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STATISTICAL MODELLING OF MOTOR VEHICLE ROAD ACCIDENTS IN BOTSWANA

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ABSTRACT

Botswana's increased road traffic accidents have become a national concern, calling for evidence-based holistic interventions. This study aims to determine a statistical model that can predict the number of motor vehicle road accidents in Botswana using the binomial and generalized Poisson regression models. The data used in the study were obtained from Botswana's Motor Vehicle Accident Fund (MVA) annual road crash claims report for 2014. And covers the years 2007-2021.

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INTRODUCTION

A motor vehicle accident is becoming one of the major factors that leads to unexpected death in the world. According to the World Health Organization (WHO, 2023) global status report, there were an estimated 1.19 million road traffic deaths in 2023, a 5% decline since 2010. The global fatality rate stood at 15 per 100,000 population people in 2021, a 16% drop since 2010. The slight reduction in deaths occurred despite the worldwide motor vehicle fleet doubling, the road network significantly expanding and the global population rising by nearly a billion. However, the target of a 50% reduction in mortality of the Decade of Action for Road Safety 2011 – 2020 was not met. At this pace, the world is not on track to achieve the 50% reduction target set out in the Global Goals for Sustainable Development. Road traffic deaths and injuries remain a major global health and development challenge. As of 2019, road crashes remain the leading killer of children and youth aged 5 – 29 years, and the 12th leading cause of death when all ages are considered. The road safety crisis is an epidemic comparable to diseases such as Malaria, Tuberculosis, or HIV (WHO 2023). That is millions of lives shattered, and millions of families torn apart. In addition to unrealized economic growth, the road safety crisis has profound consequences on the welfare of populations, undermining countries' efforts to create strong communities and build up their human capital. At the household level, the loss of income and medical expenses associated with a crash can spell financial disaster, especially for those who already live on the brink of poverty WHO (2019). In Africa, the risk of road traffic death increases annually. Statistics from the WHO Africa region show that road traffic fatality estimates increased from 24.1 per 100,000 population in 2016. If action is not taken, road trauma in Africa is expected to worsen further, with fatalities per capita projected to double from 2015 to 2030 WHO (2018). The risk of road death varies significantly from region to region, and there has been little change in the regional traffic death rate since 2010. Globally, the highest rates are still in the African region, while the European region has a rate far below the global average at 9.3 per 100,000 population, relative to the worldwide rate (WHO 2018). Between 2010 and 2021, the region recorded a 17% increase in fatalities, according to the WHO Status Report Safety 2023 for the African region. The region accounts for nearly one-fifth of all road deaths globally, despite being home to only 15% of the world population and 3% of its vehicles. The rise of multiple factors, including inadequate road safety laws and standards. No country in the region currently has laws that meet the best practice standards for the five key road safety behavioral risk factors like Speeding, drunk driving, non-use of motorcycle helmets, seatbelts, and child restraints (WHO 2023). Currently, Africa is one of the fastest-growing markets for used vehicles. WHO (2022), the total vehicle registration has almost doubled, while two- and three–wheel vehicle registration has tripled. Also, most traffic data systems in Africa capture only road-related deaths, excluding information about the injuries and severity, including medium and long-term consequences such as disability. With a growing and increasing urban global population, the rising demand for mobility is set to overwhelm transport systems on the continent, particularly those that rely heavily on private vehicles. Road traffic accidents are considered major causes of death in Botswana today apart from HIV/AIDS and this a major health problem all over the world. Road traffic crashes in Botswana have been identified as one of the major causes of death in the country. It is classified as the second major cause of death in the country following HIV/AIDS (WHO, 2020). According to the statistics on road accidents in Botswana for the year 2020 disseminated by MVA shows that there are 15,075 road traffic accidents, and 5952 causalities with 325 of them losing their lives in less than 2 million population. The most generation part of it all is that most of the people who are killed by road traffic crashes are those in the age group that constitute the workforce of this nation. It is in this regard that more attention needs to be placed on the studies of road accidents and their impact on human life in Botswana.

As a result of these tremendous effects of Road accidents on human lives and properties, many researchers have come out with causes, effects, and recommendations for road accidents in Botswana. These causes include drinking Alcohol and over-speeding (Thuso Mphela, 1995). Hence, there is a need to analyze the road accident data statistically to check whether there is evidence of increasing accidents as years go by, resulting in many people losing their lives. Researchers have been modeling vehicular crashes with different models in various parts of the world. However, it is extremely difficult to just apply models that have worked somewhere to data obtained from different countries due to the variations in the various factors about countries (Fletcher et al, 2006). There has not been much statistical research in the field of road accidents using Poisson and Negative Binomial in Botswana. This might have been because of the inadequate information available on road accidents from the government agency. These road accidents have killed a lot of people in this country and as such it is described as one of the major causes of death in Botswana. The causes of death of casualties in road accidents have been associated with secondary collisions, improper handling of casualties, and inadequate emergency services in the country. Also, the factor that contributes the road accidents in Botswana are over speeding, the influence of Alcohol, Overtaking, the Number of cattle on the road, the road surface, and the number of potholes. Therefore, this study aims to identify the major factors determining the number of human deaths per road accident in Botswana, via the appropriate count regression models.

LITERATURE REVIEW

The most common modeling approach is to consider the frequency of the crashes including all severity and collision types together with injury severities or crash types separately once the total number of crashes is determined Aguero et al (2008). However, literature has sought to develop separate crash frequency models for various injury severities and collisions. If this is done, a potentially serious statistical problem results because there is a correlation between severities and collisions. For instance, an increase in the number of crashes classified as incapacitated will also be associated with some change in the number of crashes classified by other injuries, which sets up a correlation among the various injury outcomes in frequency models. This necessitates a more comprehensive model structure for the cross-model correlation ((C, 2008)Aguero et al 2009). Accident data have been shown to exhibit over-dispersion, meaning that the variance is greater than the mean. The over-dispersion can be caused by various factors such as data clustering, unaccounted temporal correlation, and model specification but it is mainly attributable to the actual nature of the accident data. The fact is that crash data is the product of the Bernoulli trial with an unequal probability of event (Poisson Trial). (Lord et al 2005) have reported that as the number of trials increases and becomes very large, the distribution may be approximately by a Poisson distribution where the magnitude of the over-dispersion is dependent on the characteristics of the Poisson distribution, also over-dispersion can be minimized using appropriate mean structures of a statistical model as discussed in (S. P. Miaou, 1992). Although different Poisson-based distributions have been developed to accommodate the over-dispersion of Poisson lognormal, the most common distribution used for modeling crash data remains the Poisson-gamma or Negative Binomial distribution (NB). The Poisson-gamma distribution offers an uncomplicated way to accommodate the over-dispersion, especially since the final equations have a closed form and the mathematics to manipulate the relationship between the mean and the variance structure is simple (Haier, 1997). Many previous studies have been conducted, including those by (A. Melliana, 2013), which compared negative binomial regression and generalized Poisson regression to deal with the problem of overdispersion. The results show that the Generalized Poisson Regression model is better for modeling cervical cancer data that violates the overdispersion. This research is focused on modeling the number of accidents in Botswana and the factors that influence it with the Generalized Poisson Regression and Negative Binomial Regression models to overcome the overdispersion problem in the Poisson Regression model.

MATERIALS AND METHODS

Data description: The data used in the study were obtained from Botswana's Motor Vehicle Accident Fund (MVA) annual road crash claims report for 2014. and covers the period 2007-2021. The variables covered in the study studied include the following:

Independent variable: the number of accidents on the roads (Y)

Explanatory variables: The collection data were Overseeding, Influence of Alcohol, overtaking, Number of cattle on the road, Road surface, and Number of potholes on the road.

Regression Models: We consider the following regression models for counting data.

Poisson Regression: The Poisson regression model is usually used to model counting data with a small chance of occurrence depending on a certain time interval or area. The probability mass function of the Poisson distribution is as follows (Bijesh *et al*., 2021). The Poisson regression model used for count data that belong to the family of generalized linear models (C, 2008). The technique of generalized linear models (GLM) was applied to model the data in particular Poison regression model which is a standard model count data derived from Poisson distribution with parameter μ, which is the expected accident frequency (or number of accidents) for the ith road section during a period.

$$P(y_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} \qquad i = 0, 1, 2, \ldots..$$

Where $p(y_i)$ is the probability of y accidents occurring at ith the road section during a time. In the Poisson regression model, the expected accident frequency is model, the expected accident frequency is assumed to be a function of predictors such that.

$$\mu = \exp(\theta_0 + \theta_1 X_1 + \theta_2 X_2 + \theta_3 X_3 + \theta_4 X_4 + \theta_5 X_5 + --+\theta_n X_n)$$

Where $X_1, X_2, X_3, X_4 ... X_n$ are predictors and $\theta_0, \theta_1, \theta_2, \theta_3, ... \theta_n$ are model coefficients which are estimated by maximum likelihood methods as their results indicated in Table 3 (Lawless, 1987). Thus, the number of road accidents Y is modeled as a log-linear function of the predictors as shown in the equation.

$$Ln(Y) = \theta_0 + \theta_1 X_1 + \theta_2 X_2 + \theta_3 X_3 + \theta_4 X_4 + \theta_5 X_5 + \theta_6 X_6 + \varepsilon$$

Where ε is the error term.

Generalized Poisson Regression: The generalized Poisson distribution is an extension of the Poisson distribution which is useful for modeling count data that has overdispersion or under-dispersion. Generally, a response variable Y has a generalized Poisson distribution if has the following probability mass function (see Bae, *et al*., 2005).

$$P(y;\mu;\phi)=(\frac{\mu}{1+\phi\mu})^{y}\frac{(1+\phi y)^{y-1}}{y!}\exp\left[\frac{-\mu(1+\phi y)}{1+\phi\mu}\right];\quad y = 0, 1, 2, \ldots\ldots..$$

with the average value of μ and Variety $\mu(1+\phi\mu)^2$

The Equi dispersion condition occurs when the value of ϕ = 0, so that the generalized Poisson distribution returns to form of a Poisson distribution as follows:

$$P(y;\mu,\phi)=(\frac{\mu}{1+0\mu})^{y}\frac{(1+0y)^{y-1}}{y!}\exp\left[\frac{-\mu(1+0y)}{1+0\mu}\right];$$

$$=\frac{\mu^{y}}{y!}\exp[-\mu];$$

The Generalized Poisson regression model can be written as follows:

$$\log(\mu_i)=x_i^{'}\beta=\beta_0+\beta_1x_{i1}+\beta_2x_{i2}+\ldots\ldots..+\beta_kx_{ik}$$

Where x_i; dimensional vector k – 1

β: k - dimensional vector of the regression parameter.

with the average value of μ and Variety $\mu(1+\phi\mu)^2$

The equi dispersion condition occurs when the value of ϕ = 0, so that the generalized Poisson distribution returns to form of a Poisson distribution as follows:

$$l(y\setminus\beta,\phi)=\sum_{i=1}^{n}y_i\ln\left(\frac{\mu_i}{1+\phi\mu_i}\right)+(y_i-1)\ln(1+\phi y_i)-\frac{\mu_i(1+\phi y_i)}{1+\phi\mu_i}-\ln(y!)$$

Maximizing the function $l(y\setminus\beta,\phi)$ can be done by finding the derivative of each parameter and then equating it with zero (Oppong, 2015).

Negative binomial Regression: The negative Binomial distribution is an experiment that wants to see the magnitude of the probability of r successes after previously appearing failed events. Suppose r is the number of successful events and the random variable Y is the number of failed events before the r-th success event. In the form of a negative Binomial distribution with a probability of success of p and a likelihood of failure of (1 - p), the experiment is as follows (Nwaigwe, 2016).

$$P(Y=y\,|\,r.p)=\begin{pmatrix}y- & 1\\ r- & 1\end{pmatrix}p^{r}(1-p)^{y-r}\quad ;\ Y = r, r+1, r+2,\ldots\ldots.$$

The negative binomial regression model is one approach to solving the overdispersion problem based on the Poisson Gamma mixture model (Hilbe, 2011). Assuming that there is δ gamma spreading variable with a mean of 1 and ϕ variance in the mean of a Poisson distribution, for instance, m is a source of unobserved variance. Then the mean value of a mixed Poisson gamma distribution is:

$$E[y]=r\frac{(1-p)}{p}\quad \text{dan}\quad Var[y]=r\frac{(1-p)}{p^2}$$

The Negative Binomial Regression model is one approach to solving the overdispersion problem based on the Poisson Gamma mixture model (Hilbe, 2011). Assuming that there is δ Gamma Spreading variable with a mean of 1 and ϕ variance in the mean of a Poisson distribution, for instance, m is a source of unobserved variance. Then the mean value of a mixed Poisson gamma distribution is:

$$E(y_i)=\tilde{\mu}=\exp\left(x_i^T\beta+m_i\right)=\exp\left(x_i^T\beta\right)\exp(m_i)=\mu_i\delta_i$$

Using the maximum likelihood approach, we know that the probability mass function (pmf) of the negative distribution is given by

$$f(y_i\,|\,x_i,\beta,\delta_i)=\frac{e^{-(\mu_i\delta)}(\mu_i\delta_i)^{y_i}}{y_i!}$$

The variable δ_i Spread gamma with parameters α and β. The Gamma probability function is

$$g(\delta_i)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}\delta_i^{\alpha-1}e^{-\delta_i/\beta}$$

With the expected value $E(\delta_i)=\alpha\beta$, and assumption of $E(\delta_i)=1$ then $\alpha = 1/\beta$. If the parameter $\alpha = 1/\phi$, the Gamma probability function becomes.

$$g(\delta_i)=\frac{1}{\phi^{\phi^{-1}}\Gamma(\phi^{-1})}\delta_i^{\phi^{-1}-1}e^{-\delta_i/\phi}$$

The mixed Poisson Gamma distribution can be obtained by integrating the variable δ_i into Poisson probability function as follows.

$$f(y_i\,|\,x_i,\beta,\phi)=\int_0^{\alpha}f(y_i\,|\,\phi,\delta_i)g(\delta_i)d\delta_i=\frac{\Gamma(y_i+\phi^{-1})}{\Gamma(\phi^{-1})y_i!}\left(\frac{\phi\mu_i}{1+\phi\mu_i}\right)^{y_i}\left(\frac{1}{1+\phi\mu_i}\right)^{\phi^{-1}}$$

With

$\phi>0, E[y_i]=\mu_i$ and $Var[y_i]=\mu_i+\phi\mu_i^2$

The assumption of the Negative Binomial Regression coefficient parameter was carried out using the maximum likelihood assumption method. The probability function of the negative distribution is,

$$L(\beta,\phi\,|\,y,x)=\Pi_{i=1}^{n}\left\{\frac{\Gamma(y_i+\phi^{-1})}{\Gamma(\phi^{-1})y_i}\left(\frac{\phi\mu_i}{1+\phi\mu_i}\right)^{y_i}\left(\frac{1}{1+\phi\mu_i}\right)^{\phi^{-1}}\right\}$$

The natural logarithm of the probability function is as follows.

$$\ln L(\beta,\phi\,|\,y,x)=\sum_{i=1}^{n}\left\{\ln\left[\frac{\Gamma(y_i+\phi^{-1})}{\Gamma(\phi^{-1})\Gamma(y_i+1)}\right]-(y_i+\phi^{-1})\ln(1+\phi\mu_i)+y_i\ln(\phi\mu_i)\right\}$$

Assessment and Selection

The best-fit regression model amongst the Poisson, negative binomial, and generalized Poisson was selected by using Akaike's Information Criterion (AIC). AIC is given by the formula.

$$AIC=-2(L-K)$$

where L is the log-likelihood model and K is the number of parameters in the model. The best-fitting model is selected as the one with the model with the smallest AIC value ((Hilbe, 2011) and (N. M. R. Kwasari, 2014).

Discussion of Variables and Data: The current study used secondary data from the Motor Vehicle Accident Fund (MVA) of Botswana's annual road crash and claims report. For each factor (explanatory variables), fifteen (15) observations with eight (8) variables were collected from 2007 to 2021. Table 1 gives a summarized description of the data and variables used. When evaluating the count data variable, the number of occurrences is assumed to be independently identical and distributed with a discrete probability distribution (M., 2021). The Poisson and Negative Binomial distributions are the most typical probability distributions used to describe count data. The Poisson distribution is preferable since count variables are all positive integers and for rare events, as the Poisson mean > 0. Analysts typically look for alternatives to the Poisson model, such as the negative binomial model, because observed data almost always pronounce overdispersion (A. Melliana, 2013). The Poisson model's Equi dispersion restriction is relaxed through a functional form called the negative binomial model. The table below shows the description of the variables used.

Data Analysis: It is organized into two broad categories, namely, descriptive analysis and empirical analysis. Each of these categories is further developed. To illustrate this point, we consider Botswana's yearly reported road accidents. Table 2 gives a summary measure of the dataset; each variable has 14 valid observations (from 2007 to 2021). The count range of road accidents from a minimum value of (15075) to a maximum value of (20410) with a mean of (18016).

5% level, with intercept too while (Overtaking and Road surface) of the estimated coefficient is not significant because their p-value is greater than the 5% level.

Interpretation of the results of the Negative Binomial regression model: The estimated parameters of the Negative Binomial regression model are given in table (5). According to the results, it shows the (Number of road potholes) estimated coefficient is significant because the (p-value) is less than 5%, with intercept while (Over-speeding, Influence of Alcohol, Overtaking, Number of cattle on the road, and road surface) are not significant because their (p-value) is greater than the 5% level.

Table 1. Road accidents data summary in Botswana from 2007 to 2021

Variable	Unit	Descriptions
Y	Number	Road Accidents
X_1	Number	Over speeding
X_2	Number	Influence of Alcohol
X_3	Number	Overtaking
X_4	Number	Number of Cattle on the road
X_5	Number	Road Surface
X_6	Number	Number of road potholes
X7	Number	Years

Source: Motor Vehicle Accident Fund

Table 2. Botswana road traffic accident summary statistics (2007 - 2021)

Variable	Minimum	1st Quarter	Median	Mean	3rd Quarter	Maximum
Road Accident	15075	17309	17786	18016	18801	20410
Over speeding	111.0	161.0	208.0	295.7	391.0	990.0
Influence of Alcohol	155.0	210.0	422.0	392.9	555.5	675.0
Overtaking	154.0	375.5	401.0	392.2	425.0	543.0
Number of Cattle on the road	1432	1673	2008	2696	3320	6110
Road Surface	117.0	225.0	450.0	471.5	680.0	950.0
Number of road potholes	15.0	23.5	27.0	39.4	47.5	90.0

Table 3. Poisson regression model parameter estimation

Parameters	Estimate	Standard error	Z value	Pr (>|z|)
Intercept	9.674e+00	1.322e-02	731.792	<2e-16
Over speeding	-1.189e-04	1.257e-05	-9.465	<2e-16
Influence of Alcohol	9.954e-05	1.998e-05	4.982	6.28e-07
Overtaking	2.684e-06	2.519e-05	0.107	0.9151
Number of cattle on the road	6.969e-06	2.891e-06	2.410	0.0159
Road Surface	-4.608e-06	8.078e-06	-0.571	0.5683
Number of road potholes	2.569e-03	1.121e-04	22.919	<2e-16

Table 4. Test for overdispersion (dispersion and alpha parameter)

Alternative hypothesis	Z value	P – value	Sample estimates
True dispersion is greater than 1	1.9283	0.02691	30.24414
True dispersion is greater than 0	1.8453	0.0325	0.001564326

Table 5. Negative Binomial model parameter estimation

Parameters	Estimate	Standard error	Z value	Pr (>|z|)
Intercept	9.668e+00	7.435e-02	130.039	<2e-16
Over speeding	-1.214e-04	6.941e-05	-1.749	0.0803
Influence of Alcohol	1.074e-05	1.127e-04	0.953	0.3406
Overtaking	-1.839e-06	1.402e-05	-0.013	0.9895
Number of cattle on the road	8.769e-06	1.674e-05	0.524	0.6004
Road Surface	-2.526e-07	4.660e-05	-0.005	0.9957
Number of road potholes	2.540e-03	6.435e-04	3.948	7.89e-05

Interpretation of the results of the Poisson model: This section table (3) lists the regression coefficients for the Poisson regression model along with standard error values and test statistics for the coefficients of related parameters (6). As can be observed, several parameters are statistically significant at 5%, statistically considerable coefficients indicate that the relevant variable has a positive or negative impact on the road accident. We illustrate the output of the Poisson regression model in the table below according to the software used, as the data were found to be over-dispersed, the analysis of the Poisson regression model will not be the best results. When the coefficients are examined, it is seen that the following variables (over-speeding, Influence of Alcohol, Number of cattle on the road, and Number of road potholes) are significant because their (p-values) are less than

Model selection: Using the Poisson regression model, Equi dispersion assumes that the variance mean value must be met. It appears that over-dispersion is the case because this assumption is rarely true. For detecting the overdispersion, it can be seen from the value of Null Deviance/DF, which is equal (1459/14=104.21) is greater than 1, when is greater than 1, there is overdispersion; when it is less than 1, there is under dispersion. Negative Binomial regression can be used as an additional method to manage over-dispersion on the Poisson regression model. The ideal (best) model is the one with the lowest AIC. To assess the fit of the two models, the negative binomial regression model was shown, along with the smallest AIC values for each combination of variables ranging from eight combination predictor variables, the Poisson regression model of the dataset had the largest values of this criterion and indicated poor fit to the data. Using the Negative Binomial regression as an alternative to Poisson regression, it had the smallest values of the criteria when we compared it with the Poisson regression model and indicated better goodness of fit with the data and is considered the best model, where the Deviance statistics distributed is approximated to a chi-square distribution. The null Deviance is equal (45.850) as a chi-square distributed with the degree of freedom fourteen (14); but the Residual Deviance is equal (15.026) as a chi-square distributed with the degree of freedom eight (8), which also shows the AIC value of the model equal to (257.53). Hence, a model with 14 estimate parameters of the Negative Binomial regression model with the smallest value of (AIC = 257.53) will be optimal.

Table 6. Goodness of Fit for both regression models

	Null deviance	df	Residual deviance	df	AIC
Poisson	1459.5	14	460.0	8	648.52
Negative Binomial	45.850	14	15.026	8	257.53

Conclusion and Recommendations

In this study, we have modeled the number of motor vehicle accidents in Botswana from 2007 through 2021 using three regression models for count data: the Poisson, generalized Poisson, and negative binomial. The parameters of the models were estimated using the maximum likelihood method, while the Akaike Information Criterion (AIC) was used for model selection. The smaller the AIC, the better the model's fit to the data. The summary statistics for the data show that the number of annual motor vehicle road accidents, casualties, and fatalities in Botswana has been increasing with the number of registered vehicles. The results for the Poisson regression model show that there is a problem of overdispersion. i.e., the assumption of the equality of mean and variance is violated. Thus, the Poisson regression model is inappropriate for fitting the data at hand. To overcome the problem of overdispersion, we fit alternative models to the Poisson: the negative binomial and generalized Poisson regression models. The AIC values indicate that the best-fitting model is the negative binomial followed by the generalized Poisson. Based on the best-fitting negative binomial regression model, was found that the factor that significantly contributes to the number of annual motor vehicle road accidents in Botswana is the percentage of vehicles registered because of the increase in the population of Botswana every year. The following recommendations are made:

1. Public awareness and sensitization campaigns to road users on the issue of safe driving. These should be coupled with stiff penalties for violating road traffic rules through injurious behavior by offenders, such as the use of cell phones and drinking alcohol while driving.
2. The government should address the poor state of the country's roads as this is a major cause of road accidents in the present study. Efforts should be concentrated on the maintenance of roads.
3. The road accident database of the country should be expanded to include more variables so that researchers can determine the actual factors contributing to casualties and death in road accidents.
4. Finally, institutions that enforce road traffic regulations should intensify the application of the law.

Conflicts of Interest: The authors declare that there are no conflicts of interest.

REFERENCES

A, C. H. 2003. Modeling count data with excess Zero: An empirical application to traffic accidents. *Sociological Method and Research*, 90 - 116.

A. Melliana, Y. S. 2013. The Comparison of Generalized Poisson Regression and Negative Binomial Regression Methods in Overcoming Overdispersion.

Accident, M. V. 2020. *2014 Annual Road Crash and Claims Report.* Gaborone: MVA.

Botswana, G. o. 2024. *International merchandise trade statistics annual report.* Gaborone: Statistics Botswana.

C, Z. A. 2008. *Applied Econometric with R.* R Package version 0.9-0.

c., M. 2008. Aspect of road safety in Botswana. *Development Southern Africa*, 425 - 435.

Cameron A C, T. P. 1998. *Regression Analysis of Count Data.* Cambridge: Cambridge University Press.

Cameron A C, T. P. 2005. *Microeconometrics Method and Application.* Cambridge: Cambridge University Press.

D, L. 1992. Zero Inflated Poisson Regression, with An Application to Detects in Manufacturing. *Technometrics*, 1 - 14.

Hilbe, J. M. 2011. *Negative Binomial Regression.*

I, N. C. 2016. Statistical model of road traffic crashes data in Anambra State, Nigeria: A poisson regression approach . *Europian Journal of Statistics and Probability*, 41 - 60.

Lawless, J. F. 1987. Negative Binomial and Mixed Poisson regression. *Candian Journal Statistics, 15*(3), 209 - 225.

M, M. S. 2007. Classical and Censored Zero Inflated Count Data Models. *R Package Version*.

M., T. D. 2021, February. Modelling Road Traffic Accidents Counts in Tanzania: A Poisoon Regression Approach. *Tanzania Journal of Science, 47*(1), 308 - 314. doi: https://dx.doi.org/10.4314/tjs.v47il.26

Mpapho J. Motsumi, G. A. 2021. Preventable deaths following road traffic collision in Botswan: A retrospective review. *Elsevier*, 2665 - 2671.

Mphela, T. 2020. Cause of road accidenat in Botswana: An econometric model. *Transport and Supply chain Management*.

N. M. R. Kwasari, J. T. 2014. Comparison of Negative Bionomial REgression and Poisson General REgression in Overcoming Overdispersion. *Electronic Journal Mathematical*, 107 - 115.

Nwaigwe, C. H. 2016. Statistical Model of road traffic crashes data in Anambra State Nigeria: a Poisson regression approach. *European Journal Statistics Probability, 4*(1), 41 - 60.

Oppong, R. A. 2015. Comparative Assessment of Poisson and Negative Binomial Regressions as Best Models for Road Count Data. *International Journal of Scientific Research and Engineering Studies, 2*(12), 2349 - 8862.

Organisation, W. H. 2023. *World report on road Traffic injury prevention.* Geneva: WHO.

S. P. Miaou, P. S. 1992. Relationships between Truck Accidents and Highway Geometric Design: A Poisson Regression Approach. *Transportation Research Record, 1376*, 10 - 18.

T, M. 2011. The Impact of Traffic Law Enforcement on Road Accidentalities in Botswana. *Transport and supply chain management*, 264 - 277.

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