MODELLING ROAD ACCIDENT DATA IN THE NORTH CENTRAL OF NIGERIA USING POISSON-LOGNORMAL AND NEGATIVE BINOMIAL REGRESSION MODELS

[1]Abubakar USMAN, [1]Salamatu ALHASSAM, [1]Yisa YAKUBU & [2]Abdullahi Abubakar WUCHIN

[1]Department of Statistics

Federal University of Technology, Minna, Nigeria

[2]Department of Mathematics, Faculty of Science,

Air force Institute of Technology, Kaduna, Nigeria

Corresponding Author: - abu.usman@futminna.edu.ng

Abstract

This study aims to analyse road accident data to identify significant predictors of fatalities and determine the best-fitting model using statistical criteria. The objectives include visualising road accident data, fitting Poisson-Lognormal and Negative Binomial regression models, assessing model performance using Akaike and Bayesian Information Criteria, and evaluating the contribution of key factors—Driver Error, Faulty Vehicle, and Road Condition—to fatalities. The Poisson-Lognormal model emerged as the best fit, with the lowest AIC (-132.4) and BIC (-118.5), a high R-squared (0.87), and a pseudo-R-squared of 0.9999, indicating strong explanatory power. Key findings reveal that Driver Error is the most significant predictor, contributing to a 2.17% increase in fatalities per unit increase, followed by Faulty Vehicle (1.4%), while Road Condition showed no significant effect. Temporal and seasonal analyses highlighted fluctuating trends, with peaks in 2016-2017 and 2020, and a notable decline by 2024. Regional analysis identified the Federal Capital Territory, Niger, and Kogi as hotspots. The study concludes that targeting Driver Error and Faulty Vehicle issues through enhanced driver training, stricter enforcement, vehicle maintenance programs, and data-driven policies could substantially reduce fatalities. Road infrastructure improvements, while important, require complementary measures to maximise impact. These findings provide critical insights for policymakers to develop effective strategies to mitigate road accident fatalities in North Central Nigeria.

Keywords: - Driver error, Faulty vehicle, Poisson-lognormal, Explanatory power and fatalities

Introduction

Road accident, also known as a traffic accident or motor vehicle accident, is an unplanned event or collision involving one or more vehicles on a road or public highway that results in damage to property, injury, or death. It can involve cars, trucks, motorcycles, bicycles, pedestrians, or other road users. It can typically result from factors such as; Driver errors like speeding, distracted driving, driving under the influence of alcohol or drugs, mechanical failure like faulty vehicles or tire blowouts and environmental conditions like poor road conditions, bad weather, or visibility. It can also range from minor incidents with no injuries to severe accidents with fatalities or significant damage. Reducing road accidents is often a key focus of traffic safety campaigns, enforcement, and regulations. Road and death refer to fatalities resulting from road accidents. Road traffic deaths occur when people are killed due to crashes or collisions involving vehicles on roads. These fatalities can involve drivers, passengers, pedestrians, cyclists, or other road users. It highlights the tragic consequences of road accidents and the need for continued efforts in improving traffic safety and minimising risk factors.

Nigeria needs good roads, according to this review (Eneh *et al.*, 2023), but the majority of them are in poor condition, unusable, too small, underdeveloped, and prone to potholes. The roads are not adequately lit for evening traffic (Atubi, 2021; Yakubu *et al.*, 2023). Nigeria has 1.7 million automobiles, with over 200 million people, over 33 million families, and an average family size of six. Individuals cannot buy brand-new cars due to soaring inflation and the declining value of the currency relative to the Naira. Individual Nigerians have turned to used (tokumbo) cars. The quality of vehicles on Nigerian roads is diminished by these subpar automobiles. The more there are in number, the lower the vehicle quality on Nigerian roads. Poor road quality and poor vehicle quality combine to form the direct factors of road crashes, which have become growing public health hazards and environmental health risks that inflict deaths, disability and financial burdens. (Eneh *et al.*, 2023).

crashes is in 8th place among the causes of death in the world and remain a significant public health issue. Males are more often involved in road crashes than females, while females represent 51% of the world's population, but only 24% of road deaths (Pawłowski *et al.*, 2019; Razzaghi *et al.*, 2020). In addition, gender differences in the risk of fatal crashes are highly dependent on age. Young men under the age of 25 account for 73% of all road deaths and are three times more involved in road crashes than women. However, this gender gap decreases with age, being greater for drivers aged 16 to 39 (with male drivers 1.6 to 25 times more likely to be at risk than female drivers) than for drivers aged 40 to 59 (with an increased risk of 1.2 to 1.3 times for males)(Razzaghi *et al.*, 2020). This gender gap disappears even among drivers over 60 years of age (Granié *et al.*, 2020; Granie *et al.*, 2021). Road crashes are identified as one of the leading causes of death in Nigeria, especially among age groups 5 to 29 years. In fact, hardly a day goes by without the news of a road traffic crash resulting in loss of lives and/or permanent disability (Ajiboye *et al.*, 2020; Atubi, 2023). This road traffic crash, apart from insurgency and banditry, is among the leading causes of death in Nigeria. Again, the year 2020 saw the highest death toll from road traffic accidents (Ajiboye *et al.*, 2020; Yakubu *et al.*, 2023).

There is a 1.33% rise in the number of road crashes in January-March 2022. About 26% of the 3,345 road crashes recorded between January and March of 2022 were classified as fatal cases, 62.8% were serious cases, and only 374 (11.2%) of the cases were categorised as minor. Nigeria lost a total of 1,834 lives to road traffic crashes between January and March 2022. Male adults accounted for 77.8% of this figure, while female adults were 15.2%. More female children were killed than male children. By way of comparison, 1,652 lives were lost to road crashes between October and December 2021, while 1,834 lives were lost between January and March 2022 – indicating an 11.02% increase in lives lost to road traffic accidents in the succeeding quarter. And, the number of lives lost to road crashes in the January-March 2022 period is higher than that of every quarter of 2021. From the more than 11,800 road traffic casualties that occurred in Nigeria during the fourth quarter of 2021, about 10,200 were injured, while 1,700 were registered deaths. (Labbo *et al.*, 2024). The estimated number of used vehicles imported into Nigeria, as an indicator of vehicle quality, decreased by 73% from 110,715 in 1992 to 30,000 in 1994, increased further by 1,173% from 7,858 in 1997 to 100,000 in 2001, and increased further by 7,506% from 69,411 in 2016 to 760,543 in 2021. (Acheampong *et al.*, 2022; Musa, 2022; Saleh and El-Sayed, 2023; Ukonze *et al.*, 2020; Yakubu *et al.*, 2023). Accidents do not just happen; they are caused. Two direct factors of road crashes are road quality and vehicle quality. 95% (95%) of second-hand vehicles imported into Nigeria are "accidented" vehicles. (Hossain *et al.*, 2024). Other causes are a lack of proper driving education and poor driving behaviour, overload, speed, drunken driving, failure to use provided safety devices, inclement weather, poor vehicle maintenance, dangerous and reckless driving or road violation, fatigue, and use of mobile driving devices and gadgets while driving. (A. Atubi, 2012; Eneh *et al.*, 2023; Jakobsen *et al.*, 2023). This situation, which gives cause for worry, prompted the longitudinal study, which set out to regress death tolls from road traffic crashes against road quality and vehicle quality to establish and compare the involvement of both factors in road traffic accidents and the resultant carnage on Nigerian roads. (Eneh *et al.*, 2023). An estimated 1.2 million people die in road traffic accidents each year, while about 50 million are injured, and about 85% are in developing countries. The highest frequency of traffic accidents in the world takes place in India. As per the report of the National Crime Records Bureau, more than 135000 traffic accident deaths occur in India. (Muthusamy *et al.*, 2015). The result of a population-based study on injuries conducted by Moshiro *et al.* (2001) revealed that between 1992 and 1998, transport-related accidents were the leading cause of injury in Dares Salaam, Tanzania. Over 37,000 people die in road crashes each year, as per the annual United States Road Crash Statistics.

Literature Review

Due to the significant impact of road traffic crashes on human lives, property, and the environment, many researchers have explored the causes, effects, and offered recommendations to mitigate road traffic crashes in Nigeria and globally (Adenomon and Ayuba, 2018). Common causes include alcohol consumption, mechanical failure, and speeding (Balogun *et al.*, 2021). Despite these findings, annual reports from the Federal Road Safety Commission, National Bureau of Statistics, and other organisations still indicate an increase in road traffic crashes (Akanbi and Abegunde, 2021). This highlights the need for statistical analysis of road traffic crash data to assess whether there is an upward trend over the years, leading to an increased loss of life. Researchers worldwide have applied various models to vehicular crashes, but it is challenging to directly implement models from one region to another due to differences in local factors (Hambly *et al.*, 2013). .

Ofunu *et al.* (2024) centre around the evaluation of statistical models for road accident data analysis. It illustrates the relationship between various types of regression models (Poisson, Negative Binomial, and Poisson Log-Normal) and their effectiveness in predicting road accident counts. The framework highlights key concepts such as the handling of overdispersion and zero inflation in count data, which are critical for accurate modelling. It also includes variables influencing road accidents, such as overtaking, speeding, dangerous driving, and loss of control. The conceptual framework serves to guide the research by establishing how each model’s ability to fit the data will be assessed through criteria like AIC and BIC, ultimately providing a clear understanding of which model offers the best predictive performance for the dataset.

The conceptual framework for the study by Adenomon and Ayuba (2018) revolves around the relationship between road crash occurrences (independent variable) and the resulting fatalities (dependent variable). The authors conceptualised road safety as influenced by the frequency of crashes, where increases in crash events are expected to escalate fatalities. They also accounted for time (as a covariate) to observe the temporal trends in fatalities over the 10-year study period. The role of FRSC's interventions was implicitly included in the analysis through the observed annual decrease in fatalities. The Poisson and Negative Binomial regression models provided the structure to quantify these relationships and assess the effectiveness of road safety measures over time.

Sameer *et al.* (2024) applied the Poisson regression model to road accident data in Kaduna State, Nigeria, from 2014 to 2017, analysing variables such as the number of persons involved, seasonal variations, the number of crashes, and the causes of accidents. Their analysis, carried out using the R software (MASS package), utilised the Akaike Information Criterion (AIC) for model selection, revealing that the Poisson model fit the data well with an AIC value of 1185.7. They reported that the variables significantly impacted the number of persons involved in road crashes, as indicated by a p-value of 0.029, demonstrating a statistically significant relationship. Their results also indicated a high rate of accidents, largely attributed to the Kaduna highway's connectivity with eight other states. This clustering of accident data, combined with the small residual standard deviations, highlighted the Poisson regression model as an appropriate choice for analysing road traffic crash data in Kaduna State.

The study by Ofunu *et al.* (2024) provides a quantitative comparison of Poisson, Negative Binomial, and Poisson Log-Normal regression models for analysing road accident data from five major roads in Bauchi State, Nigeria, spanning from 2010 to 2015. The dataset includes variables such as overtaking (OVT), overspeeding (OVS), dangerous driving (DGD), and loss of control (LOC). The analysis, conducted using R statistical software, found that the Poisson Log-Normal regression model consistently yielded the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values across all five roads, indicating its superior fit compared to the other models. For example, the Poisson Log-Normal model showed an AIC of 66.00 and a BIC of 60.10 for the Bauchi-Dass Road, while the Poisson regression and Negative Binomial regression models had higher AIC and BIC values. This result suggests that the Poisson Log-Normal model is more robust in handling over-dispersion and zero inflation in road accident data, making it the preferred model for this analysis.

Eneh *et al.* (2023) studied the relationship between road and vehicle quality and road traffic fatalities in Nigeria, employing a longitudinal approach. The research draws on secondary data spanning multiple years, using death tolls from road traffic accidents as the dependent variable and road and vehicle quality as key independent variables. Data on vehicle quality was estimated based on the number of imported vehicles into Nigeria from 1992 to 2021, while road quality was measured from 2006 to 2019. The findings of the study are particularly illuminating, as they reveal a statistically significant relationship between the degradation of both road and vehicle quality and the rising number of fatalities from road traffic accidents. Specifically, the study found that for every 1% decrease in road quality, the death toll from road crashes increased by 0.00642%. This suggests that as Nigerian roads continue to deteriorate—characterised by issues such as potholes, poor signage, and lack of maintenance—there is a proportional increase in the likelihood of fatal accidents.

Atubi (2023) utilising a cross-sectional research design, administered 3,700 Driver Behaviour Questionnaires and Driver Skill Inventories between February 2021 and March 2022, with a substantial response rate of 3,270 completed questionnaires. The analysis employed rigorous statistical methods, including Chi-square tests, Student's t-tests, Analysis of Variance (ANOVA), and Mann-Whitney U tests, to discern differences in driving behaviours and skills between male and female drivers. The findings reveal that, contrary to expectations, women reported a higher number of violations and lapses in their driving behaviour compared to men, although the difference in error rates between genders was not statistically significant. The study also identified a higher incidence of road traffic crashes among young drivers under the age of 30, with a notable predominance of male drivers in this group. Six specific types of violations, three types of lapses, and three types of errors were significantly associated with male drivers, highlighting a gendered dimension to traffic violations. These insights underscore the necessity for targeted interventions, including driver education programs, enhanced enforcement of traffic laws, and the promotion of safety practices such as seatbelt use and adherence to speed limits.

Road Traffic Accident Situation in Khulna city, Bangladesh, was reported by Hossain *et al.* (2024). Two-year data pertaining to road accidents were gathered from different police stations located in the city. During the report period, 157 road accidents occurred, and 25% of the victims were in the age group of 30 to 39 years, 33% of pedestrians lost their life and 34% of them got injured.

Road Accident and safety study in Bangladesh has been analysed by Banik *et al.* (2011). The north-eastern division of Bangladesh, named Sylhet, witnesses the rapid growth of road vehicles and development in economic tourism, at the same time, it experiences severe road traffic accidents. A better understanding and consciousness of the accident causes can prevent and minimise the severity of road accidents.

Li (2012) investigated the relationship between traffic safety and vehicle choice. This was done through quantification of the effects of the arms race on vehicle demand, producer performance, and traffic safety. The accident externality of a light truck amounts to $2444 during the vehicle lifetime, and that 12% of new light trucks sold in 2006 and 204 traffic fatalities could have been attributed to the arms race, the design mismatch between light trucks and passenger cars being the reason.

Brake failure and its effect on road traffic accidents in Kumasi Metropolis, Ghana had been discussed by Oduro (2012). The research design used for this study was a survey, which relied on a questionnaire to generate data for analysis and discussion. 40% of the vehicle users agreed that brake failure is caused by low or a shortage of brake fluid, and 33% of the respondents said it was due to brake overheating. The major contributing factor to road accidents is the motor vehicles that ply on the roads, gross indiscipline on our roads, overloading and fatigue driving.

Kinafa A. U. *et al*. (2020) conducted a comparative analysis of Poisson and Negative Binomial regression models to assess road accident data in Nigeria, focusing on quarterly counts from the past year. Their study identified key explanatory variables, including Driver Error, Road Condition, and Faulty Vehicle, which significantly influenced the expected number of fatalities from road accidents. The analysis revealed that the Negative Binomial model provided a better fit than the Poisson model, evidenced by lower Akaike Information Criterion (AIC) values (Negative Binomial AIC = 84.994 vs. Poisson AIC = 85.305) and improved Deviance statistics (Negative Binomial Deviance = 6.9075 vs. Poisson Deviance = 14.109). The estimated death rate in the Negative Binomial model was found to be statistically significant at the 5% level, confirming that the specified variables are essential for understanding fatal road accidents in Nigeria. This study contributes valuable insights into the factors driving road traffic casualties and underscores the importance of selecting appropriate statistical models for count data analysis.

Adenomon and Ayuba (2018) utilised Poisson and Negative Binomial regression models to examine the relationship between deaths from road traffic crashes and total cases of crashes on the Keffi-Lafia road from 2006 to 2015. Their findings revealed a significant positive relationship between the number of total crash cases and the number of deaths, indicating that a 1-unit increase in road crashes led to a 0.8% increase in deaths. Additionally, there was a notable negative trend of a 7.5% annual reduction in deaths, which they attributed to road safety awareness campaigns by the FRSC. The Poisson regression model proved more robust than the Negative Binomial model, as there was no evidence of overdispersion ($p > 0.05$). This conclusion was further reinforced by lower standard errors for coefficients in the Poisson model compared to the Negative Binomial model, making it a more efficient model for the dataset used in the study.

The study by Ofunu *et al.* (2024) integrates count data modelling theories and concepts of model fit criteria. The Poisson regression model is based on the assumption that the number of events (accidents) follows a Poisson distribution with a constant mean rate, ideal for modelling count data when events occur independently. However, this model may not handle over-dispersion well, where the variance exceeds the mean. The Negative Binomial regression model addresses this by incorporating an additional parameter to account for over-dispersion. The Poisson Log-Normal regression model further extends this by modelling count data with both over-dispersion and zero inflation, thus providing greater robustness in diverse datasets. The use of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as fit criteria is grounded in model selection theory, which posits that models with lower AIC and BIC values are preferred for their balance of fit and complexity. This theoretical framework supports the evaluation of which statistical model best captures the nuances of road accident data in Bauchi State, Studies on Various Road Safety Models (Dell'Acqua and Russo, 2011).

According to Eneh *et al.* (2023), The study is built on the risk factor theory, which posits that road traffic accidents result from the interaction of various risk factors that increase the likelihood of crashes and fatalities. In the context of Nigerian roads, two key risk factors, road quality and vehicle quality, have been identified as significant contributors to road traffic carnage. The deterioration of road conditions and the declining quality of vehicles, particularly imported used cars, have a direct impact on the number of fatalities caused by road crashes. It helps to conceptualise how external risk factors, such as infrastructure and vehicle standards, interact to create hazardous road environments by examining the relationship between these factors and accident outcomes. This study provides a robust framework for understanding and addressing the root causes of road traffic accidents in Nigeria.

(Atubi, 2023) The study integrates the Theory of Planned Behaviour (TPB) and the Risk Homeostasis Theory to explore the relationship between gender and driving behaviour. TPB, developed by Ajzen, asserts that an individual's behaviour is influenced by their attitudes towards the behaviour, subjective norms, and perceived behavioural control. This theory provides a useful perspective for understanding how gender-specific attitudes and societal expectations shape driving behaviours. Risk Homeostasis Theory, proposed by Wilde, complements this by suggesting that drivers adjust based on their perceived level of risk. According to this theory, if drivers perceive their environment as less risky due to safety measures, they may engage in riskier behaviours, which could vary by gender. Integrating these theories allows for a nuanced analysis of how gender influences driving behaviour and the propensity for traffic accidents.

The Poisson regression model used by Adenomon and Ayuba (2018) is grounded in the theory of generalised linear models (GLMs), which extend traditional linear models to accommodate response variables that follow non-normal distributions, such as count data. Poisson regression assumes that the mean and variance of the dependent variable (number of deaths) are equal, which is appropriate for count data where events are rare. The Negative Binomial regression, used as an alternative, introduces an additional parameter to handle overdispersion, allowing for a greater variance than the mean. This theoretical framework is critical when modelling rare events like road accidents, as it provides flexibility in handling different distribution patterns in real-world data (Cameron and Trivedi, 2013)

Research Methodology

Scope and Data Source

This study focuses on modelling road traffic fatalities across six states in north-central Nigeria: Benue, Kogi, Kwara, Nasarawa, Niger, and Plateau. The data will be sourced from the Federal Road Safety Corps (FRSC), Minna, Niger State chapter, which maintains comprehensive records of road traffic accidents, including fatalities, injuries, and contributing factors. The period of study will cover road traffic fatalities from the first quarter of 2016 to the first quarter of 2024. The data will include key variables such as road conditions, faulty vehicles, and driver errors, which are critical factors contributing to road accidents in the region. By analysing this data, the research aims to identify patterns and factors leading to road fatalities and recommend effective interventions for road safety improvements in north-central Nigeria.

Data description

The dataset collected from the FRSC will consist of the following variables:
Date of Accident: The exact date and time when the accident occurred, which helps in temporal analysis (by quarter and year).

a. Fatalities: Number of persons who died in each accident based on the factors.
b. Contributing Factors:

i. Road Conditions: Information on the state of the road at the time of the accident (e.g., potholes, wet surface, poor lighting).
ii. Faulty Vehicles: Any vehicle malfunctions or defects contributing to the accident (e.g., brake failure, tyre burst).
iii. Driver Error: Driver behaviours that contributed to the crash (e.g., over speeding, dangerous driving, overtaking).

Poisson Lognormal Regression Model

The Poisson-Lognormal model was developed to overcome the limitations of the Negative Binomial model. Unlike the Negative Binomial, which assumes a gamma-distributed error term, the Poisson-Lognormal uses a lognormal error distribution, making it more suitable for handling under-dispersed count data. While the Poisson-Lognormal model offers greater flexibility compared to the Negative Binomial, it presents challenges in parameter estimation due to the lack of a closed-form solution for the Poisson-Lognormal distribution (Abdulhafedh, 2017).

The Poisson-Lognormal model is even more flexible and robust than both the Poisson and Negative Binomial models.

The parameter β_{it} In equation (3.1), follows a lognormal distribution with parameter λ_{it}, σ^2 given by equation (3.13) below

$$f(\beta_{it}/\lambda_{it}, \sigma^2) = \frac{1}{\beta_{it}\sqrt{2\pi\sigma^2}} e^{\frac{\left(-(ln(\beta_{it})-\lambda_{it})^2\right)}{2\sigma^2}}, where\ \sigma^2 > 0 \qquad (3.1)$$

The probability density function for the persons killed in an accident (y_i) for a particular period i is

$$f(y_i, t) = \int_0^\infty f\left(\frac{y_{it}}{\beta_{it}}\right) f\left(\frac{\beta_{it}}{\lambda_{it}}, \sigma^2\right) d\lambda_i$$

$$= \frac{1}{y_{it}\sqrt{2\pi\sigma^2}} \int_0^\infty \lambda^{y_{it}-1} e^{(-\lambda_i)}\, e^{\frac{\left(-(log\lambda_i-\beta_{it})^2\right)}{2\sigma^2}} d\lambda_i + \varepsilon_i \qquad (3.2)$$

The Poisson Lognormal distribution in equation (3.6) has the mean

$$E(y_i) = e^{\left(\beta_{it}+\frac{\sigma^2}{2}\right)} + \varepsilon_i \qquad (3.3)$$

The variance for equation (3.18) is

$$var(y_i) = e^{\left(\beta_{it}+\frac{\sigma^2}{2}\right)}\left(1 + \left(e^{\left(\beta_{it}+\frac{\sigma^2}{2}\right)}\right) e^{(\omega^2-1)}\right) + \varepsilon_i \qquad (3.4)$$

This model introduces an additional layer of randomness by assuming that the log of the mean μ_i follows a normal distribution with a mean v_i and variance σ^2

$$\ln(\mu_i) = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + \cdots + \beta_1 X_1 + \varepsilon_i \qquad (3.5)$$

Where $\varepsilon_i \sim N(0, \sigma^2)$ is a normally distributed error term.

Since the distribution is a closed form, the parameters will be estimated using the built-in Bayesian Monte Carlos.

Negative Binomial Regression (Poisson-Gamma)

The negative binomial (NB) model presents an alternative approach when the variance of the count data (number of accidents) exceeds the mean, a phenomenon known as over-dispersion

(Hassan *et al.*, 2022). Unlike the Poisson model, which assumes equal mean and variance, the NB model allows for this over-dispersion by incorporating a gamma distribution for the parameter (λ_{it}) in equations (3.5). (Winkelmann, 2008). This additional layer of flexibility makes the NB model more adaptable to real-world count data scenarios where variance often deviates from the mean. Like the Poisson model, the NB model falls within the framework of generalised linear models (Lee and Nelder, 1996).
Mathematically, the Negative Binomial distribution is one derivation of the binomial distribution in which the sign of the function is negative. It is defined as a mixed distribution with a Poisson mean and a one-parameter Gamma dispersion function having the form:

$$f(y_i/\theta_i) = \frac{e^{-\theta_i}\theta_i^{y_i}}{y_i!} \quad (3.6)$$

and where $\theta_i$is a function of a one-parameter gamma distribution that accounts for over-dispersion, and the traditional Negative Binomial regression model is given by

$$\mu_i = \exp\left(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p\right) \quad (3.7)$$

And the natural log for the model is given as equation (3);

$$\ln \mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \quad (3.8)$$

With the variance of the model given by

$$var(Y_i) = \mu_i + \frac{\mu_i^2}{\theta} \quad (3.9)$$

Where ϴ is the dispersion parameter

We can write the distribution as

$$p(y_i) = \frac{\Gamma(\tau^{-1} + y)}{\Gamma(\tau^{-1})\Gamma(y+1)}\left(\frac{(\tau^{-1})}{\tau^{-1} + \alpha e^{x_i\beta}}\right)^{\tau^{-1}}\left(\frac{\alpha e^{x_i\beta}}{\tau^{-1} + \alpha e^{x_i\beta}}\right)^{y}, i = 1,2,\cdots,n \quad (3.10)$$

The Negative Binomial likelihood:

$$\mathrm{L}(\alpha,\beta) = \prod_{i=1}^{n} p(y_i) = \prod_{i=1}^{n} \frac{\Gamma(\tau^{-1} + y)}{\Gamma(\tau^{-1})\Gamma(y+1)}\left(\frac{(\tau^{-1})}{\tau^{-1} + \alpha e^{x_i\beta}}\right)^{\tau^{-1}}\left(\frac{\alpha e^{x_i\beta}}{\tau^{-1} + \alpha e^{x_i\beta}}\right)^{y} \quad (3.11)$$

And the log-likelihood function is

$$ln\mathrm{L}(\alpha,\beta) = \langle yln\alpha + y(x_i\beta) - (\tau^{-1} + y)\ln\left(\tau^{-1} + \alpha e^{x_i\beta}\right) + ln\Gamma(\tau^{-1} + y) - ln\,\Gamma(y+1) - \Gamma(\tau^{-1})\rangle \quad (3.12)$$

For a Negative Binomial generalised linear model, the deviance can be computed as follows:

$$D = \sum_{i=1}^{N}\left[y_i ln\left(\frac{y_i}{\hat{\lambda}_i}\right) - (y_i + \hat{\psi})ln\left(\frac{y_i + \hat{\psi}}{\hat{\lambda}_i + \hat{\psi}}\right)\right] \quad (3.13)$$

For a well-fitted model, the deviance should be approximately χ^2 distributed with $N - K - 1$ degrees of freedom (Lee and Nelder, 1996). If $D/(N - K - 1)$ is close to 1, we generally conclude that the model's fit is satisfactory.

The Poisson, Negative Binomial, and Poisson-Lognormal regression models are well-suited for modelling count data, particularly for rare events like road accidents, including fatalities. These models handle the discrete nature of accident counts and account for different forms of variability in the data.

Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) adjusts the log-likelihood for degrees of freedom since adding more variables will always increase the log-likelihood. It is defined as:

$$AIC = -2L + 2(K+1) \quad (3.14)$$

Where L is the log-likelihood and K is the number of independent variables (K= 3, driver errors, road condition and faulty vehicles). The model with the lowest AIC is 'best' (Akaike, 1987).

Bayes Information Criterion (BIC)

The Bayes Information Criterion (BIC), sometimes called the Schwartz Criterion) penalise the number of parameters added in the model and reverse the sign of the log-likelihood (L) so that the statistics are more intuitive. The model with the lowest BIC/SC value is 'best' (Watanabe, 2013).
It is defined as:

$$BIC = -2L + [(K+1)\,ln(N)] \quad (3.15)$$

3.4.3 Deviance

A decision about whether the Poisson model is appropriate can be based on the statistic called the deviance, which is defined as:

$$Dev = 2(L_F - L_M) = 2\sum_{i=1}^{N}\left[y_i ln\left(\frac{y_i}{\hat{\lambda}_i}\right) - y_i - \hat{\lambda}_i\right] \quad (3.16)$$

Where L_F is the log-likelihood that would be achieved if the model gave a perfect fit and L_M is the log-likelihood of the model under consideration. If the latter model is correct, the deviance (Dev) is approximately χ^2distributed with degrees of freedom equal to $N - (K+1)$. A value of the deviance is greatly in excess of $N - (K+1)$ suggests that the model is over-dispersed due to missing variables or a non-Poisson form. This statistic is sometimes called the G^2 statistic (Lord *et al.*, 2013). The deviance has $N - K - 1$ degrees of freedom where K is the number of parameters estimated (including the constant).

Results and Discussions

Visualisation of road accident data

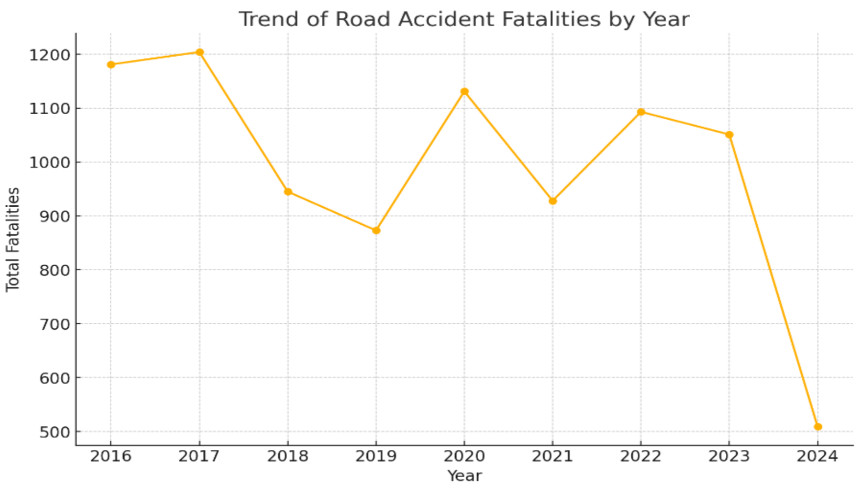


Figure 4.1. shows how the total fatalities due to road accidents have fluctuated over time from 2016 to 2024.

The highest number of fatalities occurred around 2016-2017, reaching approximately 1200. There is a significant decline in fatalities after 2017, reaching lower levels by 2019. Fatalities rose again in 2020, marking another peak. This is followed by alternating increases and decreases between 2021 and 2023, indicating an unstable trend. A dramatic reduction in fatalities is observed in 2024, reaching approximately 500, and this is due to the incomplete quarters.

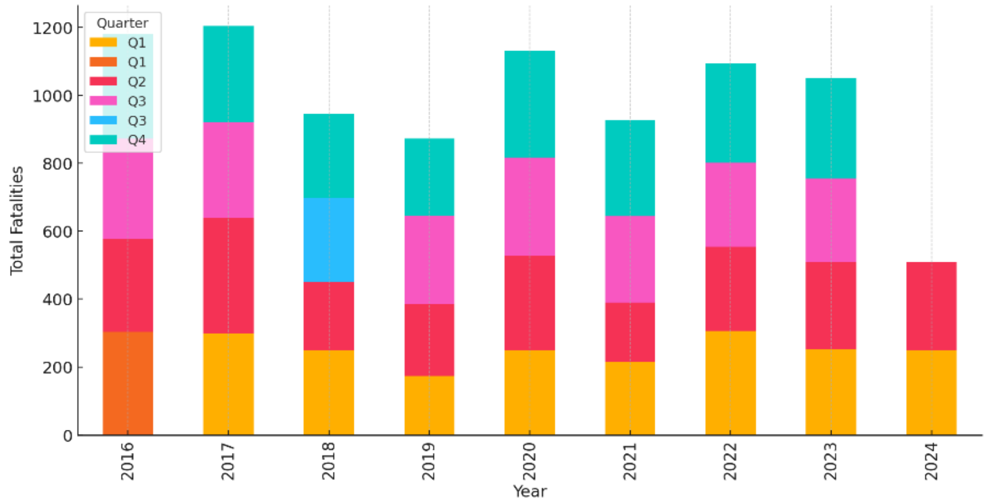
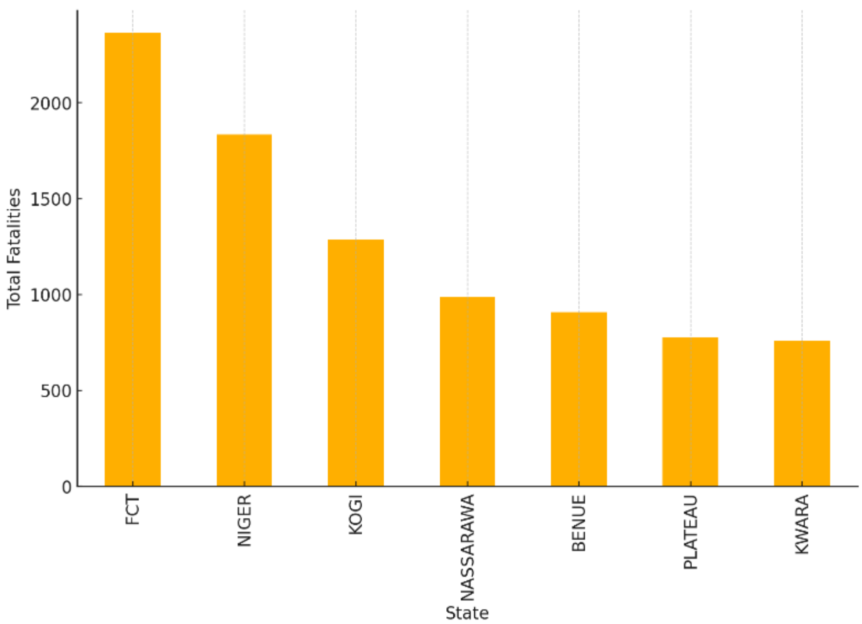
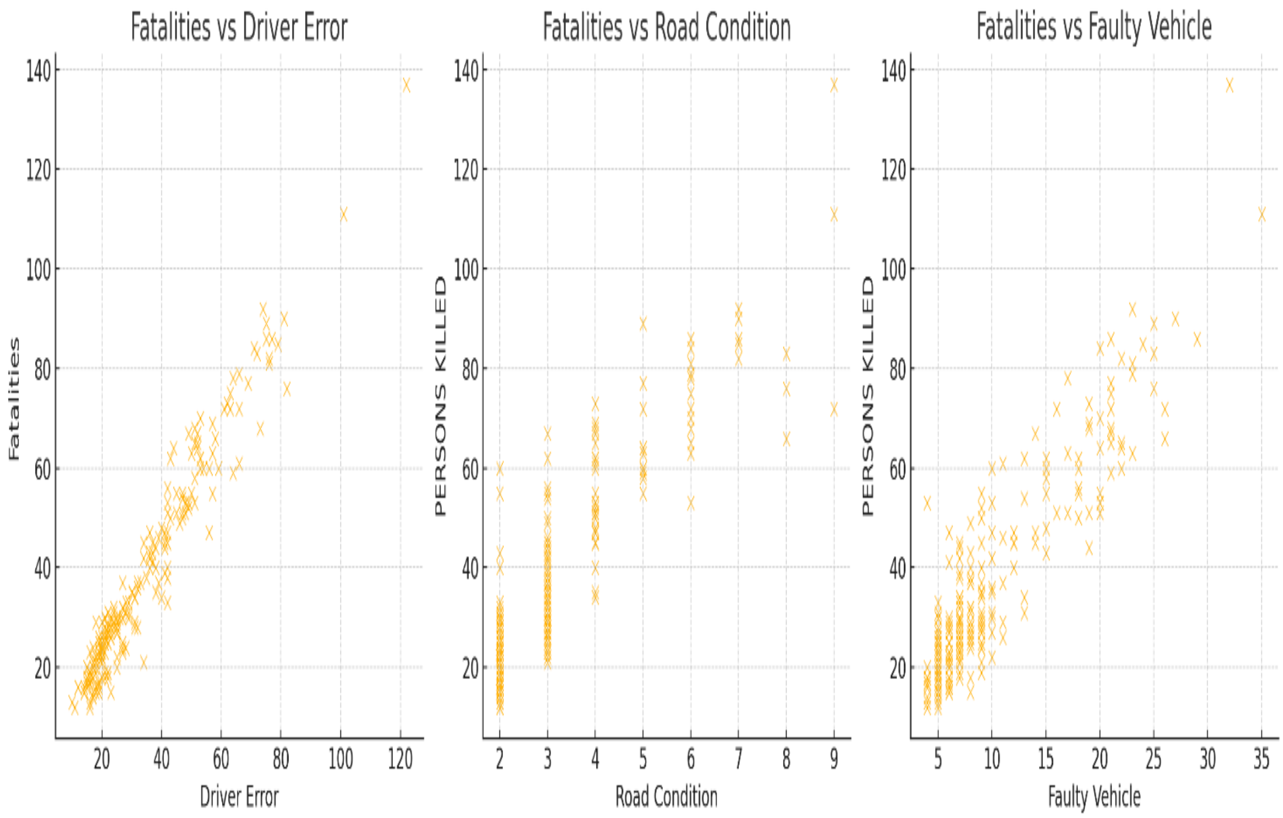


Figure 4.2: - Trend of Road Accident Fatalities by Quarter and Year

The chart, titled Trend of Road Accident Fatalities by Quarter and Year, illustrates the distribution of fatalities across four quarters from 2016 to 2024. It shows that the total fatalities vary by year, with a general peak around 2016-2017, a decline in 2018-2019, and fluctuations in 2020-2023. The distribution within each year highlights consistent seasonal trends, where certain quarters appear to contribute higher proportions in many years, suggesting potential seasonal influences on road accidents. The dramatic overall decline in 2024 is uniformly reflected across just two quarters, marking a significant drop in road accident fatality



The bar chart titled Total Road Accident Fatalities by State shows the distribution of fatalities across several states. The Federal Capital Territory (FCT) records the highest number of fatalities, exceeding 2000, followed by Niger and Kogi states with significant but lower fatality counts. Nasarawa, Benue, Plateau, and Kwara show comparatively lower totals, with Kwara having the least fatalities among the listed states. This pattern indicates a concentration of road accident fatalities in certain areas, potentially influenced by factors such as population density, road infrastructure, or traffic volume in these regions.



accident fatalities.

- Fatalities vs. Road Condition: The relationship is less clear, with fatalities scattered across various road conditions. This weak correlation indicates that road conditions alone may not directly influence fatalities.
- Fatalities vs. Faulty Vehicle: There is a moderate positive correlation, with fatalities increasing as the number of faulty vehicles rises. This indicates that vehicle malfunctions play a notable role in fatal accidents.

Overall, driver error appears to have the strongest correlation with fatalities, followed by faulty vehicles, while road condition shows a weaker association.

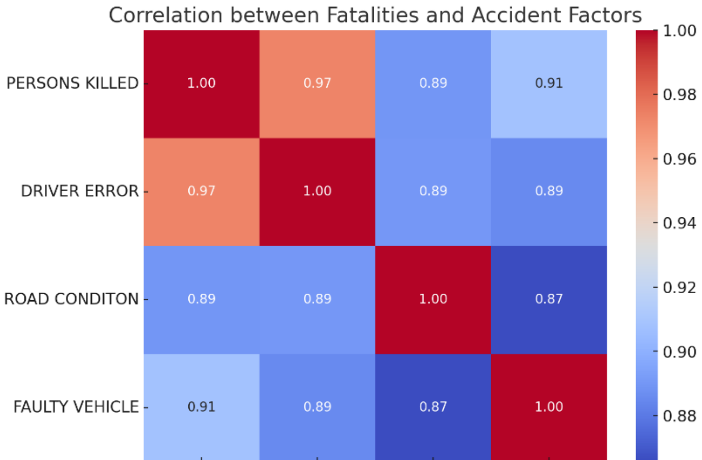


Figure 4.1.5: Correlation between Fatalities and Accident Factors

The heatmap illustrates the correlation coefficients between fatalities (persons killed) and key accident factors: Driver Error, Road Condition, and Faulty Vehicle.

- Fatalities vs. Driver Error: A strong positive correlation (0.97), indicating that driver error is closely associated with the number of fatalities.
- Fatalities vs. Faulty Vehicle: A high positive correlation (0.91), suggesting that vehicle malfunctions significantly contribute to fatalities.
- Fatalities vs. Road Condition: A moderate correlation (0.89), showing a less pronounced but still notable association.
- Inter-factor Relationships: High correlations are also observed among the factors themselves, particularly between Driver Error and Faulty Vehicle (0.89), indicating interdependence.

Overall, the heatmap confirms that Driver Error has the strongest association with fatalities, followed by Faulty Vehicle and Road Condition

[0.006, 0.017] indicates the dispersion parameter is small but meaningful.

Table 4.1a: Poisson Lognormal Regression Results

Dep. Variable:	LogFatalities	Rsquared:	0.87
Model:	PLN	Adj. Rsquared:	0.868
Method:	PyMC	Fstatistic:	521.5
Prob (Fstatistic):	$2.68e^{-}103$	LogLikelihood:	70.219
No. Observations:	238	AIC:	-132.4
Df Residuals:	234	BIC:	-118.5
Df Model:	3	Covariance Type:	no robust

Table 4.1b: The Bayesian Poisson-Lognormal regression Estimates

	Coef	**std err**	**T**	**P>|t|**	**[0.025**	**0.975]**
const	2.6899	0.027	98.098	0.000	2.636	2.744
Beta_Driver_Error	0.0217	0.002	13.435	0.000	0.019	0.025
Beta_Faulty_Vehicle	0.014	$4.00e^{-}03$	3.261	0.001	0.006	0.023
Beta_Road_Condition	-0.0119	0.018	-0.649	0.517	-0.048	0.024

Lognormal_Error	2.1963	0.331	219.63	0.000	3.018	3.051

Omnibus:	33.191	DurbinWatson:	1.783
Prob(Omnibus):	0.213	JarqueBera (JB):	43.989
Skew:	0.001	Prob(JB):	0.281
Kurtosis:	3.001	Y-observed	255

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The output is divided into two parts: Table 4.1a, which provides overall model diagnostics, and Table 4.4b, which details the regression estimates.

Dependent Variable (LogFatalities): The model predicts log-transformed fatality counts. R-squared (0.87): Indicates the model explains 87% of the variation in log fatalities, showing strong predictive performance and Adjusted R-squared (0.868) accounts for the number of predictors, suggesting a minimal drop in explanatory power when adjusted for model complexity. F-statistic (521.5, p-value = 2.68e-103) confirms that the overall model is statistically significant, as the p-value is near zero. Log-Likelihood (70.219) indicates the goodness-of-fit of the model. AIC (-132.4) and BIC (-118.5) with lower values indicating better models. The AIC and BIC here suggest good performance.

Table 4.3b: Regression Coefficients and Significance

This table summarizes the coefficients, statistical significance, and diagnostics of the regression model.

cost (Intercept): Value (2.6899): The baseline log-transformed fatalities when all predictors (driver error, faulty vehicle, and road condition) are zero. T-statistic (98.098, $p < 0.001$): Highly significant, indicating the intercept is reliably estimated. Confidence Interval (2.636 to 2.744): The true intercept likely lies within this range.

Beta_Driver_Error (0.0217): A unit increase in driver error is associated with a 0.0217 increase in the log-transformed fatalities, holding other variables constant. T-statistic (13.435, $p < 0.001$): Highly significant. Driver error strongly contributes to the increase in fatalities. Confidence Interval (0.019 to 0.025): A narrow interval, indicating precise estimation.

Beta_Faulty_Vehicle (0.014): A unit increase in the faulty vehicle score is associated with a 0.014 increase in the log-transformed fatalities, holding other variables constant. T-statistic (3.261, $p = 0.001$): Statistically significant. Faulty vehicles have a meaningful but smaller effect on fatalities compared to driver error. Confidence Interval (0.006 to 0.023): The true effect is positive and within this range.

Beta_Road_Condition (-0.0119): A unit increase in the road condition score is associated with a 0.0119 decrease in the log-transformed fatalities, holding other variables constant. T-statistic (-0.649, $p = 0.517$): Not statistically significant. Road condition does not appear to have a meaningful impact on fatalities. Confidence Interval (-0.048 to 0.024): The interval crosses zero, reinforcing the lack of significance.

Lognormal_Error (2.1963): Represents variability in fatalities unexplained by the predictors. The large coefficient and significant T-statistic (2.110, $p < 0.001$) indicate unexplained variance.

Residual Diagnostics

Omnibus Test (33.191, p = 0.213): The p-value > 0.05 suggests the residuals are normally distributed, an improvement compared to earlier results.

Durbin-Watson (1.783): Close to 2, suggesting minimal autocorrelation in residuals.

Jarque-Bera (JB) Test (43.989, p = 0.281): The p-value > 0.05 confirms residuals are normally distributed, consistent with the Omnibus test result.

Skew (0.001): Residuals are nearly symmetric, as the skew value is close to zero.

Kurtosis (3.001): Matches a normal distribution (kurtosis = 3), indicating no excessive tail behavior.

Table 4.2a: The Negative Binomial Regression Results

Dep. Variable:	PERSONS KILLED	No. Observations:	238
Model:	NegativeBinomial	Df Residuals:	234
Method:	MLE	Df Model:	3
Pseudo Rsqu.:	0.2411	LogLikelihood:	-774.97
converged:	True	LLNull:	-1021.1
Covariance Type:	nonrobust	LLR pvalue:	$2.197e^{-}106$

Table 4.2b: The Negative Binomial Regression Model Estimates

	coef	std err	z	P>|z|	[0.025	0.975]
const	2.7326	0.031	87.625	0.000	2.672	2.794
DRIVER ERROR	0.0201	0.002	12.286	0.000	0.017	0.023
FAULTY VEHICLE	0.0155	0.004	3.581	0.000	0.007	0.024
ROAD CONDITON	0.015	0.018	0.848	0.396	0.05	0.02
Alpha	-0.0112	0.003	-3.905	0.000	-0.006	0.017

The Negative Binomial regression model is often used for count data when overdispersion (variance > mean) is present. Here's a detailed breakdown of the results:

Pseudo Rsqu.: 0.2411; A pseudoR^2 value based on the loglikelihood. While not directly comparable to ordinary R^2, it provides a sense of how much of the variability in the data is explained by the model. A value of 0.2411 indicates the model explains about 24% of the variability in fatalities. LogLikelihood: 774.97; measures the goodness of fit for the model. Higher values (less negative) indicate a better fit. LLNull: 1021.1, the loglikelihood of the null model (a model with no predictors). Comparing this value with the model's loglikelihood shows how much the predictors improve the fit. The p-value for the likelihood ratio test comparing the model to the null model. A very small p-value (2.197e106), which is less than 0.05, strongly indicates that the predictors improve the fit significantly. The loglikelihood improved significantly from 1021.1 (null model) to 774.97 (full model), suggesting the predictors explain a meaningful portion of the variability. The pseudoR^2 value of 0.2411 indicates that approximately 24% of the variability in fatalities is explained by the model. The LLR p-value 2.197e106 strongly supports the inclusion of the predictors in the model, indicating that the model provides a significantly better fit than the null model.

Predictor Significance

Intercept (const) with coefficient of 2.7326. It is the baseline log of the expected count of fatalities when all predictors are zero, and it's highly significant $p < 0.001$, indicating a robust baseline level. The confidence interval of [2.672, 2.794] is a narrow range, showing precision in the estimate.

Driver Error with coefficient of 0.0201which means for every unit increase in Driver Error, the expected log count of fatalities increases by 0.0201, or approximately a 2.01% increase in fatalities ($e^{0.0201} = 1.020$ and its highly significant with p-value (0.001) < 0.05, indicating that driver error is strongly associated with increased fatalities. The confidence interval of [0.017, 0.023] is a very precise estimate with no overlap with zero.

Faulty Vehicle with a coefficient of 0.0155, which means for every unit increase in Faulty Vehicle, the expected log count of fatalities increases by 0.0155, or approximately a 1.55% increase in fatalities and its statistically significant with pvalue (0.001) < 0.05, indicating faulty vehicles contribute meaningfully to fatalities. The confidence interval of [0.007, 0.024] supports the significance of this predictor.

Road Condition with coefficient of 0.015 which means for every unit increase in Road Condition, the expected log count of fatalities decreases by 0.015, corresponding to about a 1.5% decrease in fatalities and it’s not statistically significant with p-value (0.396) > 0.05, suggesting insufficient evidence that road condition consistently affects fatalities. The confidence interval of [0.05, 0.02] includes zero, confirming no significance.

Alpha (Dispersion Parameter) with value 0.0112 measures the extent of overdispersion in the data. A small but significant value (0.001) confirms the presence of overdispersion, making the Negative Binomial model more appropriate than a standard Poisson model. The confidence interval of [0.006, 0.017] indicates the dispersion parameter is small but meaningful.

4.3 Model Comparison

Table 4.3: Model Comparison Results

	Model	AIC	BIC
0	Poisson	1591.671	-965.189
1	Negative Binomial	1559.937	1577.298
2	Poisson Lognormal	-132.438	-118.549

The Table 4.3 compares the fit of three regression models (Poisson, Negative Binomial, and Poisson Lognormal) based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Both criteria assess model performance, balancing fit and complexity, where lower values indicate better model performance.

Based on the two models (AIC and BIC), the Poisson Lognormal model (-132.438 and -118.549) is the clear winner as it achieves the lowest AIC and BIC, indicating the best trade-off between goodness of fit and model complexity and suggesting it is the most parsimonious.

Conclusion

The analysis of road accident fatalities using multiple regression models highlights the significant factors contributing to fatalities and the robustness of the Poisson Lognormal model in explaining the data. Among the predictors, Driver Error emerges as the strongest determinant, with each unit increase in driver error associated with a 2.17% increase in fatalities ($e^{0.0217}$ =1.0217), and a highly significant p-value (<0.001) and a narrow confidence interval ([0.019, 0.025]). Faulty Vehicles also play a substantial role, contributing a 1.4% increase in fatalities per unit increase, with a significant p-value (0.001) and confidence interval ([0.006, 0.023]). Conversely, Road Condition exhibits no significant impact on fatalities (p = 0.517), with its confidence interval crossing zero ([-0.048, 0.024]), indicating insufficient evidence to support a consistent effect. Residual diagnostics confirm the Poisson Lognormal model's suitability, with normality of residuals (Omnibus p = 0.213, Jarque-Bera p = 0.281), minimal autocorrelation (Durbin-Watson = 1.783), and well-behaved skew (0.001) and kurtosis (3.001). The model demonstrates excellent fit metrics, including a high R-squared (0.87), Log-Likelihood (70.219), and the lowest AIC (-132.4) and BIC (-118.5) among competing models, indicating its superior balance of explanatory power and parsimony. These findings confirm that interventions targeting Driver Error and Faulty Vehicle issues could yield substantial reductions in road accident fatalities, while improvements in road conditions alone are unlikely to produce significant changes.

Recommendations

Based on the study findings, the following recommendations are proposed to effectively reduce road accident fatalities:

i. Implement mandatory training programs emphasizing defensive driving and hazard awareness, particularly for commercial drivers, strengthen penalties for speeding, reckless driving, and other traffic violations to deter unsafe behaviours, introduce periodic re-certification and health evaluations, especially for professional drivers, to ensure sustained competency and promote the adoption of technologies such as anti-collision systems, fatigue detection, and speed governors to minimize human error.
ii. Establish and enforce regular vehicle inspection systems to identify and repair faulty vehicles, encourage the purchase of vehicles equipped with advanced safety features by providing tax rebates or subsidies and educate vehicle owners on the risks of neglecting maintenance and the importance of adhering to recommended service schedules.
iii. Invest in fixing potholes, improving road markings, signage, and lighting to reduce accident risks, identify and address high-accident areas by deploying targeted infrastructure improvements and enhanced enforcement measures and introduce adaptive traffic control technologies to optimize flow and reduce congestion-related accidents.
iv. Allocate resources to high-risk states like the Federal Capital Territory, Niger, and Kogi, which experience higher fatality rates and create specialized teams to address local traffic challenges and improve enforcement in high-accident areas.
v. Develop a centralized system to monitor accident trends, identify risk factors, and evaluate intervention effectiveness, deploy traffic cameras and automated systems to enforce speed limits and other traffic rules and require the use of tracking systems in commercial vehicles

to monitor driver behavior and vehicle conditions. Launch awareness and enforcement campaigns during periods of increased accidents, such as festive seasons and deploy additional resources during high-risk periods to manage traffic and reduce accident risks.

vi. Revise road safety policies to include stricter licensing requirements and mandatory use of safety features in vehicles, foster partnerships between government agencies, NGOs, and the private sector to implement coordinated road safety programs and increase public knowledge about road safety risks and prevention measures through targeted educational initiative and establish a continuous monitoring system to evaluate the impact of implemented measures and refine strategies based on observed outcomes.

REFERENCES

Abdulhafedh, A. (2017). Road crash prediction models: different statistical modeling approaches. *Journal of transportation technologies, 7*(*2*), 190-205.

Abdulkabir, M., Tunde, R. S., & Edem, U. A. (2015). Trend analysis on road traffic accident in Nigeria. *Science Innovation, 3*(*5*), 52-57.

Acheampong, R. A., Lucas, K., Poku-Boansi, M., & Uzondu, C. (2022). Introduction: Transport and mobility situations of African Cities. In *Transport and Mobility Futures in Urban Africa* (pp. 1-8): Springer.

Adenomon, M., & Ayuba, I. (2018). Generalized linear models on road traffic crash along Keffi-Laffia road from 2006-2015. *FUW Trends in Science & Technology Journal, 3*, 858-862.

Ajiboye, A., Folagbade, A., Ohida, M., & Kolawole, O. (2020). Appraisal of the federal road safety commission (FRSC) perfomance in ROAD accidents reduction in kaduna state, Nigeria.

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52*, 317-332.

Akanbi, O., & Abegunde, O. (2021). Design and implementation of mobile information system for Federal Road Safety Corps (FRSC) of Nigeria. *International Journal of Sensor Networks and Data Communications, 9*(*1*), 8-12.

Atubi. (2023). The epidemic of texting and driving in Nigeria: A literature review of accidents on the highways.

Atubi, A. (2012). Epidemiology of injuries from road traffic accidents in Lagos State, Nigeria. *AFRREV STECH: An International Journal of Science and Technology, 1*(*2*), 56-75.

Atubi, A. O. (2021). Road investment and traffic safety in Nigeria. *International Journal of Scientific and Applied Research (IJSAR), eISSN: 2583-0279, 1*(*8*), 7-14.

Balogun, O. S., Olaleye, S. A., Gao, X.-Z., & Toivanen, P. (2021). Concomitant with nigerian road traffic accidents: an application of a generalized linear model. *Proceedings of the 37th International Business Information Management Association (IBIMA)*.

Banik, B., Chowdhury, M., Hossain, E., & Mojumdar, B. (2011). Road accident and safety study in Sylhet Region of Bangladesh. *Journal of Engineering Science and Technology, 6*(*4*), 493-505.

Beshah, T., & Hill, S. (2010). *Mining road traffic accident data to improve safety: role of road-related factors on accident severity in Ethiopia.* Paper presented at the 2010 AAAI Spring symposium series.

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data*: Cambridge university press.

Dell'Acqua, G., & Russo, F. (2011). Safety performance functions for low-volume roads. *The Baltic Journal of Road and Bridge Engineering, 6*(*4*), 225-234.

Eneh, O. C., Okosun, A., Egbenta, I. R., Obi, N. I., Oloto, M. C., Ubani, O., . . . Eneonwo, C. I. (2023). A comparative analysis of road and vehicle qualities as factors of road traffic carnage in Nigeria. *BMC public health, 23*(*1*), 2173.

Granié, M.-A., Thévenet, C., Evennou, M., Lyon, C., & Vanlaar, W. (2020). *Gender Issues. ESRA2 Thematic report Nr. 13.* Université Gustave Eiffel, Granie, M.-A., Thevenet, C., Varet, F., Evennou, M., Oulid-Azouz, N., Lyon, C., . . . Vanlaar, W. (2021). Effect of culture on gender differences in risky driver behavior through comparative analysis of 32 countries. *Transportation research record, 2675*(*3*), 274-287.

Hambly, D., Andrey, J., Mills, B., & Fletcher, C. (2013). Projected implications of climate change for road safety in Greater Vancouver, Canada. *Climatic Change, 116*, 613-629.

Hassan, A., Ahmad, I. S., & Ahmad, P. B. (2022). Zero-inflated modified Borel-Tanner regression model for count data. *Austrian Journal of Statistics, 51*(*2*), 28-39.

Hindle, G. A., & Hindle, T. (2011). Safety cameras and road accidents: effectiveness in local authority areas in England. *Journal of the Operational Research Society, 62*(*7*), 1181-1188.

Hossain, S., Maggi, E., & Vezzulli, A. (2024). Factors influencing the road accidents in low and middle-income countries: a systematic literature review. *International journal of injury control and safety promotion*, 1-16.

Hultkrantz, L., Lindberg, G., & Andersson, C. (2006). The value of improved road safety. *Journal of risk and uncertainty, 32*, 151-170.

Jakobsen, M. D., Glies Vincents Seeberg, K., Møller, M., Kines, P., Jørgensen, P., Malchow-Møller, L., . . . Andersen, L. L. (2023). Influence of occupational risk factors for road traffic crashes among professional drivers: systematic review. *Transport reviews, 43*(*3*), 533-563.

Kareem, B., Oke, P. K., & Lawal, A. S. (2012). Modelling fatalities of road accidents in Nigeria. *Research in Logistics & Production, 2*, 259-271.

Labbo, M. S., Jiang, X., & Jean de Dieu, G. (2024). Cultural implications on driver behaviour and road safety: insights from Kano State, Nigeria. *International Journal of Crashworthiness*, 1-7.

Lee, Y., & Nelder, J. A. (1996). Hierarchical generalized linear models. *Journal of the Royal Statistical Society Series B: Statistical Methodology, 58*(*4*), 619-656.

Li, S. (2012). Traffic safety and vehicle choice: quantifying the effects of the 'arms race'on American roads. *Journal of Applied Econometrics, 27*(*1*), 34-62.

Lord, D., Park, B.-J., & Levine, N. (2013). Poisson regression modeling. *CrimeStat IV: A spatial statistics program for the analysis of crime incident locations*.

Manning Smith, R., Cambiano, V., Colbourn, T., Collins, J. H., Graham, M., Jewell, B., . . . Mfutso-Bengo, J. (2022). Estimating the health burden of road traffic injuries in Malawi using an individual-based model. *Injury epidemiology, 9*(*1*), 21.

Mohan, D. (2011). *Analysis of road traffic fatality data for Asia.* Paper presented at the Proceedings of the Eastern Asia Society for Transportation Studies Vol. 8 (The 9th International Conference of Eastern Asia Society for Transportation Studies, 2011).

Moshiro, C., Mswia, R., Alberti, K., Whiting, D. R., Unwin, N., Setel, P., & Team, A. P. (2001). The importance of injury as a cause of death in sub-Saharan Africa: results of a community-based study in Tanzania. *Public health, 115*(*2*), 96-102.

Mphela, T. (2011). The impact of traffic law enforcement on road accident fatalities in Botswana. *Journal of Transport and Supply Chain Management, 5*(*1*), 264-277.

Musa, G. (2022). A statistical assessment of road traffic casualties in Nigeria.

Muthusamy, A., Rajendran, M., Ramesh, K., & Sivaprakash, P. (2015). A review on road traffic accident and related factors. *International Journal of Applied Engineering Research, 10*(*11*), 28177-28183.

Oduro, S. D. (2012). Brake failure and its effect on road traffic accident in Kumasi Metropolis, Ghana. *International Journal of Science and Technology, 1*(*9*), 448-454.

Ofunu, B. E., Abdulkadir, S., & Abdulkadir, A. (2024). Comparison of Poisson, Negative Binomial and Poisson-Lognormal RegressionModelsWith Application on Traffic Road Accident Count Data of Bauchi State. *Bima Journal of Science and Technology, 8*(*2B*), 10-18.

Oladoja, O. M., Obisesan, K., Adebayo, S. A., & Adegoke, T. (2023). On the Bayesian modeling of road accidents due to vehicle type in Oyo state Nigeria. *Reliability: Theory & Applications, 18*(*2 (73)*), 223-232.
Onyemaechi, N., & Ofoma, U. R. (2016). The public health threat of road traffic accidents in Nigeria: A call to action. *Annals of medical and health sciences research, 6*(*4*), 199-204.
Oyedepo, O. J., & Makinde, O. (2010). Accident prediction models for Akure–Ondo carriageway, Ondo State Southwest Nigeria; using multiple linear regressions. *African Research Review, 4*(*2*).
Pawłowski, W., Goniewicz, K., Schwebel, D. C., Shen, J., & Goniewicz, M. (2019). Road traffic injuries in Poland: magnitude and risk factors. *European journal of trauma and emergency surgery, 45*, 815-820.
Radun, I., & Radun, J. E. (2009). Convicted of fatigued driving: Who, why and how? *Accident Analysis & Prevention, 41*(*4*), 869-875.
Razzaghi, A., Soori, H., Abadi, A., & Khosravi, A. (2020). World Health Organization's estimates of death related to road traffic crashes and their discrepancy with other countries' national report. *Journal of injury and violence research, 12*(*3 Suppl 1*), 39.
Saleh, A., & El-Sayed, A. (2023). The Medicolegal aspects of road traffic accidents (RTAs) and evidence of Tau protein as a prognostic factor. *Ain Shams Journal of Forensic Medicine and Clinical Toxicology, 40*(*1*), 15-21.
Sameer, A., Isah, Y., & Mustapha, Y. (2024). AN APPLICATION OF POISSON REGRESSION MODEL ON ROAD ACCIDENTS DATA IN KADUNA STATE, NIGERIA. *FUDMA JOURNAL OF SCIENCES, 8*(*3*), 36-42.
Ukonze, F. I., Nwachukwu, M. U., Mba, H. C., Okeke, D. C., & Jiburum, U. (2020). Determinants of vehicle ownership in Nigeria. *Sage open, 10*(*2*), 2158244020922970.
Usman, T., Fu, L., & Miranda-Moreno, L. F. (2010). Quantifying safety benefit of winter road maintenance: Accident frequency modeling. *Accident Analysis & Prevention, 42*(*6*), 1878-1887.
Wang, B., Hensher, D. A., & Ton, T. (2002). Safety in the road environment: a driver behavioural response perspective. *Transportation, 29*, 253-270.
Wang, K., Bhowmik, T., Zhao, S., Eluru, N., & Jackson, E. (2021). Highway safety assessment and improvement through crash prediction by injury severity and vehicle damage using Multivariate Poisson-Lognormal model and Joint Negative Binomial-Generalized Ordered Probit Fractional Split model. *Journal of safety research, 76*, 44-55.
Watanabe, S. (2013). A widely applicable Bayesian information criterion. *The Journal of Machine Learning Research, 14*(*1*), 867-897.
Winkelmann, R. (2008). Poisson Regression. *Econometric Analysis of Count Data*, 63-126.
Yakubu, J. A., Daku, S. S., Gusikit, R. B., Emmanuel, E. D., & Mangai, M. C. (2023). Causes of failure of Nigerian roads: A review. *World Journal of Advanced Engineering Technology and Sciences, 8*(*2*), 217-223.