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Time Series Modeling of Determinants of Road Accident Mortalities in Rwanda: A Case of Kigali City

Nyawanda Marygorretty Achieng[1], Dr. Patrick Mulyungi[2]

[1, 2]Jomo Kenyatta University of Agriculture and Technology

Abstract: ***Despite the stringent measures that Rwanda government has instituted to ensure safety in our roads and reduce accidents, there is still an upward trend in the number of road accident occurrences in Rwanda. The general purpose of this study was to model road accident mortalities in Rwanda. Specifically to assess the influence of nature of road on road accidents mortalities in Rwanda, to determine the influence of nature of vehicle on road accident mortalities in Rwanda, to analyze the influence of drivers condition on road accident mortalities in Rwanda and lastly tocompare poison regression and negative binomial regression in modeling road accident mortalities in Rwanda. Time series data for a period of 10 years ranging from 2008 to 2017 was utilized in this research. The study adopted descriptive quantitative design approach. Moreover it's also more of an explanatory research design. Data was sourced from Rwanda National Police and WHO database and NISR Statistical Yearbooks. The researcher analyzed the data using Eviews and R software after which the results were presented in form of tables and graphs. The findings indicated that nature of road, nature of vehicle and drivers' condition have a positive significant influence on road accident mortalities in Rwanda. Driver's condition was the most cause of road accident mortalities in Rwanda within the study period. Further, the Negative binomial is superior to Poisson regression in modeling road accidents in Rwanda. The study recommends that the government should give much focus to driver's conditions in order to reduce road accidents in Rwanda. Moreover, more traffic to be deployed in roads near residential and commercial places in addition to enhancing control department to conduct thorough check on all vehicles to ensure vehicles on the roads are in good condition.This research is of essential benefit to the Rwandan government and the various road users since they are able to know the critical factors that contribute to the persistent rise in road accidents hence able to take caution in order to reverse the trend of road accidents in Rwanda.***

Keywords: Road Accident, Mortality, Generalized linear models

1. Introduction

From 1990 to 2013 the world experienced an upward trend in the number of traffic casualties 90% of which occurred in low middle income countries in Africa (WHO, 2013). This is a confirmation that Africa records the highest rate of road traffic fatalities. Rising incomes in many developing countries have led to rapid motorization, while road safety management and regulations have not kept pace. The number of deaths due to road traffic accidents is highest in low middle income countries. According to WB (2018) report, in 2015 road traffic deaths stood at 34 deaths per 100,000 people. According to the report, the number of global traffic deaths is expected to even go a notch higher accounting for more than 35% by 2020. This prediction is based on the fact that there is increased economic development and motorization overtime. This scenario has prompted United Nations General Assembly and the World Health Organization to create a "Decade of Action for Road Safety" as a global strategy to address global road traffic menace. (Patel & Krebs, 2016). Vulnerable road users (VRUs) such as motorcyclists, pedestrians, and bicyclists accounts for a larger percentage of road traffic injury (WHO, 2004). Motorcycle transportation is rapidly growing across African Countries Rwanda included. However it's heavily faced with a challenge of frequent accidents which in most cases caused by reckless driving and lack of training. According to WHO (2017), Motorcycles and three wheelers accounts for a quarter of the global road traffic fatalities.

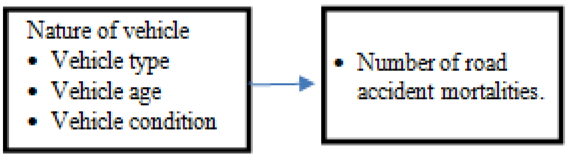
2. Statement of the Problem

The road accidents in Kigali have been on the rise overtime with most of them being vehicle accidents, motorbike accidents, pedestrians and pedal cycling accidents. In East Africa, Rwanda is ranked number one in terms of road transport management and hence relatively less road accidents. This is due to the stringent measures that the government has put in place regarding traffic regulations and making a follow up to ensure that they are adhered to and the offenders facing heavy penalties. (Patel & Krebs, 2016). Despite the measures, there is still an upward trend in the number of road accident occurrences on Rwanda roads specifically Kigali city and road traffic deaths prone in rural areas a scenario blamed on poor road network (RNP, 2017). According to National Road safety Commission, accidents are classified as fatal, serious and minor depending on the extent of damage caused to human life and assets. The purpose of the current research is to analyze the influence of vehicle related factors, drivers related factors and road related factors on road accident mortalities.

3. Objectives of the Study

The general objective of this study was to model road accident mortalities in Rwanda. Its second specific objective was to determine the influence of nature of vehicle on road accident mortalities in Rwanda

4. Conceptual Framework



5. Research Methodology

- **Research Design**: Descriptive quantitative research design was used in this study. Since it's an investigative study which aims to describe the features of a phenomena or population and finding the relationship or comparison between variables with ultimate goal of getting credible results, descriptive design fitted well.
- **Target Population:** The study targeted accident mortalities in Rwanda roads for the period of 10 years from 2008 to 2017. This forms the target population.
- **Sample size:**the study sample covered the entire 10years period.
- **Data Analysis and presentation:** Data analysis involves application of statistical techniques in description, illustration and evaluation of data in order to discover meaningful information. The data was analyzed using Eviews and R Software. The output was presented in form of tables and graphs.
- **Generalized Linear Models:** Modeling of count data such as accident mortalities data is popular in sciences. An accident crash in several occasions may result in either fatality or non-fatality. The Poisson regression model is the simplest model in modeling count data limited by the assumption of equal mean and variance as count data may typically exhibit over-dispersion or excess zeros (zero-inflated data) in the data (Yesilova et al., 2010). Therefore, this can be handled by using Negative Binomial regression which belongs to the family of generalized linear models.

Poison Regression model

This is the basic count model upon which other count models are based. According to Ehsan and Adnan (2011), Poison regression and negative binomial regression are the two commonly known models for count data. The Poison regression model can be written as

$$P_Y(y)=\frac{e^{\mu}\mu_i^{y_i}}{y_i!}$$

In the above equation, the mean of poison distribution given by μ is assumed to be linear function of independent variable x_i given by

Log $(\mu_i)= x_i\beta$

y_i denotes dependent variable having a poison distribution

x_i denotes independent variables

Suppose the dependent variable (Yi) is a count response variable that follows a Poisson distribution, Yi can be modeled as follows with the probability of Yi given by the equation below.

$$f_i\ (y_i, \mu_i, \alpha) = \left(\frac{\mu_i}{1+\alpha\mu_i}\right)\frac{(1+\alpha y_i)^{y_i-1}}{y_i!}exp\left(\frac{-\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}\right)$$

Where $y_i = 0,1,2 \ldots..$

$\mu_i = \mu_i(X) = e^{XB}$,where X is a (k-1) dimensional vector of covariates and B is a (k-1) dimensional vector of regression parameters. αis the dispersion parameter.

The parameter of dispersion is being observed on three cases (1) equi-dispersion; when α = 0 , and equation (2.3) reduce to PR, case (2) over-dispersion; when $\alpha > 0$, equation (2.3) will always sum to 1 and case (3) under-dispersion; when $\alpha < 0$, equation (2.3) may not sum to 1 as the equation get truncated. The variance and the mean of the response variable Yi are given by

Variance: $V(Y_i|X_i) = \mu_i(1+\alpha\mu_i)^2$

Mean: $(\mu_i) = E(Y_i|x+i)$

Negative Binomial Regression

The Negative Binomial regression model is given by

$$f(y_i) = p(Y_i = y_i) = \frac{\Gamma(\theta+y_i)}{\Gamma(\theta)y_i}\left(\frac{\theta}{\theta+\mu_i}\right)^{\theta}\left(\frac{\mu_i}{\mu_i+\theta}\right)^{y_i}, y_i = 0,1,2..$$

Where $\theta = \frac{1}{\alpha}$, α is the dispersion parameter, Γ(.) is a gamma function, the dependent variables (Y_i) has a NB distribution with the two parameters $\mu_i \geq 0$ and θ ≥0, where the mean and variance are given by $\theta\mu_i$ and $\theta\mu_i(1+\mu_i)$ respectively.(Garay et al, 2011)

Mean: $E(Y_i) = \theta\mu_i$

Variance: $\text{var}(Y_i) = E(Y_i)(1+\mu_i) = \theta\mu_i(1+\mu_i)$

Generalized linear model are a set of models used when the response variable violates some important assumptions of linearity hence does not exhibit normal distribution. If the response variable is not normally distributed, the GLMs which assume a link linear relationship based on a chosen link function may be utilized to complete the analysis. The GLMs are statistical models that can be written as

$$y = g(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + e$$

The GLMs are the members of exponential family that take the form

$$f(y,\theta,\emptyset) = exp\left[\frac{(y\theta - b(\theta))}{\alpha(\emptyset)} + c(y,\emptyset)\right]$$

Where, **Y** is a vector of response variable`s counts; the variables are the $x_i$ explanatory variables linearly associated covariates, β`s are the regression coefficients, e is the error variability that cannot be accountable for by the predictor (x_i) variables, $(\ldots)$ is a monotonic function relating the mean of the response variable to the linear predictors and some functions$(.), b(.), c(.)$. The values of the regression coefficients (β`s) were obtained by Maximum Likelihood (ML) estimations as follows;

Here we wished to estimate parameters which are related to the explanatory variables through

$E(Y_i) = \mu_i$and

$$g(\mu_i) = X^T\beta$$

For eachY_i, the log likelihood function is given by

$$\iota_i = y_i b(\theta_i) + c(\theta_i) + d(y_i)$$

Where the functions b,c, and d are known functions. Also

$$E(Y_i) = \mu_i = -C'(\theta_i)/b'(\theta_i)$$

$\text{Var}(Y_i) = [b''(\theta_i)c'(\theta_i)b'(\theta_i)]/[b'(\theta_i)]^3$

And $g(\mu_i) = X^T\beta = \eta_i$, where X is a vector with elementsX_{ij}, $j = 1, \ldots. p$

The log-likelihood function for all the Y_i`s is

$$\iota = \sum_{i=1}^{N} \iota_i = \sum y_i\, b(\theta_i) + \sum c(\theta_i) + \sum d(y_i)$$

Therefore to obtain the maximum likelihood estimator for the parameter β_j we need

$$\frac{\partial \iota}{\partial \beta_j} = U_j = \sum_{i=1}^{N}\left[\frac{\partial \iota_i}{\partial \beta_j}\right] = \sum_{i}^{N}\left[\frac{\partial \iota_i}{\partial \theta_i}.\frac{\partial \theta_i}{\partial \mu_i}.\frac{\partial \mu_i}{\partial \beta_j}\right]$$

Using the chain rule for differentiation by considering each term on the right hand side and we obtain the following equation:

$$U_i = \sum_{i}^{N}\left[\frac{(y_i-\mu_i)}{var(Y_i)}X_{ij}\left(\frac{\partial \mu_i}{\partial \eta_i}\right)\right]$$

The variance covariance matrix of the U_j`s has terms $\xi_{jk} = E[U_j U_k]$.Therefore, the maximum likelihood estimation formula is given by

$$b^{(m)} = b^{(m-1)} + \left[\xi^{(m-1)}\right]^{-1} U^{(m-1)}$$

Where the difference between successive approximation $b^{(m-1)}$ and $b^{(m)}$ is sufficiently small.

Generalized Poison Regression Model

For GLMs, the glm command as used in the study for the estimation of the response variable,μ was used in expressing the mean instead of λ which is used in many statistical literature for expressing the mean (Hardin & Hilbe, 2015).The count data for the response variable and explanatory variables modeled with the Poisson regression as follows

$$H_{Y_i}(y_i) = \frac{e^{\mu_i}\mu_i^{\,y_i}}{y_i!}, y_i = 0,1,2\,\ldots., \mu_i > 0$$

Where,$\mu_i = \exp(X'\beta)$is the fitted mean of the model, X is a vector of explanatory variables) and Yi is the counts of the response variable. The Poisson distribution assumes equal mean and variance therefore they are both equal toμ.

If the response variable (Y_i) is a count that follows a Poisson distribution, the response Yi will be modeled as follows with the probability of Yi given by the equation below

$$f_i(y_i, \mu_i, \alpha) = \left[\frac{\mu_i}{1+\alpha\mu_i}\right]\frac{(1+\alpha y_i)^{y_i-1}}{y_i!}exp\left[\frac{-\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}\right] \quad (2.2)$$

Where y_i=0, 1, 2…

6. Summary of Research Findings

6.1 Descriptive statistics

Table 1: Descriptive statistics of variables

	Mean	Std. deviation	Maximum	Minimum
Nature of road	37.5	1.65	54	23
Nature of vehicle	52.9	2.35	69	40
Drivers condition	78.9	4.77	103	54
Road accident deaths	240.4	10.78	366	187

Source: Researcher computation, 2019.

6.2 Average number of mortalities per variable within the study period

From the data on road accident deaths, there has generally been a rising trend of road accident deaths in Rwanda for the past 10years. These accidents are caused by various factors of which the study focused on the most integral causes of road accident mortalities in Rwanda namely nature of road, nature of vehicle and drivers condition. The average deaths per variable for the period between 2008 and 2017 are summarized in the figure below. The figure shows that among the three causes of road accidents which the study focused on driver's condition was prominent as the greatest cause of road accident mortalities followed by nature of vehicle and lastly nature of the road. However its worthy noting that other factors not reflected in this study summed up also had greater impact on road accident. Needless to say that there are so many causes of road accident and this study focused on only there factors. The other factors that cause road accident save for the three were summed up as 'others' and they had a greater impact on road accident mortalities in Rwanda within the study period. Moreover, from the figure most accidents deaths occurred in 2015 while the least occurred in 2008 but there is rising trend of road accident mortalities from 2008 to 2015 thereafter it dropped for the next 2 years.

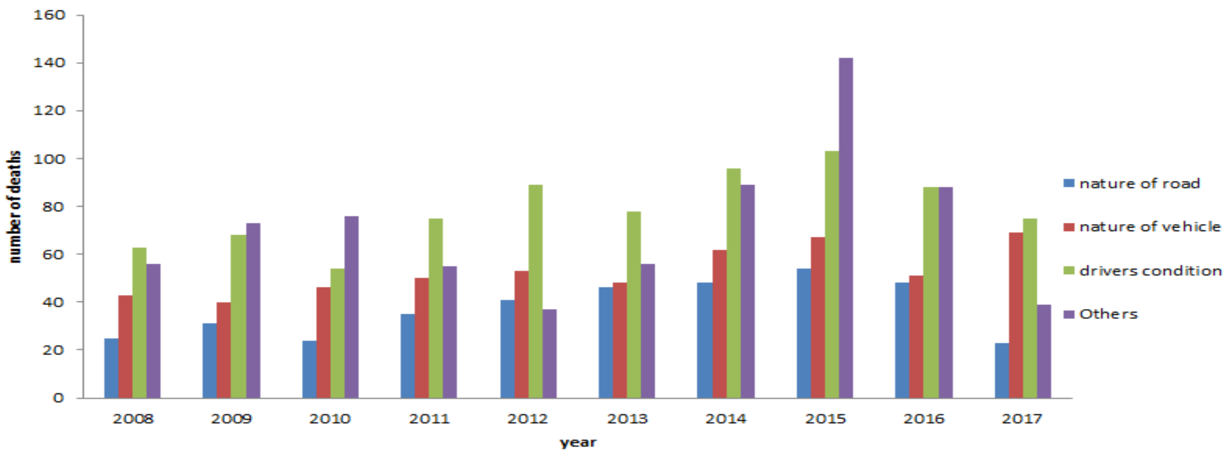


Figure 1: Average number of mortalities per variable
Source: Researcher, 2019

6.4 Analysis of road accident mortalities per variable

6.4.1 Nature of road related factors

This was analyzed using conical graph as shown in the following figure. The nature of road related factors considered included wet and dry roads, meandering roads, roads near residential and commercial places and others. The findings in the figure below indicate that most accidents related to nature of the road occurred in roads near residential and commercial places, followed by meandering roads. Wet and dry areas accounted for the least occurrence of nature of road related accidents deaths.

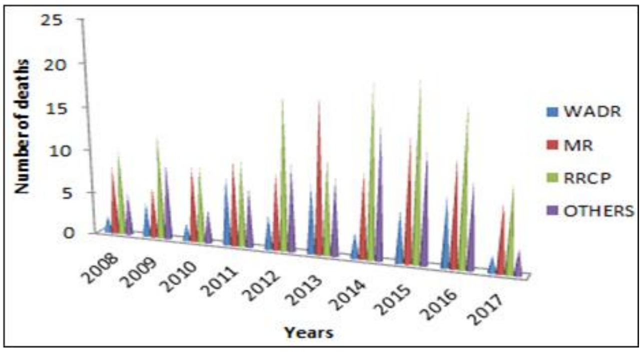


Figure 2: Factors related to nature of road
Source: Researcher, 2019

6.4.2 Nature of vehicle related factors

Factors related to nature of vehicle that were considered included type of vehicle, vehicle age and vehicle condition. The findings from the figure below indicated that most accident deaths caused by nature of vehicle were related to bad condition of the vehicle. This was followed by the age of the vehicle and the least accidents related to nature of the vehicle were explained by vehicle type. Other factors related to nature of the vehicle also explained a significant share of road accident deaths within the study period.

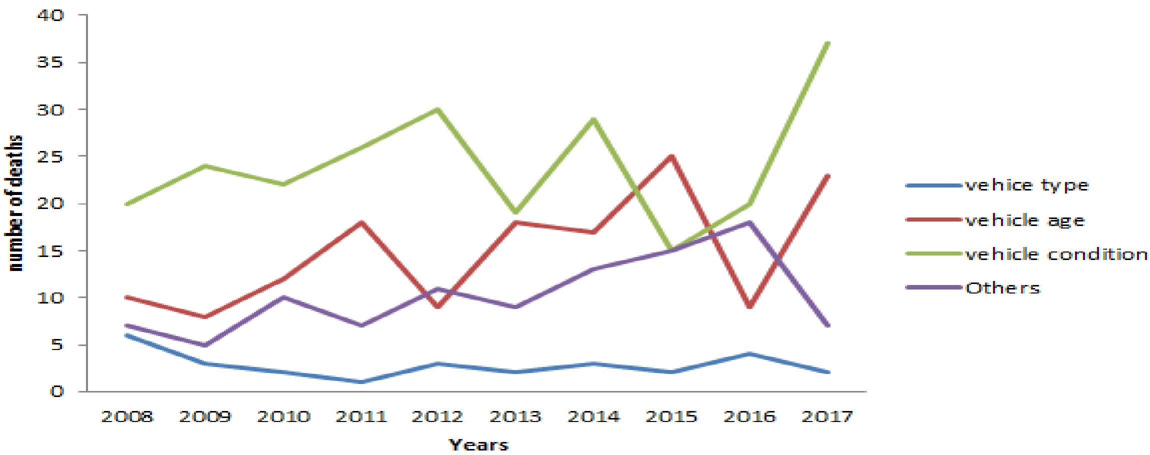


Figure 3: Factors related to nature of vehicle
Source: researcher, 2019

6.4.3 Driver's condition related factors

The study considered reckless driving, sickness and drunkardness as prominent factors related to driver's condition that cause road accident deaths. From the findings in the following figure its evidenced that reckless driving accounted for most road accident mortalities related to drivers condition between 2008 and 2017. This was followed by drunk driving and lastly sickness of the driver. The study found that drivers conditions are the highest cause of road accident mortalities in Rwanda. Other factors related to condition of the driver such as fatigue, experience were summed up under 'others' and also explained a number of road accident mortalities as evidenced in the following graph.

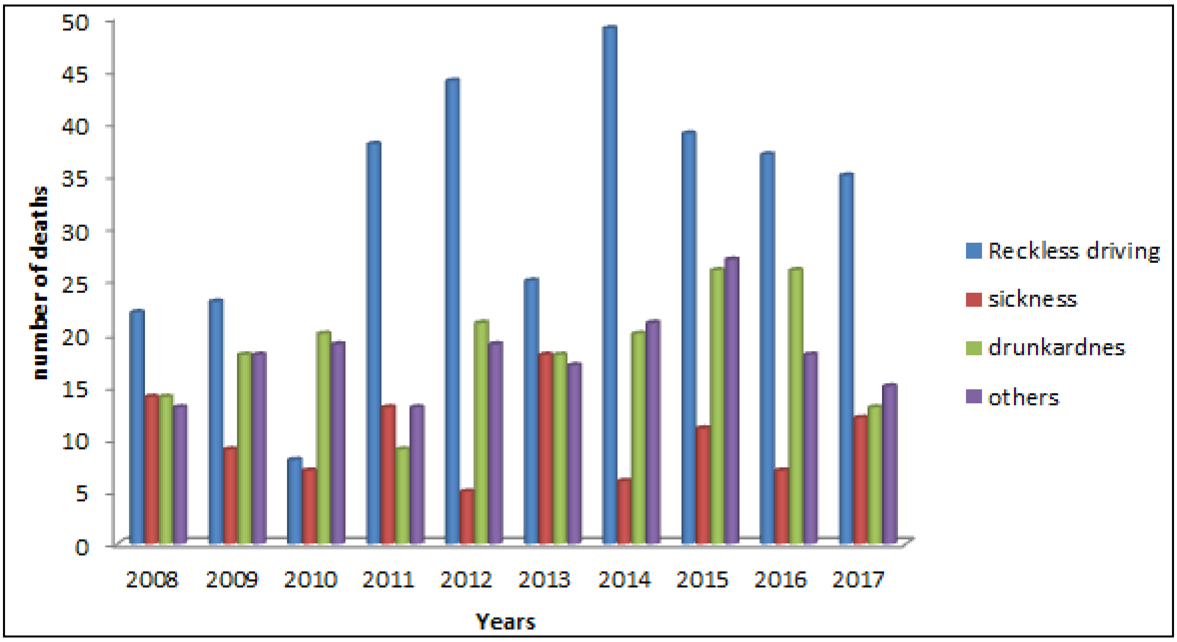


Figure 4: Drivers condition factors
Source: researcher, 2019

6.5 Unit Root Tests

The stationarity of the variables that is nature of road (NOR), nature of the vehicle (NOV), driver's condition (COD) and total road accident deaths (RAD) was tested using ADF test method at trend and intercept. This was necessary in order to avoid the risk of getting spurious results. A stationary series is one with a constant mean, variance and covariance. The results are presents in the following table.

Table 2: Unit Root Test Results

Augmented Dickey Fuller Test		
	Probability at level	probability at 1st difference
RAD	0.698	0
NOV	0.5709	0
NOR	0.8641	0.0002
COD	0.2576	0

Source: researcher 2019

The researcher tested the following hypothesis for stationarity of data set.

Ho: Presence of unit root in the data set

$H1$: No unit root in the data set

Decision criteria: The null hypothesis is rejected if the probability is less than 5% otherwise we fail to reject.

From the findings in the table2 above, the probabilities for all variables at level are greater than 5% hence we accept null hypothesis of presence of unit root hence no stationarity at level. At the first difference, the probabilities for all variables are less than 5% hence we reject null hypothesis of presence of unit root and conclude that the data set is stationary at first difference.

6.6 Generalized Linear Regression Model Findings

This study adopted the generalized linear model to analyze the determinants of road accident mortalities in Rwanda. The dependent variable was road accident deaths while the independent variables were nature of vehicle, nature of road and drivers conditions. From the results in the following table, the coefficients for nature of vehicle, nature of road and driver's condition and constant term were 0.1358, 0.1962, 1.0812 and 9.6813. The corresponding probabilities were 0.0033, 0.0000, 0.0481 and 0.0104 respectively. the generalized linear model fitted in chapter three relating road accident deaths to nature of the road, nature of the vehicle and drivers condition can be written as;

$$RAM = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + e$$

$RAM = 9.68 + 0.196x_1 + 0.136x_2 + 1.081x_3 + e$where RAM, x_1, x_2 and x_3 are road accident deaths, nature of road, nature of vehicle and drivers condition respectively.

Table 3: Generalized linear regression model

Dependent Variable: ROAD_ACCIDENT_DEATHS				
Method: Generalized Linear Model (Quadratic Hill Climbing)				
Sample: 1 40				
Family: Normal				
Link: Identity				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
NATURE_OF_VEHICLE	0.135808	0.046186	-2.940480	0.0033
NATURE_OF_ROAD	0.196233	0.201894	5.925055	0.0000
DRIVER_S_CONDITION	1.081169	0.252781	0.321105	0.0481
C	9.681341	3.780771	2.560679	0.0104

Mean dependent var	24.96350	S.D. dependent var	1.179071
Sum squared resid	18.05533	Log likelihood	-40.95599
Akaike info criterion	2.247799	Schwarz criterion	2.416687
Hannan-Quinn criter.	2.308864	Deviance	18.05533
Deviance statistic	0.501537	Restr. deviance	54.21814

Source: researcher, 2019

6.7 Comparison between Poison and negative binomial regression for goodness of fit test

The last objective of this study was to test the best model between Poisson regression and negative binomial regression model in modeling road accident mortalities in Rwanda. The study computed five parameters for each model and the findings are shown in the following table. From the previous chapter, this decision was to be arrived at by comparing the Akaike Information Criteria as the parameter of focus. The findings indicated that the AIC for generalized Poisson model was 11.547 whereas generalized negative binomial had an AIC of 0.271. Moreover the values for the deviance, probability and dispersion parameters for the generalized negative binomial were smaller than those of generalized Poisson.

Table 4: Comparison of generalized Poisson and Negative binomial regressions

Parameter	Generalized Poison model	Generalized Negative binomial model
Deviance	48.63	41.17
Degrees of freedom	38	38
dispersion	0.472	0.271
Akaike Information Criteria	11.547	9.110
Probability	0.0458	0.0259

Source: researcher, 2019

6.8 Discussion

6.8.1 Influence of nature of road on road accident mortalities in Rwanda.

Nature of the road is one of the factors that can cause road accidents and lead to death. The factors considered under nature of road included wet and dry areas, meandering roads and roads near residential and commercial places. The findings indicated that most accidents related to road nature occur along the roads which are near commercial and residential places while the least number of road accident deaths occur in wet and dry areas. The findings on the generalized linear model indicated that there is a positive significant influence of road nature on road accident deaths in Rwanda. This means that as the number of road accident mortalities related to nature of road increases the total number of road accidents deaths increases. Moreover, 1% changes in the number of road accident mortalities related to nature of the road leads to a 19.62% change in total road accident mortalities in Rwanda, ceteris paribus. These findings are similar to the ones of Allan (2017) and Frempong (2016) who also found significant effects of road nature on traffic fatalities in Uganda and Ghana respectively. The results also confirms the ones of Paweenusch (2015) who also found that most accidents occur along shops and residential places in Tokyo.

6.8.2 Influence of Nature of Vehicle on road accident mortalities in Rwanda

Nature of the vehicle is another factor that causes most accidents. This is because some vehicles for example develop defects such as break failure, being too old and others which can lead to accident. The factors related to nature of vehicle considered included vehicle age, vehicle type and vehicle condition. The findings indicated that most accidents in Rwanda related to nature of the vehicle are caused by vehicles condition or defects while the least are caused by vehicle type. The generalized model indicated that there is positive significant relationship between nature of the vehicle and road accident mortalities in Rwanda. This implies that vehicle defects, age and type significantly increases number of road accident mortalities. From the model findings, 1% change in number of road accidents mortalities related to the nature of the vehicle increases the total number of road accident mortalities by 13.58% ceteris paribus.The findings of this research confirms the ones of Bereket and Kidus (2016) who found a significant effect of vehicle type on traffic injuries in Wolaita Zone and also the findings of Allan (2017) in Uganda who confirmed a positive significant effect of vehicle type on traffic injuries.

6.8.3 Influence of drivers condition on road accident mortalities in Rwanda.

This was the most significant cause of road accident mortalities in Rwanda within the study period according to the findings. Most accidents of late are caused by conditions of the driver according to past researches. The study considered reckless driving, sickness and drunkardness as driver's conditions. From the findings, reckless driving was the major factor that caused accidents deaths related to drivers conditions in Rwanda within the study period while least factor was sickness. From the findings of the GLM model there is a positive significant influence of driver's conditions on road accident deaths in Rwanda. an increase in road accident deaths related to drivers conditions increases the total road accident mortalities. The GLM model coefficient of driver's condition implies that a 1% increase in road accidents related to driver's condition increases the total road accident mortalities by 108.12% keeping other factors constant. The findings of this study resemble the findings of Olemo Cliford (2016) who found a significant effect of drivers on road traffic accidents in Kenya. However the findings goes against those of H Fitrianti et al (2019) who found that driving under influence of alcohol doesn't have significant influence on road traffic accidents in Indonesia.

6.8.4 Comparison of Poisson and Negative Binomial in modeling road accident mortalities in Rwanda.

The last specific objective of this research was to compare generalized Poisson and generalized negative binomial regression models to ascertain the best one for modeling road accident mortalities in Rwanda. This was achieved through computing the AIC parameter as outlined in the previous chapter among other parameters that is dispersion deviance and probability. The findings indicated that generalized negative binomial has a smaller AIC than the Poisson regression. This confirms that the generalized negative binomial is superior to Poisson regression in modeling road accident mortalities in Rwanda. These findings resembles those of Frempong(2016) and Allan (2017) who found that negative binomial outperforms Poisson in modeling road accidents in Ghana and Uganda respectively.

7. Conclusions and Recommendations

7.1 Conclusions

This study came up with a number of conclusions from the findings. First the study concluded that the major determinant of road accident mortalities in Rwanda is driver's condition. Under this it's worth noting that reckless driving is the most prominent cause of road accident deaths in Rwanda. Regarding nature of the road and nature of vehicle, the study concluded that roads near residential and commercial places and vehicle condition were also major causes of road accidents deaths Rwanda.

Secondly from the GLM model, the study concludes that nature of road, nature of vehicle and driver's conditions have positive significant influence on road accident mortalities in Rwanda. a 1% change in nature of road, nature of vehicle and drivers condition leads to a 19.62%, 13.58% and 1.08% change in road accident mortalities in Rwanda keeping other factors constant.

Lastly, the AIC for negative binomial ids smaller than the AIC for Poisson regression implying that negative binomial regression is forms the best model fit for modeling road accident mortalities in Rwanda.

7.2 Recommendations

Based on the study results and discussions, the researcher recommends the following policy implementations. The study recommends that much focus be given to drivers conditions in order to reduce road accidents in Rwanda. Heavy penalties and new measures to curb traffic law offenders should be devised. Reckless driving should attract heavy penalties and the Police force should be on the watch at every point along the roads to ensure that road users adhere to the set rules and regulations pertaining to traffic. Further, the government should deploy more traffic police along roads near residential and commercial places to keep watch on the traffic users. Lastly there is need to enhance the operations of the traffic control department to ensure that all vehicles are regularly well checked to ensure that they are in good condition to avoid causing accidents on the roads due to vehicle defects.

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