-3

[26] Obite CP, Bartholomew DC, Nwosu UI, Anyiam KE, Aminu SA. Marriage to first birth interval in Nigeria: Analysis of the roles of social-demographic and cultural factors. SN Social Sciences 2021; 1: 120. https://doi.org/10.1007/s43545-021-00112-x

[27] Fentaw KD, Fenta SM, Biresaw HB, Agegn SB, Muluneh MW. Bayesian shared frailty models for time to first birth of married women in Ethiopia: Using EDHS 2016. Computational and Mathematical Methods in Medicine 2022; 5760662. https://doi.org/10.1155/2022/5760662

[28] Alazbih NM, Kaya AH, Mengistu MY, Gelaye KA. Determinants of time to first marriage and birth intervals among women of childbearing age in Dabat Health and Demographic Surveillance System site, Northwest Ethiopia. PLoS One 2023; 18(2): e0281997. https://doi.org/10.1371/journal.pone.0281997

[29] Bongaarts J, Potter RG. Fertility, biology, and behaviour: An analysis of the proximate determinants. Academic Press 1983, New York, USA.

[30] Marphatia AA, Ambale GS, Reid AM. Women's marriage age matters for public health: A review of the broader health and

social implications in South Asia. Frontiers in Public Health 2017; 5: 269.
https://doi.org/10.3389/fpubh.2017.00269

[31] Sarkar P. Determinants of age at first birth in Bangladesh. Journal of Modern Mathematics and Statistics 2010; 4: 1-6.
https://doi.org/10.3923/jmmstat.2010.1.6

[32] Al-Shanfari NSS, Islam MM. Survival analysis and predictors of time to first birth after marriage in Jordan. International Journal of Statistics and Applications 2021; 11(3): 51-60.
https://doi.org/10.5923/j.statistics.20211103.01

[33] Haque MA, Sayem AM. Socioeconomic Determinants of Age at First Birth in Rural Areas of Bangladesh. Asia Pacific Journal of Public Health 2009; 21(1): 104-111.
https://doi.org/10.1177/1010539508329207

[34] Chowdhury AH, Karim A. Patterns and differentials of birth intervals in Bangladesh. Global Journal of Science Frontier Research: Interdisciplinary 2013; 13(2): 11-24.

[35] Islam MM, Rob U, Chakroborty N. Regional variations in fertility in Bangladesh. Genus 2003; 59(3/4): 103-145

Nie W. The effect of spousal separation and reunification on fertility: Chinese internal and international migration. Demographic Research 2020; 43: 851-888. https://creativecommons.org/licenses/by/3.0/de/legalcode.

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