ORIGINAL RESEARCH ARTICLE

Parametric Models for First Birth Interval in North-East India: Identifying A Suitable Model

Chanambam Rajiv Mangang[1*], Kshetrimayum Anand Singh[2]

[1,2]Department of Statistics, Manipur University, Imphal, India

DOI: 10.55489/njcm.161220255927

ABSTRACT

Background: Birth intervals are often modelled to understand the health implications of the mother as well as the newborn. Shorter birth intervals are linked with higher risks of maternal and infant mortality. Short birth intervals in North-East India are linked to higher maternal and infant mortality risks, necessitating accurate model for targeted intervention. On the other hand, a longer birth interval has shown substantial reduction in the risk of maternal health issues and a better health outcome of the babies.

Methods: Time-to-event data are often modelled by implementing the popular Cox proportional hazards model. However, the popularity of the Cox model can't overrule the use of parametric models if the distribution of the survival time has a known parametric form that is derived from past experience in previous research studies. Choosing an appropriate model from amongst various competing models is a topic of interest where different characteristics, such as the nature of censoring and the shape of hazards, are present in different dimensions for different events. We use information criteria and model fit measures to help select the best-fitted model among the five competing models for the data. Further graphical comparisons are made to conclude for a final which best fit the first birth interval.

Conclusion: The three-parameter generalized gamma model shows one of the most appropriate models for modelling first birth interval after marriage data with low proportion of censored data with a mix of hazards. Statistical tests such as the Anderson-Darling and Kolmogorov-Smirnov tests are significantly affected by the presence of extreme values of the time variable at the later observed times. The generalised gamma model can inform policies to extend first birth intervals, reducing risks of adverse maternal and child health outcomes in such datasets which are typical of demographic surveys.

Keywords: First birth interval, AIC, log-likelihood, Generalized gamma

ARTICLE INFO

Financial Support: None declared

Conflict of Interest: The authors have declared that no conflict of interests exists.

Received: 21-08-2025, **Accepted**: 03-11-2025, **Published**: 01-12-2025

***Correspondence:** Chanambam Rajiv Mangang (Email: mangangrajiv@gmail.com)

How to cite this article: Mangang CR, Singh KA. Parametric Models for First Birth Interval in North-East India: Identifying A Suitable Model. Natl J Community Med 2025;16(12):1213-1220. DOI: 10.55489/njcm.161220255927

www.njcmindia.com | pISSN: 0976-3325 | eISSN: 2229-6816 | Published by Medsci Publications

INTRODUCTION

Birth interval is referred to as the time between two successive live births by a woman. The duration between the date of marriage and the first live birth is the first open birth interval (FBI) after marriage. The mean age at which a woman conceives their first child is considered a great interest to researchers as it symbolises the strong association of a woman's fertility level and the onset of the parenting journey. The fertility rate and number of births are affected by the maternal age at first birth, which also influences the population size, diversity and growth prospects. Through the reproductive phase, women have to control the number of babies.[1]

The length of the successive birth intervals and the women's reproductive pattern are impacted by the FBI.[2] Examining the duration of birth intervals provides information on infant and childhood mortality and maternal health. Short birth intervals are considered to be those intervals which are less than two years, and it is associated with a higher risk of mortality for both the mother and infant.[3] In developing countries, the demographic characteristics of women are significantly affected by the first birth. Thus, age at marriage and age at first birth are considered proximate determinants of fertility.[4]

Setu SP et.al studied the Bangladesh Demographic and Health Survey data, (2017-18) and found that among the parametric accelerated failure time models, the log-normal distribution provides best best-fitted model in estimating the covariates associated with the first birth interval of ever-married Bangladeshi Women.[5]

Nagdeve DA and Pradhan MR studied ever-married women in the 15-49 age group from NFHS-5, and found that the duration between first marriage to the first birth interval was 23 months in India and was associated with age at first marriage, educational level of women, place of residence, family economic status, exposure to mass media, contraceptive used and pregnancy termination history.[6]

According to Singh NS et. al studied Manipur, a small state in North East India, in 2009, found that age at marriage of wife, parity and sex of child are significant covariates associated with.[4]

In North-East India, where adolescent marriages are common, understanding FBI patterns can guide community-level interventions like family planning education to promote longer intervals and lower fertility rates, ultimately reducing population growth pressures. This region has unique demographic features like high ethnic diversity and varying marriage customs, influencing FBI and warranting region-specific models for equitable health policies.

Many techniques employed to describe the first birth interval after marriage were mainly non-parametric approaches, whose estimates cannot be projected into the future. Also, data on first birth interval data can't be well fitted to a normal distribution because (i) they are skewed and (ii) there is the presence of censored or incomplete observations. Further, a time variable can't be negative. To compensate these complexities the Cox proportional hazards model becomes the usual way to model such data on birth intervals. While fitting regression models for survival data, the Cox proportional hazards regression model[7] is so popular that no other model could replace it. There are two very important reasons that make the Cox model so popular: first, the technique does not require specifying the hazard function completely. Secondly, with a reduced set assumption, the hazard ratios are easily interpreted and clinically meaningful. While the Cox model is widely used, parametric models may be better if prior studies suggest a specific shape for the distribution, offering more precise predictions for public health planning. Some advantages of fully parametric model are: (i) full MLE can be obtained, (ii) the clinically meaningful estimates of effect are provided by estimated coefficients, (iii) estimates of survival time is provided by fitted values from the model and (iv) the differences between observed and predicted values of time is residual. These advantages motivate the use of parametric models in this study while the main objective is to identify the most appropriate model among a wide range of available parametric models.

The problem of testing whether some given data comes from one of two distributions is quite old in the statistical literature. The problem is to select the correct model appropriate for the given data from two or more existing models. These issues are discussed by Atkinson AC[8], Chen W[9], Dumonceaux R[10], Jackson OAY[11] and Dyer AR[12]. Burke and Noufaily have been investigating survival data modelling, generally to cover some of the most popular parametric models, and to discover some of the better modelling choices that can be made using data from lung cancer, melanoma, and kidney function studies[13].

The present paper discusses some methods for choosing an appropriate parametric model for the First birth interval after marriage data. After choosing the most appropriate model, we also examine the goodness of fit for each model, which could support the model selection and confirm the selection.

METHODOLOGY

Parametric survival models:

While modelling the First birth interval after marriage data, a parametric model assumes a certain distribution for the underlying time variable. Literally, it means that the models assume that the time data follows a specific distribution. The more popular distributions, such as Weibull and log-normal, have been listed in the previous section. An obvious advantage of using a parametric model over a non-parametric or semi-parametric model is its accuracy of predictions. However, the assumption of the specific distribution of the data should be made with a high degree of accuracy. This critical decision on the assumption of the specific distribution can be performed with prior knowledge of the population under study. However, in the case of unavailability of any prior knowledge, the researcher may choose an appropriate distribution from among the variety of distributions available in the literature.

There are similar parametric models which almost predict the outcome variable with the same amount of accuracy. For example, an analysis assuming a log-normal distribution will usually produce the same conclusions as assuming a gamma distribution.[14,15] The choice of a particular model may be based on the corresponding interpretation of parameters. Firth proves that analysing gamma data assuming log normality has less efficiency than log-normal data assuming a gamma distribution.[16] From a clinical trial, Wiens concludes that the two distributions do not agree at all in a real dataset obtained.[17]

Understanding the dataset thoroughly is crucial for deciding the final model to be fitted and interpreted. The suitability of each of the available models also needs to be understood while choosing the one for the relevant data. While understanding the underlying data, we used the shape of the hazard function to understand the researcher's prior knowledge of the phenomenon under study.

The Weibull distribution is a versatile choice for modelling Time-to-event data. With two parameters β (shape) and λ (scale), density, survival, and hazard functions of the Weibull distribution are:

$$f(x,\beta,\lambda)=\frac{\beta}{\lambda}\left(\frac{x}{\lambda}\right)^{\beta-1}e^{-\left(\frac{x}{\lambda}\right)^{\beta}},\beta>0,\lambda>0,x\geq 0$$

$$S(x)=\exp\left(-\left(\frac{x}{\lambda}\right)^{\beta}\right)$$

$$h(x)=\frac{\beta}{\lambda}\left(\frac{x}{\lambda}\right)^{\beta-1}$$

It is used for modelling public health data where the risk of an event changes over time, such as disease onset, recovery of health behaviour, etc.

The Gompertz distribution with scale parameter θ and shape parameter η is characterized by the following density function, survival function and hazard functions

$$f(x,\eta,\theta)=\theta e^{\eta x}\exp\left(-\frac{\theta}{\eta}(e^{\eta x}-1)\right)\ \eta\geq 0,\theta>0,x\geq 0$$

$$S(x)=\exp\left(-\frac{\theta}{\eta}(e^{\eta x}-1)\right)$$

$$h(x)=\theta e^{\eta x}$$

It is used to model data where the hazard rate increases or decreases exponentially over time, such as human mortality etc.

The log-normal distribution with parameters (μ,σ) is characterized by the following density function, survival & hazard functions

$$f(x,\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{1}{2\sigma^2}(\log x-\mu)^2},x,\sigma>0$$

where $\log(X)\sim N(\mu,\sigma^2)$

$$S(x)=1-\phi\left(\frac{\ln(x)-\mu}{\sigma}\right)$$

$$h(x)=\frac{\frac{1}{x\sigma\sqrt{2\pi}}e^{-\frac{1}{2\sigma^2}(\log x-\mu)^2}}{1-\phi\left(\frac{\ln(x)-\mu}{\sigma}\right)}$$

where $\phi(x)$ is the cumulative distribution function of the standard normal distribution.

It is used to model in time-to-event data where data are positively skewed, such as incubation period of disease, etc.

The gamma distribution with shape parameter ϕ and inverse scale parameter $\beta(=\frac{1}{\theta})$ is characterized by the following density, survival and hazard functions

$$f(x,\phi,\beta)=\frac{\beta^{\phi}}{\Gamma\phi}e^{-\beta x}x^{\phi-1},x>0,\phi>0,\beta>0$$

$$S(x)=\sum_{t=0}^{\phi-1}\frac{e^{-\beta x}\phi x^{t}}{t!}$$

$$h(x)=\frac{\beta^{\phi}e^{-\beta x}x^{\phi-1}}{\Gamma\phi\sum_{t=0}^{\phi-1}\frac{e^{-\beta x}\phi x^{t}}{t!}}$$

It is used in positively skewed data where the event rate changes over time but does not follow simple linear pattern.

The generalized-gamma distribution is a highly flexible parametric model used to accommodate a wide range of data shapes. It is a generalisation of the two parameters of the gamma distribution and can also be generalized for many well-known distributions, such as exponential, Weibull, lognormal, etc. It has three parameters, viz. μ(location), σ(scale) and Q(shape). The density, survival and hazard function of generalized gamma are

$$f(x,\mu,\sigma,Q)=\frac{|Q|}{\sigma\Gamma\left(\frac{1}{Q^2}\right)}\left(\frac{x-\mu}{\sigma}\right)^{\frac{1}{Q^2}-1}\exp\left(-\left(\frac{x-\mu}{\sigma}\right)^{Q}\right)$$

$$S(x)=1-\frac{\gamma\left(\frac{1}{Q^2},\left(\frac{x-\mu}{\sigma}\right)^{Q}\right)}{\Gamma(\frac{1}{Q^2})}$$ where $\gamma(s,x)=$ lower incomplete gamma

$$h(x)=\frac{\frac{|Q|}{\sigma\Gamma\left(\frac{1}{Q^2}\right)}\left(\frac{x-\mu}{\sigma}\right)^{\frac{1}{Q^2}-1}\exp\left(-\left(\frac{x-\mu}{\sigma}\right)^{Q}\right)}{1-\frac{\gamma\left(\frac{1}{Q^2},\left(\frac{x-\mu}{\sigma}\right)^{Q}\right)}{\Gamma(\frac{1}{Q^2})}}$$

It is used in modelling data that require a flexible distribution capable of representing many shapes of risk over time.

Table 1: Some common parametric models

Distribution	Parameter	Hazard Shape	Public health suitability
Weibull	shape $=\beta$ scale= λ	Decreasing/increasing/constant	It is used if hazard of an event changes over time, such as disease onset, recovery of health behaviour, etc.
Log-normal	Location=μ scale= σ	Bell-shaped (Rises then falls)	It is used to model in time-to-event data where data are positively skewed, such as the incubation period of a disease, etc.
Gompertz	scale = θ shape = η	Exponential increase or decrease over time	It is used to model data where the hazard rate increases or decreases exponentially over time, such as human mortality etc.
Generalised Gamma	location=μ scale=σ shape=Q	Increasing/Decreasing/Hump-shaped(bell-shaped)	It is used in modelling data that requires a flexible distribution capable of representing many shapes of risk over time.
Gamma	shape $=\phi$ scale=β	Increasing/Decreasing	It is used in positively skewed data where the event rate changes over time but does not follow a simple linear pattern.

Data and Methods

We use data from the National Family Health Survey (NFHS-5, 2019-20)[18] conducted during 2019-20 in the eight North East states of India. From this data, duration is determined from ever-married women aged 15-49 with complete marriage and birth dates were included; durations more than 10 years were excluded to minimize recall bias and focus on typical community patterns. For those women who are yet to give birth to a child at the time of the survey, this duration is the censored duration from the date of marriage to the date of the interview; this right censoring for women without births was incorporated via maximum likelihood estimation in all parametric models. The final sample size on which the present analysis is carried out from the eight North-east states of India is 60820, out of which 5.8% are right censored which reflects low non-response in NFHS-5, ensuring robust estimates for policy on reproductive health in North East India's diverse population. Studies on the first birth interval show that it is an influencing factor for the future number of children[19], which is a determining factor for population growth.

The Akaike Information Criterion (AIC) is a statistical measure that provide an easy way to select a model from a set of models and based on information theory. The lower the value of AIC for a model, the better it is. The formula is given by

$$AIC = -2(loglikelihood) + 2k$$

where k is the number of free parameters in the model and likelihood is the probability of the data given in model[20].

RESULTS

We have fitted five parametric models, each for the duration variables for the First birth interval after marriage, using R programming tools. The five parametric models are discussed in the previous section. All fitted models are null models without any predictors from which the parameters of the underlying distribution are estimated. The method of maximum likelihood estimation is used to obtain the parameter estimates. Table 1 shows the values of the estimated parameters for the five distributions along with the standard error of estimates, 95% confidence intervals, log-likelihood for testing significance and AIC (Akaike Information Criteria) values.

Table 2: Parameter estimates of the distributions for First birth interval after marriage

Distribution	Parameters	Std. Error	95% Confidence interval		Log-likelihood	AIC*
Weibull	β =1.62507	0.00462	1.61604	1.63416	-230217.1	460438.2
	λ =27.07706	0.07300	26.93436	27.22051		
Log-normal	μ =3.01247	0.00218	3.00820	3.01675	-218365.1	436734.3
	σ =0.53240	0.00158	0.52931	0.53551		
Gompertz	η =0.013663	0.000186	0.013298	0.014028	-238519	477042
	θ =0.031085	0.000184	0.030727	0.031447		
Generalised Gamma	μ =2.59318	0.00562	2.58217	2.60419	-211539.7	423085.4
	σ =0.30492	0.00373	0.29771	0.31231		
	Q =-1.99933	0.03827	-2.07433	-1.92433		
Gamma	ϕ =3.246989	0.018232	3.211450	3.282921	-224534.6	449073.2
	β =0.135860	0.000836	0.134231	0.137508		

*AIC: Lower AIC (Akaike Information Criterion) indicates better model fit by balancing accuracy and simplicity, useful for selecting tools to predict birth spacing in public health surveillance.

Table 3: Median Survival Times for the First birth interval (in months) (K-M and Five distributions)

Distribution/ Method	Median	S.E.	95% Confidence interval	
			Lower	Upper
Kaplan-Meier	19	0.58	18.997	19.113
Weibull	21.609	0.064	21.484	21.736
Log-normal	20.337	0.045	20.254	20.426
Gompertz	19.465	0.079	19.303	19.612
Generalised Gamma	17.445	0.047	17.349	17.533
Gamma	21.496	0.051	21.394	21.591

In Table 2, the estimated parameters for the five models are shown for the First birth interval after marriage. All the estimated parameters lie within the 95% confidence interval, thereby showing the significance of the estimated parameters. The AIC value for the three-parameter generalised gamma model is 423085.4 and is the smallest out of the five models, thereby suggesting that the generalised gamma for this event could be the best choice. However, we will confirm this as we proceed further with checking the distributions and survival curve with the help of graphs.

Table 3 gives the estimated median survival times, standard error and 95% C.I. for the First birth interval using the five models, along with the non-parametric Kaplan-Meier estimate in the first row of each table. In this table, the median Time to marriage estimated using the K-M estimator is 19 years. All the other estimated median durations are in the neighbourhood of 21 years. We can see that the median duration of 19.46, estimated by the Gompertz, is the closest to 19 among the five medians. The K-M median of 19 months suggests a short FBI in North-East India, raising concerns for maternal depletion; the Gompertz model median of 19.46 months aligns closely, aiding forecasting of intervention needs. Thus, the choice of our models suggested by the AIC values, as compared to the non-parametric K-M model, is different, so we have to verify with graphical methods.

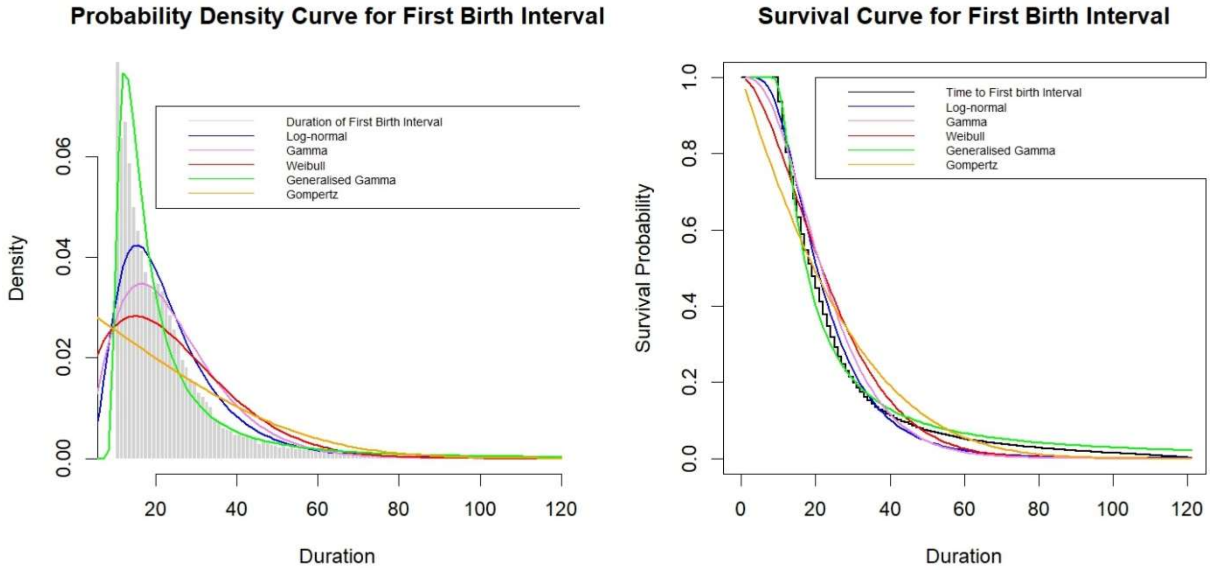

Figure 1: Density Curves and Survival curves for First birth interval

In Figure 1, the probability density curves of the five distributions are drawn superimposed on the histogram of the data on the duration of the First birth interval. This will give a visual examination of how appropriate a particular distribution is for describing the data. The green curve representing the generalized gamma distribution visually matches the observed histogram of FBI most closely. In the second column of Figure1, the survival probability curves for the five parametric models, along with the non-parametric Kaplan-Meier survival curve, are drawn. This supports using generalized gamma for community health models predicting fertility delays.

A **Q-Q plot** (quantile-quantile plot) is a graphical tool used in statistics to compare two probability distributions by plotting their quantiles against each other. The Q-Q plot is a major diagnostic tool for checking model adequacy. The more closely the plot pattern is to the straight line, the more evidence there is in support of the model.[21] This method allows for a visual assessment of how closely the two distributions align, particularly in terms of their shape, location, scale, and skewness. In a Q-Q plot, each point represents the quantiles of one distribution plotted against the corresponding quantiles of another distribution. If the two distributions are similar, the points will approximately lie along a **45-degree reference line.** In other words, if the two data sets come from a population with the same distribution, the points should fall approximately along this reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two data sets have come from populations with different distributions. Q-Q plots are a powerful diagnostic tool in statistics for comparing distributions and assessing assumptions about data. They provide an intuitive visual representation that can reveal insights into data characteristics and relationships between datasets.

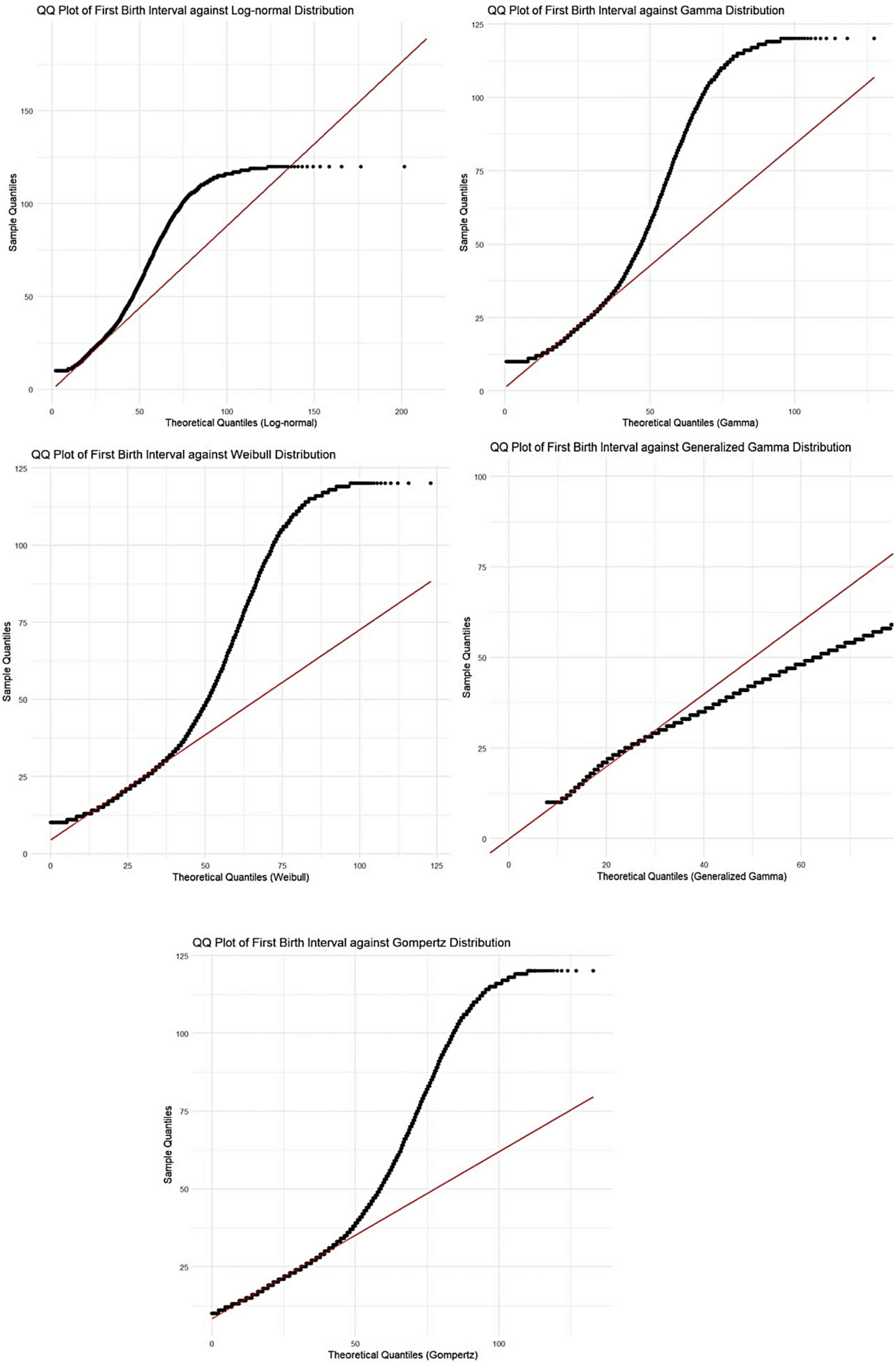

Figure 2: Q-Q plots for First birth interval

Table 4: Statistical tests for goodness of fit

Duration of First birth interval (Distribution: Gen. Gamma)		
Name of test	**Test Statistic**	**P-value**
Kolmogorov-Smirnov	0.061188	<0.001
Anderson-Darling	386.2	<0.001

Figure 2 displays the Q-Q plots of the First birth interval data versus the five estimated models. The theoretical quantiles, which are the quantiles of the assumed distributions, are plotted on the X-axis, and the sample quantiles are plotted along the Y-axis. The Q-Q plot for the Generalised Gamma distribution shows that the points are perfectly on the reference line up to a reasonable level of data points and shows departure from the reference line at the later data points. The departure of the points from the reference line indicates the presence of some extreme values in the data, which is inevitable in the analysis. All the remaining Q-Q plots do not show adequate evidence to conclude similarity of the distributions with the data.

Some statistical tests are available in the literature to test whether the assumed distribution significantly agrees with the sample distribution. Table 4 shows result from the Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests for the assumed distribution as Generalized gamma for Duration of First birth interval. Both tests produce extremely low p-values, indicating statistically significant deviations from the assumed distributions. However, in statistical model evaluation, it is generally discussed and found that AIC remains a reliable criterion in cases where goodness-of-fit (GOF) tests are overly sensitive due to large samples, providing guidance on balancing model complexity and fit without overfitting.[22] GOF tests are prone to indicate statistically significant discrepancies in large datasets. These sources argue that AIC and graphical diagnostics, like QQ plots, provide a more practical model fit assessment when tail deviations are minor.[23,24] Goodness-of-fit testing in logistic regression acknowledges GOF tests' limitations with large samples. It recommends using alternative model assessment tools, such as residual analysis and AIC, for practical model evaluation.[25]

Thus, despite significant test results due to a large sample size, AIC and QQ plots confirm practical fit. In public health, this means the model reliably estimates FBI risks without overfitting for policy simulation.

Discussion

The study explores five parametric models to fit duration variables arising from Demographic events, i.e., First birth interval after marriage. The data used in the present analyses come from NFHS-5 (2019-20) for the eight states of North East India. The duration of the First birth interval data shows a moderately right-skewed distribution with a low percentage of right-censored data.

Among the five parametric models, the lowest AIC values are found in the Generalized gamma distribution with 423085.4, followed by the Log-normal distribution with 436734.3. This shows that the generalized gamma could be a good choice for the FBI parametric model.

The non-parametric (Kaplan-Meier) estimate of the median survival time for the First birth interval after marriage for North East India is found to be 19 months. But the median estimate for the birth interval for India is 23 months.[6] The Gompertz model gives the closest value of the median First birth interval of 19.46 months to that of the non-parametric (K-M) estimate.

Short FBI in North-East India suggesting potential risk of maternal health and infant mortality risks, as per WHO guidelines. This is also supported by a close estimate of the Gompertz model with 19.46 months, and also helps in predicting whether future interventions may be needed.

For visual examinations by using probability curves, survival curves, and the Q-Q plots, we found that generalised gamma curves show the best overlays by visually matching observed data for the FBI in North East India.

From the three conditions, Generalised Gamma is considered the best fit for the parametric model of the First birth interval after marriage.

The Generalized Gamma Model is a flexible statistical model used for analysing time-to-event data, particularly in survival analysis. Here are some key properties and characteristics of the Generalized Gamma distribution relevant to modelling time-to-event data. The Generalized Gamma distribution can mimic various other distributions, such as the Weibull, lognormal, and exponential distributions, depending on its parameters. This flexibility allows it to fit a wide range of data patterns, making it suitable for different types of survival data. It is defined by three parameters: shape (k), scale (θ), and a second shape parameter (p). The ability to adjust these parameters enables the model to capture different hazard functions and survival patterns. By changing parameters, it reflects rising, falling, or steady fertility risk over time, ideal for diverse public health situations based on the parameter values, allowing it to represent increasing, decreasing, or constant hazard rates over time. This adaptability is crucial for accurately modelling survival times that may not follow a simple pattern. The Generalized Gamma model offers significant flexibility and adaptability for modelling time-to-event data, but requires careful consideration regarding sample size and computational complexity. Its ability to represent various hazard functions makes it a powerful choice in survival analysis when traditional models do not suffice.

Limitations

The present study includes the use of null models without covariates, limiting insights into specific risk factors; future work should extend to accelerated failure time models incorporating factors like education, residence, and contraceptive use for comprehensive public health recommendations.

Conclusion

From the above condition using AIC values, graphical comparison (survival, probability, Q-Q plot) and median estimate, the Generalized gamma distribution has the lowest AIC value and is supported by the Graphical comparison from three different graphs. We can select the Generalized gamma distribution as the best choice for fitting the parametric model of the FBI after marriage.

And as the median age of the FBI is short, the Generalized gamma model's fit enables tailored interventions like premarital counselling to extend the interval beyond 24 months.

Individual Authors' Contributions: CRM contributed data analysis and model fitting. KAS contributed in literature review and conclusion writing with overall fine tuning of paper.

Availability of Data: The National Family Health Survey (NFHS-5) provides openly accessible data through the DHS Program's online data platform.

Declaration of No use of generative AI tools: This article was prepared without the use of generative AI tools for content creation, analysis, or data generation. All findings and interpretations are based solely on the authors' independent work and expertise.

References

1. Gillespie DO, Russell AF, Lummaa V. The effect of maternal age and reproductive history on offspring survival and lifetime reproduction in preindustrial humans. Evolution. 2013 Jul;67(7):1964-1974. DOI: https://doi.org/10.1111/evo.12078 PMid:23815653
2. Kamal A, Pervaiz MK. Determinants of higher order birth intervals in Pakistan. J Stat. 2012;19:54-82.
3. Miller R, Karra M. Birth spacing and child health trajectories. Popul Dev Rev. 2020;46(2):347-371. DOI: https://doi.org/10.1111/padr.12335
4. Singh SN, Singh N, Narendra RK. Demographic and Socioeconomic Determinants of Birth Interval Dynamics in Manipur: A Survival Analysis. Online J Health Allied Scs. 2010;9(4):3. Available from: http://www.ojhas.org/issue36/2010-4-3.htm
5. 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 Glob Public Heal. 2024;4(12):e0004062. DOI: https://doi.org/10.1371/journal.pgph.0004062 PMid:39693329 PMCid:PMC11654928
6. Nagdeve DA, Pradhan MR. Determinants of The First Birth Interval Among Women in India. J Fam Reprod Heal. 2023;17(4):229-239. DOI: https://doi.org/10.18502/jfrh.v17i4.14595 PMid:38807621 PMCid:PMC11128726
7. Cox DR. Regression models and life-tables. J R Stat Soc Series B Stat Methodol. 1972;34(2):187–220. DOI: https://doi.org/10.1111/j.2517-6161.1972.tb00899.x
8. Atkinson AC. A test of discrimating between models. Biometrika. 1969;56(2):337-347. DOI: https://doi.org/10.1093/biomet/56.2.337
9. Chen W. On the tests of separate families of hypotheses with small sample size. J Stat Comput Simul. 1980;11(3-4):183-187. DOI: https://doi.org/10.1080/00949658008810406
10. Dumonceaux R, Antle CE. Discrimination between the lognormal and the weibull distributions. Technometrics. 1973;15(4):923-926. DOI: https://doi.org/10.1080/00401706.1973.10489124
11. Jackson OAY. Some Results on Tests of Separate Families of Hypotheses. Biometrika. 1968;55(2):355-363. DOI: https://doi.org/10.1093/biomet/55.2.355
12. Dyer AR. Hypothesis testing procedures for separate families of hypotheses. J Am Stat Assoc. 1974;69(345):140-145. DOI: https://doi.org/10.1080/01621459.1974.10480140
13. Burke K, Jones MC, Noufaily A. A Flexible Parametric Modelling Framework for Survival Analysis. J R Stat Soc Ser C Appl Stat. 2020;62(2):429-457. DOI: https://doi.org/10.1111/rssc.12398
14. McCullagh, P and Nelder JA. Generalized Linear Models (2nd ed.). London: Chapman and Hall; 1989.
15. Atkinson AC. Regression Diagnostics, Transformations and Constructed Variables. J R Stat Soc. 1982;44(1):1-22. DOI: https://doi.org/10.1111/j.2517-6161.1982.tb01181.x
16. Firth D. Multiplicative errors: log-normal or gamma? J R Stat Soc Ser B Stat Methodol. 1988;50(2):266-268. DOI: https://doi.org/10.1111/j.2517-6161.1988.tb01725.x
17. Wiens BL. When Log-Normal and Gamma Model Give Different Results: A Case Study. Amer Stat. 1999;53(2):89-93. DOI: https://doi.org/10.1080/00031305.1999.10474437
18. IIPS ICF. National Family Health Survey (NFHS-5): 2019-21 India. Mumbai Int Inst Popul Sci. 2021.
19. Moultrie TA, Sayi TS, Timæus IM. Birth intervals, postponement, and fertility decline in Africa: a new type of transition? Popul Stud (Camb). 2012 Nov;66(3):241-258. DOI: https://doi.org/10.1080/00324728.2012.701660 PMid:22891624
20. Lawless JF. Statistical models and methods for lifetime data. John Wiley & Sons; 2011.
21. Collett D. Modelling survival data in medical research. Chapman and Hall/CRC; 2014. DOI: https://doi.org/10.1201/b18041
22. Anderson KPBDR. Model selection and multimodel inference: a practical information-theoretic approach Springer-Verlag New York. NY, USA. 2002.
23. Nattino G, Pennell ML, Lemeshow S. Assessing the goodness of fit of logistic regression models in large samples: A modification of the Hosmer-Lemeshow test. Biometrics. 2020 Jun;76(2):549-560. DOI: https://doi.org/10.1111/biom.13249 PMid:32134502
24. Rossi R, Murari A, Gaudio P, Gelfusa M. Upgrading Model Selection Criteria with Goodness of Fit Tests for Practical Applications. Entropy (Basel). 2020 Apr 15;22(4):447. DOI: https://doi.org/10.3390/e22040447 PMID: 33286221 PMCID: PMC7516921
25. Hosmer Jr DW, Lemeshow S, Sturdivant RX. Applied logistic regression. John Wiley & Sons; 2013. DOI: https://doi.org/10.1002/9781118548387