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# Bayesian Poisson Log-Linear Model To Estimate The Effect of Factors Responsible For Road Traffic Accident Fatalities In Nigeria

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## Abstract

*Road accidents have been one of the leading causes of mortality in Nigeria. Some identified risk factors responsible for this ugly trend are; errors from the driver, number of persons involved, age, vehicles safety and road conditions. The aim of this study is to estimate the effect of these factors on road-related fatalities. The Bayesian Simulation Modeling Approach was employed to estimate these parameters. This was done using the Markov Chain Monte Carlo Algorithm implemented on the Windows Bayesian Inference Using Gibbs Sampler platform. The gamma and normal prior distributions were assumed and the Poisson likelihood as the preferred distribution to estimate the posterior parameters. A Random sample of 32 accidents reported cases at Federal road safety office in Makurdi town was retrieved and used as training dataset for the Algorithm. Results show that the coefficients* $\beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ *for the parameters; drivers age, mechanism of mobility, driver error, road condition and unsafe vehicle shows a positive significant affect on the fatality rate due to accident. An increase in the number of persons conveyed on a particular transport mechanism increases the expected death rate due to accident by 8%. Furthermore, there will be an increase in fatalities caused by driver error, road condition, and unsafe vehicle by 52%, 72% and 99% respectively. Furthermore, the expected deaths due to accident on motorbike is twice (0.52) as much as the corresponding deaths on motor vehicle with same condition of road, human factors and unsafe vehicles. It was also observed that increase in drivers' age decreases the rate of deaths due to accident by 1%. Visually inspecting the history plot has confirmed the model convergence. Density plot reflect the target distribution which further validates the prior distribution selected. Deviance Information Criteria (DIC) of 65.439 verified the model fit and adequacy. It was concluded that Bayesian modeling via simulation is suitable for estimating stochastic parameters in the face of scarce and incomplete data.*

**Keywords**: Autocorrelation, Bayesian Models, density plot, fatalities, Likelihood, Posterior distribution, Prior distribution, Road accidents

**Introduction**

According to data released by the World Health Organization (WHO, 2023), an estimated 65.81 million people died worldwide in the year 2022 through road traffic accident. Of these, 1.3 million were due to road injuries, equating to roughly 3500 each day from road traffic injuries. By these statistics road traffic accidents ranked among the top 10 leading causes in 2022, a reality that was not existent a decade ago almost at par with chronic diseases such as HIV/AIDS and diabetes mellitus. By 2030, car accidents will be the fifth leading cause of death in the world, if this trend were to continue (WHO, 2023). Globally, road traffic accidents are the leading cause of injury related deaths. Traffic accidents have high economic burden for society (Sargazi *et al.,* 2016).

Different authors have found several influencing factors for predicting the rate of fatal accidents. Factors like drug usage, not using seat belt, being at rainy days, high risk roads, and absence of emergency care services, risky driving, and level of education e.t.c. were some of these factors (Vakili *et al*., 2016).

Nigeria tops the list of countries with the most fatalities from traffic crashes, according to a 2014 report by the Global Road Safety Facility (Onyemaechi & Ofoma, 2016). Nigeria also has the highest road injury death rate (52.4 per 100,000 people) of any country in the world (Krug *et al*., 2002). 4387 lives were lost due to road traffic accidents in Nigeria in the first six months of 2023 (Businessday Newspaper, 2023). This staggering statistics translates to an average of 731 fatalities each month or about 24 lost lives daily due to accidents. It is reviewed that a significant factor contributing to the accidents is the involvement of untrained, partially trained and inexperienced drivers, sign light violations, dangerous driving, route violation, failure to meet essential safety standards and wrongful overtaking are some of the other leading causes of road traffic crashes in Nigeria.

In Nigeria today, the issue of road accidents has become an early stage trouble. There has been a significant issue of the cardinal elements liable for road accidents in Nigeria. Another issue is to know whether mishaps in Nigeria are identified with overloading of passengers, type of mobility used, sex, age and qualification of driver and instructive foundation of road clients. Analysis of accident victims by age and sex showed victims are predominantly young adult males with an age range of 26-30 years (Asogwa, 1980). There is additional misconception regarding the significant reasons for road accidents in Nigeria. One of such obvious concern is the face of incomplete data to properly analyze the causes of road accidents leading to deaths. The above issues have been our central sparks in this factual research work.

An analytical technique that captures the relationship of accident-related fatalities to significant factors causing these accidents such as the age and sex of driver, his/her qualification and experience in driving and the number of passengers involved in the accident is the Poisson regression technique.

A Poisson Regression Model also known as Poisson log-linear model (using a log link function) is the statistical technique that is employed oncount based data to show whether changes observed in the dependent variable (in this case, the accident –related fatalities) are associated with changes in one or more of the explanatory variables (in this case, the age and sex of driver, his/her qualification and experience in driving and the number of passengers involved in the accident).

According to Sherafati *et al*. (2017), the following are the risk factors of road traffic accidents with fatalities

**i. Driver error:** Most of the fatal accidents occur due to over speeding. over speeding by the driver is directly related to the likelihood of a crash occurring and severity, his experience and qualification, driving under the influence of alcohol and other psychoactive substances, non-use of helmets, seat belts, use of mobile phone while driving among others are collectively regarded as human factors that are responsible for the accident related fatalities in Nigeria

ii. **Number of passengers involved**: the number of passengers conveyed in a vehicleis a significant factor that can lead to accidents (WHO, 2023)

iii. **Mechanism of accident**: two means of transportation are identified for the research; motorbike (0) and motor Vehicle (1)

iv. **Age**: road traffic accidents are the leading cause of death for children and young adults aged 5 – 29 years (WHO, 2023)

v. **Road condition:** Potholes, damaged road, eroded road merging of rural roads with highways, diversions, illegal speed breakers. More than 90% of road traffic deaths occur in low and middle income countries. Road traffic death rates are highest in Africa

vi. **Unsafe vehicles:** safe vehicles play a critical role in averting crashes and reduce the likelihood of serious injury or death. These include vehicles meeting front and side impact regulations such as electronic stability control to prevent over-steering) and to ensure airbags and seat-belts fitted in vehicle, non-availability of side mirror, availability of fire extinguisher among others. Failure of brakes or steering, tyre burst, insufficient headlights, overloading, projecting loads

Furthermore, accident data is scarce and incomplete, this is due to the fact that most cases of accidents are either not documented or reported. The most contentious concern is the scarce or inadequate available records of the factors or circumstance responsible for the vehicle accidental cases. So in order to estimate the effects of these parameters in the face of this incomplete data, we employ the Bayesian based modeling approach.

There are various existing classical methods of modeling the relationship between the rate of deaths and contributory (regressor) variables. However, there are limited works on the application of the Bayesian approach which is more reliable in face of incomplete count based data. This is because Bayesian approach allows for greater flexibility in evaluating model fit, using Marco Chain Monte Carlo algorithm to sample parameters that are not directly estimated from the model, handling missing and incomplete data as well as making predictions that captures greater uncertainty.

Bayesian statistics is a statistical approach that allows researchers to assign a prior distribution to an unknown parameter based on previous beliefs (Giovagnoli, 2008). The argument is that everyone is an ex ante belief about something (Rigollet, 2016). The aim of this article is to apply Bayesian based approach to estimate the mortality rate due to accident in Nigeria.

## Materials and Methods

We assume that the response variable $y_i$ is the number of deaths due to accident over a period of time t in which we want to estimate the mean $\mu$. The probability model for this data is a Poisson distribution given as

$y_i \sim poisson\ (\mu)$

That is $f(y) = \frac{e^{-\mu}\mu^y}{y!}$ y = 0,1,2,… (1)

E(y) = $\mu$ and var(y) =

The Poisson regression model can be written as

$$y_i = E(y_i) + \varepsilon_i \quad i = 1,2,\ldots \quad (2)$$

We assume that the expected value of the observed response can be written as

E($y_i$) =

And there is a function g that relates to the mean of the response to the linear predictor, say

$$g(\mu_i) = \eta_i = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k = X_i'\beta \quad (3)$$

$$\mu_i = g^{-1}(\eta_i) = g^{-1}(X_i'\beta) \quad (4)$$

The function g is the link function which is the relationship between the mean and the linear predictor. In our case, we shall use the log link function which is given as

$$g(\mu_i) = \ln(\mu_i) = X_i'\beta \quad (5)$$

Therefore $\mu_i = g^{-1}(X_i'\beta)$ (6)

Among other link functions, the log link function is more suitable for Poison regression model because it ensures that all predicted values of the response variable are nonnegative (Montgomery *et al.,* 2006)

**Method of Estimation of Posterior distribution**

The maximum likelihood procedure in conjunction with the prior distribution is use to estimate the model parameters. That is

Posterior = likelihood x prior distribution

If we have a sample of n observations on the response y and the predictor's $x_i$'s the likelihood

function is

$$L(y,\beta) = \prod_{i=1}^{n} f_i(y_i/\mu) = \prod_{i=1}^{n} \frac{e^{-\mu}\mu_i^{y_i}}{y_i!} \quad (6)$$

$$= \frac{\prod_{i=1}^{n}\mu_i^{y_i}\exp(-\sum_{i=1}^{n}\mu_i}{\prod_{i=1}^{n}y_i!} \quad (7)$$

Where $\mu_i = g^{-1}(X_i'\beta)$

Since we select the log-link function, we maximize the log – likelihood

$$\text{LnL}(y,\beta) = \sum_{i=1}^{n} y_i \ln(\mu_i) - \sum_{i=1}^{n}\mu_i - \sum_{i=1}^{n}\ln(y_i!)$$

(8)

Iteratively reweighted least squares can be used to find the maximum likelihood estimates of the parameters.

**The Model**

The model log-linear model is stated as follows:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i}$$

*where*

$y_i = death\ rate\ due\ to\ accident$

$\beta_0 = constant$

$x_1 = number\ of\ passengers\ involved\ in\ an\ accident$

$x_2 = age\ of\ driver\ of\ the\ vehicle\ involved\ in\ an\ accident$

$x_3 = mechanism\ involved\ (0 = motorbike, 1 = motorvehicle)$

$x_4 = driver\ error\ (0 = no,\ 1 = yes)$

$x_5 = road\ condition\ (0 = no,\ 1 = yes)$

$x_6 = unsafe\ vehicle\ (0 = no,\ 1 = yes)$

**Prior distribution**

All parameters in the model are assumed to follow a priori independent with the structure

$$f(\beta,\tau) = \prod_{i=1}^{n}(\beta_j)f(\tau) \quad (9)$$

$$\beta_j \sim N(\mu_{\beta_j}, c_j^2) \quad (10)$$

$$\tau \sim gamma(a,b) \quad (11)$$

The gamma prior of the precision parameter induces prior mean and variance given by

$E(\tau) = \frac{a}{b}$ an var( = respectively.

Once the parameter estimates are obtained, the fitted Poisson regression model is

$$\hat{y}_i = g^{-1}(X_i'\hat{\beta})$$

The prediction equation becomes

$$\hat{y}_i = g^{-1}(X_i'\hat{\beta}) = \exp(X_i'\hat{\beta}) \quad (13)$$

The simulation was run for 1000 burn-ins after which samples were collected for 6000 iterations. A thinning of 40 would be maintained throughout the simulations and the overlay check box in WINBUG checked to reduce autocorrelation. Other modeling requirements are as stated by the WINBUG Software documentation.

All statistical analysis was done on the WINBUG software version 1.4.3

**Method of estimating the Posterior Distribution**

We employed the simulation approach to estimate the posterior distribution. The posterior distribution is described using the descriptive measures and density plots.

**Model Convergence and Diagnostic Check**

Model convergence diagnostics was done using history plots, density plots and autocorrelation plots. The plots were produced when the model parameters and measures were monitored on WINBUG. Our approach for investigating convergence issues is by inspecting the mixing and time trends within the chains of individual parameters. The history plots are the most accessible convergence diagnostics and are easy to inspect visually. The history plot of a parameter plots the simulated values for the parameter against the iteration number. The history plot of a well-mixing parameter should traverse the posterior domain rapidly and should have nearly constant mean and variance. The density plots of the model parameters were checked against their actual probability distributions to see whether the right distribution is simulated.

Though, the Gibbs, MCMC algorithm typically generates less-correlated draws, there is a need to monitor the autocorrelation of each parameter to ensure samples are independent. The autocorrelation plot that comes from a well mixing chain becomes negligible fairly quickly, after a few lags.

**Results and Dicussion**

***Data:*** A sample of 32 accidents cases reported and recorded at Federal Road Safety Corps, Benue State Command, Makurdi, Benue State, Nigeria for a period of two months ( May and June, 2023) was retrieve and used as training dataset for this study.

**Posterior Summary Result:**

Table 2 shows the estimates of the posterior mean of the node (unknown quantity), standard deviation of the node, computational accuracy of the mean (MC error), lower and upper endpoints (2.5% and 97.5% respectively) of the credible intervals and quantiles (including median) for the generated sample. The generated sample size (iterations) used to approximate the posterior distribution is 6000 and the discarded burn-in period is 1000.

**Table 1: Posterior Summaries**

| node | mean | sd | MC error | 2.5% | median | 97.5% | start | sample |
|---|---|---|---|---|---|---|---|---|
| **beta0** | -3.514 | 1.406 | 0.1137 | -6.33 | -3.516 | -0.8107 | 1001 | 6000 |
| **beta1** | 0.07938 | 0.07109 | 0.002753 | -0.0654 | 0.08386 | 0.2129 | 1001 | 6000 |
| **beta2** | -0.01442 | 0.02901 | 0.001942 | -0.07 | -0.01413 | 0.04064 | 1001 | 6000 |
| **beta3** | 0.5219 | 0.4631 | 0.01491 | -0.3765 | 0.5187 | 1.441 | 1001 | 6000 |
| **beta4** | 2.508 | 0.9587 | 0.06168 | 0.7794 | 2.459 | 4.523 | 1001 | 6000 |
| **beta5** | 0.7201 | 0.7446 | 0.04453 | -0.7392 | 0.7322 | 2.138 | 1001 | 6000 |
| **beta6** | 0.9905 | 0.6985 | 0.04144 | -0.3616 | 1.005 | 2.33 | 1001 | 6000 |

From the result obtained a point estimate is based on the posterior mean $(\lambda)$. Hence, the posterior estimated model can be summarized by

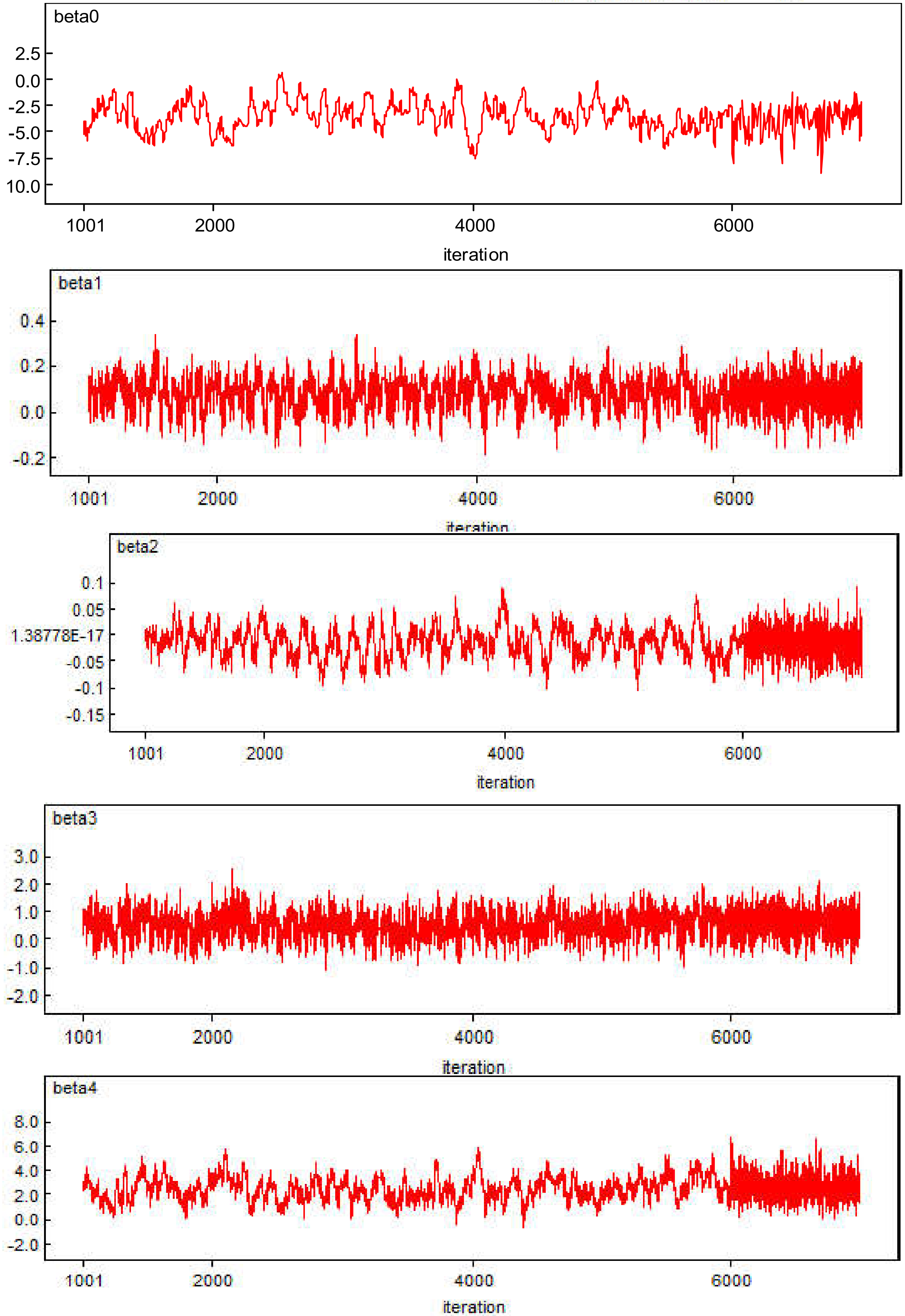
$$\log \lambda_i = -3.51 + 0.079(persons\ involved_i) \\ -0.014(age_i) + 0.52(mechanism\ used_i) \\ +2.5(\text{driver error}_i) + 0.72(Road\ \text{condition}_i) \\ +0.99(unsafe\ vehicle_i)$$

The coefficient $\beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ for the parameters $x_2$, $x_3$, $x_4$, $x_5$ and $x_6$ are positive, this implies that the regressors; drivers age, mechanism of mobility, driver error, road condition and unsafe vehicle significantly affect the fatality rate due to accident. Additional persons involved in a particular means of accident increases the expected death rate by 8%. Furthermore, there will be an increase in fatalities caused by driver error, road condition, and unsafe vehicle by 52%, 72% and 99% respectively.

Furthermore, the expected deaths due to accident on motorbike is twice (0.52) as much as the corresponding deaths on motor vehicle with same condition of road, human factors and unsafe vehicles. It is observed that increase in driver's age decreases the rate of deaths due to accident by 1%.

**Convergence checks**

Figure 1 below shows the history plot for parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ $and$ $\beta_6$.



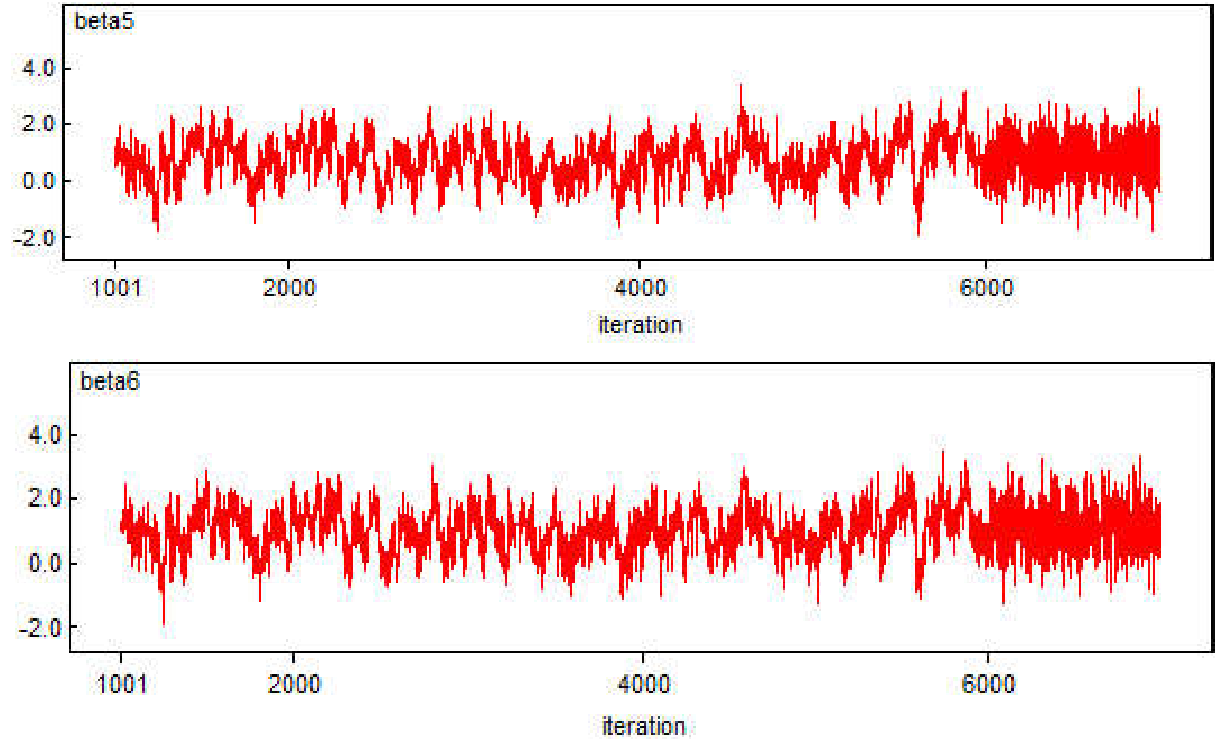
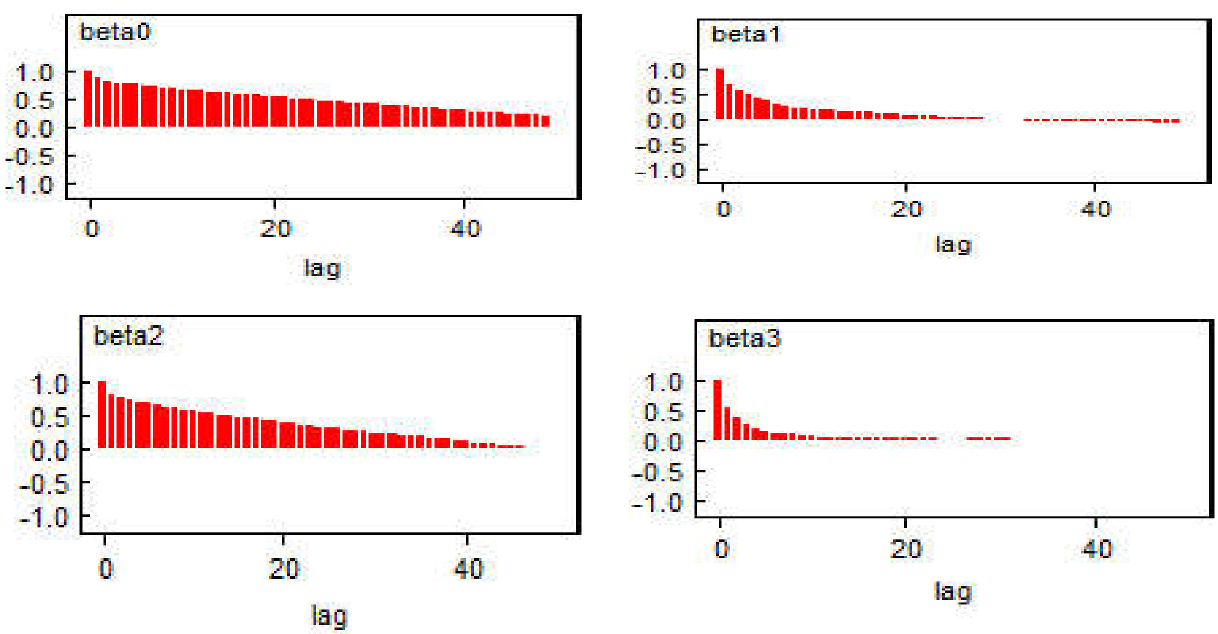


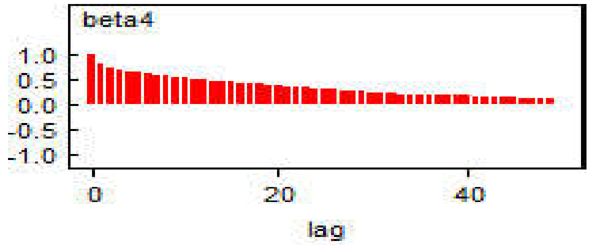

**Figure 1**: History plots for the simulated parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ *and* $\beta_6$

Monitoring the patterns for the parameters shows that no patterns or irregularities exist and therefore convergence can be assumed. Plotting the trace plot also shows similar results. It is therefore conclude that the algorithm has reached its equilibrium implying that the generated sample comes from the correct target distribution.

**Autocorrelation Plot:**

Figure 2 shows the autocorrelation plot. This is used to test for independence of samples generated from the simulation.





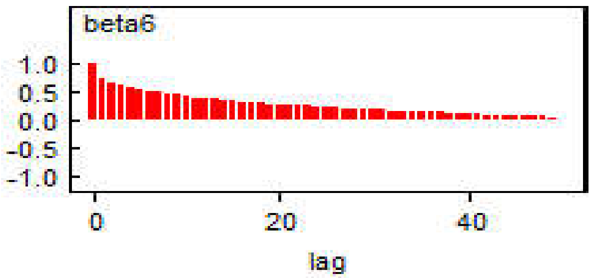
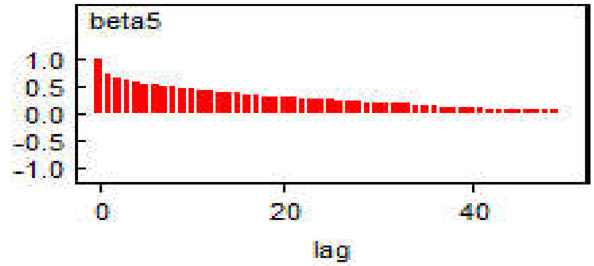




**Figure 2**: autocorrelation plot for parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$

It is observed that for all parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ become low only after considering a lag equal to 40. This implies that an independent sample can be obtained by running the algorithm within *thin* set equal to 40 at the update tool. The

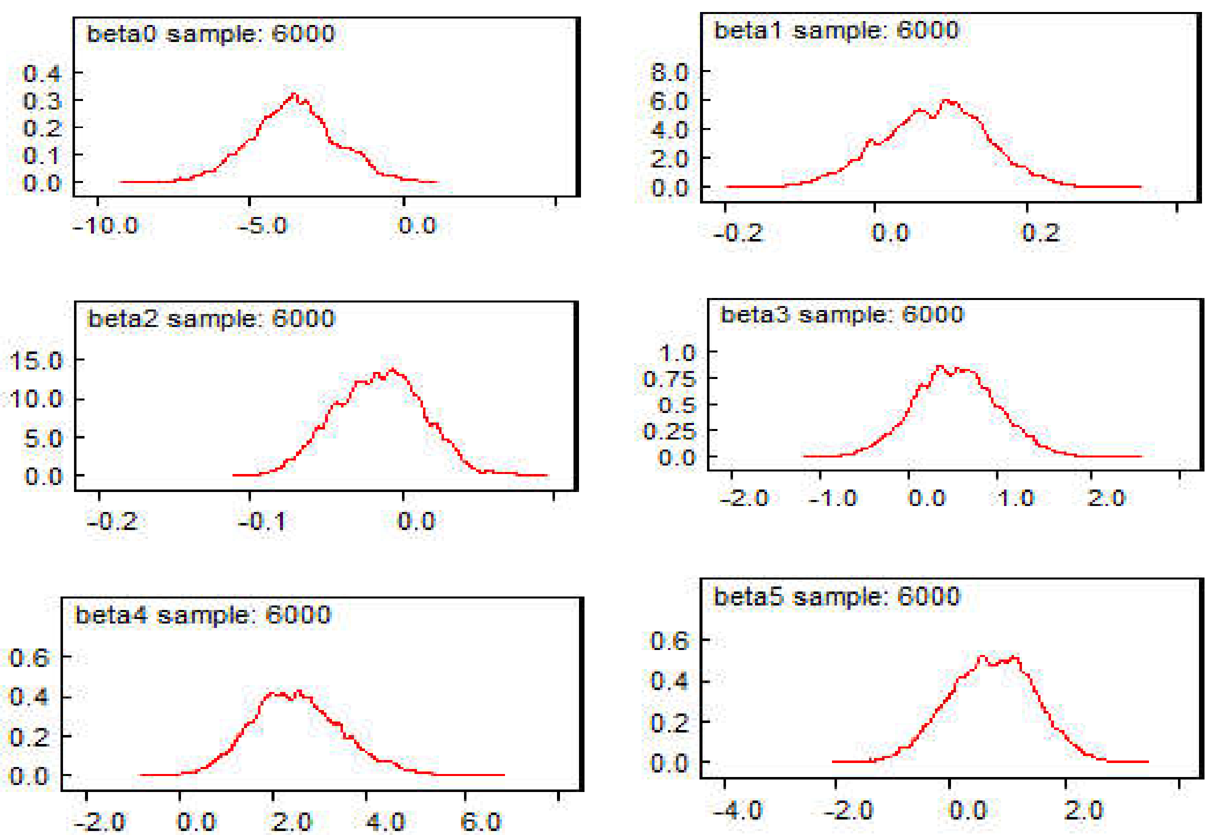



autocorrelation plots of each parameter and measure depict the independence of the samples generated. This is because the autocorrelations become negligible fairly quickly, after 40 lags.

It is also observed that autocorrelation for parameters () became low only after considering a lag equal to 40. Thus an independent sample was obtained by running the algorithm with a thin set to 40 at the update tool.

**Kernel density plots**:

Figure 3 shows the density plot. This is used to graphical estimates of the posterior density.



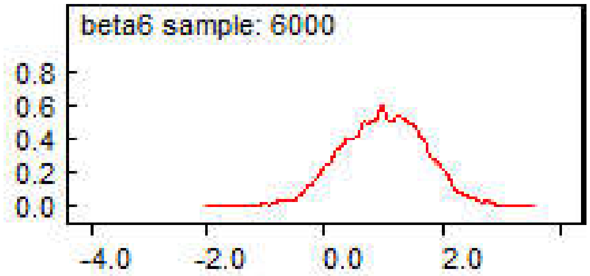


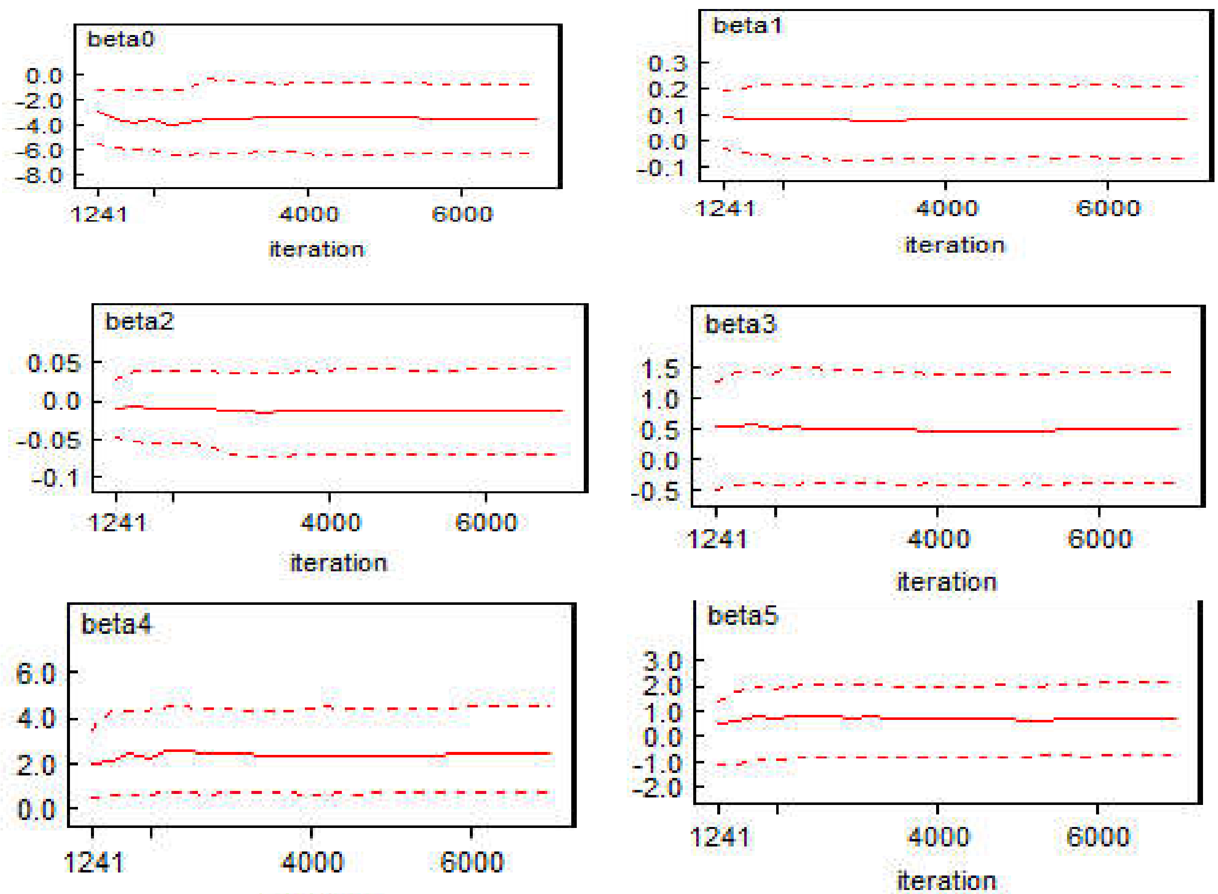

**Figure 3**: Density Plots for parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$

The kernel density provides a graphical presentation of the posterior density estimate for each node. From above it can be deduces that all the parameter estimates follows the assumed approximate normal distribution on the prior and likelihood

.

**Quantiles**:

The quantiles was used to monitor the evolution of the modelparameters. Figure 4 shows the quantiles for the estimated parameters



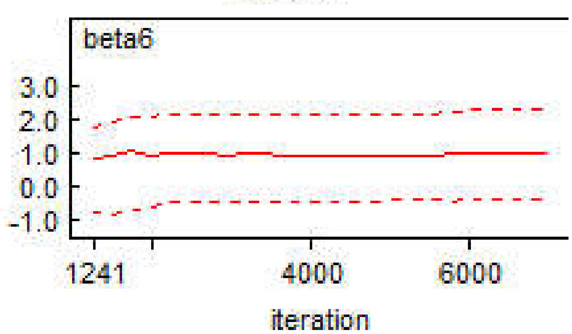




**Figure 4**: Quantile plots for parameters

These plots were used to monitor the evolution of the model parameters by taking into account the 25% (first quartile), second quartile (median) and the third quartile (75%)

**Model checking for adequacy and goodness of fit**

The deviance information Criterion proposed by spiegelhalter *et al.* (2002) was used to measure the model fit usually estimated by the posterior mean deviance, $\overline{D(\theta)}$ where

$$D(\theta) = -2\ln(f(D/\theta))$$

For this study, the deviance information Criterion was used to check for model adequacy. Output from the WINBUG syntax produced the result below

| | Dbar | Dhat | pD | DIC |
|---|---|---|---|---|
| **death** | 58.976 | 52.513 | 6.463 | 65.439 |
| **total** | 58.976 | 52.513 | 6.463 | 65.439 |

Dbar = post.mean of -2logL; Dhat = -2LogL at post.mean of stochastic nodes

The DIC value of 63.439 indicates a good-fitted model. It interprets therefore that the observed data is sufficient to construct the posterior distribution and to evaluate the estimated model

**Conclusion**

Despite Nigeria's high burden of road traffic accidents, defining the full magnitude of the problem has been hampered by lack of robust empirical data. There is no framework for accurate data reporting of road traffic accidents, involved casualties, probable physical and environmental determinants. This research used a small aggregated data to generate data via simulation and conveniently model the relationship between the fatalities and identified risk factors. After developing the model, convergence diagnostic checks were conducted for each model parameter in order to ascertain model adequacy. The history plot, density plots and autocorrelation plots were used for this purpose. Though, all these plots were made for each model parameter ($\beta_i$), sample plots were presented in Figure 2 observe that the history plots shows that the model parameters are well – mixed. This is because they traverse the posterior domain rapidly with nearly constant mean and variance. The model prior distribution for parameters$\varepsilon_i$ and $\beta_i$ are gamma and normal distributions respectively.

The density plots of these priors reflect this distribution which further validates the model. The density plots of the model parameters were checked against their actual probability distributions to see whether the right distribution is simulated. The autocorrelation plots of each parameter and measure depict the independence of the samples generated. This is because the autocorrelations become negligible fairly quickly, after a 40 lags.

Also Monte Carlo errors (MC error) is lower in comparison to the standard deviation (sd), then we can conclude that the estimated posterior mean was estimated with high precision

In this paper, our approach for investigating convergence issues was by inspecting the mixing and time trends within the chains of individual parameters. The history plots are the most accessible convergence diagnostics and are easy to inspect visually. It plots the simulated values for the parameter against the iteration number. The history plot of a well-mixing parameter should traverse the posterior domain rapidly and should have nearly constant mean and variance.

We can use data simulated to identify the burden and risk factors of road accidents, design and test interventions that will address these, and then translate the interventions for implementation in our communities.

**Competing Interest**: The authors declare that they have no competing interest

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