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The Analysis of Road Traffic Accidents in Cameroon Using Poisson Regression Model from 2011 – 2020: A Case Study of Bamenda-Douala Expressway

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ABSTRACT: The roads in Cameroon have become grim islands as more and more accidents occur, leading to a constant stream of deaths and causing devastation in families Researchers have been modelling vehicular accidents with accident prevention models in various parts of the world. Considering that road traffic accident along Cameroonian roads is observed to be on the increase, especially in recent times, this study examines the relationship between death from road accidents and total cases of road accidents along the Bamenda-Douala expressway, and also to examine the trend of death from road accidents on the road using Poisson regression model. By using data obtained from Sector Command, of the Road Safety Corps, the Poisson regression model was fitted. It was found that If cases of Road Traffic Accident increase by 1 unit, it will lead to 0.8% increase in death resulting from Road Traffic Accidents. Furthermore, death resulting from Road Traffic Accidents decrease by 7.5% annually on Bamenda-Douala Road. The coefficients in the model (cases, time and constant) are significantly different form 0 with $p < 0.05$. The goodness of fit test for the Poisson regression model revealed that death from Road Traffic Accident on Bamenda-Douala Road follows the Poisson distribution with (p value > 0.05). The fitted model provides an effective way of predicting death arising from accidents along the road, hence useful for policy creation and planning.

KEY WORD: Road traffic, Accident, Poisson regression, Cameroon, Bamenda-Douala

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INTRODUCTION

The roads in Cameroon have become grim islands as more and more accidents occur, leading to a constant stream of deaths and causing devastation in families. Indeed, since 2024, the situation has been escalating with numerous accidents on Cameroon's major roads. To try to curb the situation, the Ministry of Transport, has implemented a series of punitive measures, including the suspension of nearly 24 transport companies and the revocation of 1025 driver's licenses, specifically targeting bus drivers who often fail to strictly adhere to recommendations, such as refraining from using their phones. As of today, it seems that despite these efforts, the accident rate continues to rise at an alarming pace. It cannot be stressed enough that vigilance must remain a priority, and it is important to follow road safety and prevention guidelines.

Road traffic accidents (RTAs) represent a significant global public health and economic burden, particularly in low- and middle-income countries (LMICs) [WHO, 2023]. Road traffic accidents (RTAs) impede the achievement of Sustainable Development Goals (SDGs) related to health (SDG 3) and sustainable cities (SDG 11) [UN, 2023].

Reducing RTAs is essential for improving public health and promoting sustainable urban development (Kingham et al., 2021; Norton et al., 2020). The economic costs of RTAs are substantial, encompassing direct (medical, vehicle) and indirect (lost productivity, mortality) costs (Andersson et al., 2019; El-Darier & Ghouri, 2020; Stevens et al., 2018). These costs disproportionately affect LMICs with strained healthcare systems (Bhalla et al., 2022). A wide array of factors contributes to RTAs: speeding, drunk driving, distracted driving, fatigue, poor road design, inadequate vehicle maintenance, and lax enforcement (European Commission, 2022; FHWA, 2023; WHO, 2021). The relative importance varies by context (Høye, 2019). Effective road safety strategies include:

Engineering improvements to roads (Austroads, 2023; ITE, 2022,) Enforcement of traffic laws (SWOV, 2023), Education and awareness campaigns (Road Safety GB, 2023) and post-crash care (ATLS, 2018). Addressing RTAs crisis requires data-driven analysis to identify risk factors and inform targeted interventions (Bhalla et al., 2022; Tiwari et al., 2021).

Africa faces disproportionately high RTA rates, with Cameroon experiencing a substantial burden (AfDB, 2023). This is linked to rapid motorization, infrastructure deficits, and challenges in traffic law enforcement (Mock et al., 2020; Odero, 2019; Peden & Hyder, 2018). The Bamenda-Douala Expressway is a key transport corridor connecting Northwest and Littoral regions (MINTP, 2021) but has a high RTA incidence due to: High traffic, Variable terrain, Pedestrians and non-motorized vehicles and speeding and reckless driving. According to Cliford & Lawrence,2021, road accidents create both social and economic costs on the country's economy in general and the city. Following World Health Organization, 2018 report; Road traffic accident causes death, life-long disability and property damage in this world more than tuberculosis and HIV/AIDS.

The causes of road traffic accidents are multi-factorial. These factors can be divided broadly into driver factors, vehicle factors and roadway factors. Accidents can be caused by a combination of these factors. Driver factor solely contributes to about 57 per cent of road traffic accidents and 93 per cent either alone or in combination with other factors. Driver factors in road traffic accidents are all factors related to drivers and other road users such as driver behaviour, visual and auditory acuity, decision making ability and reaction speed, drug and alcohol using while driving, speeding, travelling too fast above the speed limit, contributes to road traffic accidents (Bun, 2022).

Many researchers have come out with the causes, effects and recommendations to traffic accidents. These causes include drink driving, machine failure and over speeding (Adeyemi, 2015). Yet every year the Federal road safety commission, National Bureau of Statistics and other organizations would report an increase in Road traffic accidents (NRTR, 2004). The mere increase in the number of Road traffic accidents is not enough for one to conclude that really there is an increase in Road traffic accident; hence the need to analyze the Road Traffic accidents data statistically to check whether there is any evidence of increasing road traffic accidents as years go by resulting to large number of people losing their lives.

In Cameroon, the situation is particularly alarming. The country has witnessed a rising trend in road traffic accidents, attributed to factors such as poor road infrastructure, inadequate enforcement of traffic regulations, and a lack of driver education Elvis and Lilian, 2020. According to the National Road Safety Agency of Cameroon, over 1,000 fatalities are recorded annually due to road traffic accidents, with thousands more suffering serious injuries.

Previous research has highlighted the need for effective interventions to mitigate this crisis, emphasizing the importance of data-driven approaches to understand the underlying causes of these accidents.

Cliford & Lawrence 2021 assess the level of implementation of the road safety policy and surveillance in the city over a period of six months and found that there is a lack of collaboration among the stakeholders involved in the implementation of road safety measures in the city. Elvis, &, Lilian, 2020, commented on the road safety situation in Cameroon and recommended solutions based on the five key areas of the Ottawa charter for health promotion and realized that the main problem with road safety in Cameroon is the enforcement of laws and regulations. They recommended that the government should enforce policies on overloading, over-speeding, drink-driving, not wearing a helmet or seat-belt and vehicle road worthiness to curb frequent road accidents, create the enabling environment to enforce road safety, strengthen community action towards road safety, develop personal skills for drivers, the populace and law enforcement agencies to practice road safety and reorient the health services regarding road safety.

Other researches have been tailored toward this end; they include: Heidi (2006) who reported that 1.2 million people in the world lose their lives through road traffic accidents every year. This number has rising to 1.3 million people who lose their lives globally every year and between 20 and 50 million people sustain various forms of injuries annually as a result of road traffic accident. Salim and Salimah (2005) indicated that road traffic accident was the ninth major cause of death in low-middle income countries and predicted that road traffic accident was going to be the third major cause of deaths in these countries by 2020 if the trend of Road traffic accident was to be allowed to continue. Media reports reveal that there is a high road accident in Keffi-Lafia road, when compared with other Road in Nasarawa state. In 2001, the road was ranked as the first highest road traffic accident-prone road in the state with 41 deaths per 74 road traffic accidents, (Federal road safety commission annual report, 2009).

Despite the increasing incidence of road traffic accidents in Cameroon, there remains a significant gap in understanding the factors contributing to these incidents. Existing studies have often focused on descriptive statistics or limited analyses without employing robust statistical models that can provide deeper insights. The lack of comprehensive data analysis hampers policymakers' ability to formulate effective interventions aimed at reducing accidents and enhancing road safety. Therefore, there is an urgent need for a systematic analysis of road traffic accidents in Cameroon using advanced statistical methods.

Statistical modeling, particularly Poisson regression, is valuable for understanding the relationship between RTAs and contributing factors (Agresti, 2015; Cameron & Trivedi, 2013), providing insights for resource allocation. Poisson regression is a generalized linear model suitable for analyzing count data, such as the number of RTAs, assuming that the dependent variable follows a Poisson distribution (Agresti, 2015; Cameron & Trivedi, 2013). Its ability to model the relationship between RTA frequency and various explanatory variables makes it a valuable tool for road safety research (Lord & Mannering, 2018).

Poisson regression analysis is a technique used to model dependent variables that describe count data (Cameron and Trivedi 1998). It is often applied to study the occurrence of small number of counts as a function of a set of predictor variables, in experimental and observational study in many disciplines, including Economy, Demography, Psychology, Biology and Medicine (Gardener et al, 1995). It regression model has often been applied to estimate standardized mortality and incidence ratios in cohort studies and in ecological investigations (Breslow, et al., 1987).

Numerous studies have applied Poisson regression to analyze RTA data, identifying key risk factors. Oyedepo and Makinde (2010) applied Poisson regression to examined accident data on the 52km Akure-Ondo carriage way and spot speed data between 2002-2007. Abdulkabir et al. (2015) study the trend of road traffic accident in Nigeria using Ibadan, Oyo state as a case study. They employed time series analysis and their results revealed an increase in the number of accidents occurring in the future. Nwanko and Nwaigwe (2016) analyzed data on road traffic accidents from Anambra State Command of the FRSC using Poisson regression, Negative binomial regression and Generalized Poisson regression model. Oyenuga et al (2016) examined monthly accident data on Oyo- Ibadan express road. Adenomon et al. (2017) investigated the trend in vehicular accident cases in Nigeria using annual data from 1995 to 2015. Kim et al (2005) used generalized log-linear models and Garber and Wu (2001) applied stochastic models in fitting models to road accidents data.

This study seeks to address accident severity indicators by utilizing available RTA data from the National Institute of Statistics and other sources; focusing on the Bamenda-Douala Expressway as a case study; and applying a Poisson regression model to identify key severity indicators and inform targeted interventions.

This study aims to analyze the determinants of RTAs on the Bamenda-Douala Expressway in Cameroon using a Poisson regression model, identifying key severity indicators and contributing to the development of effective road safety policies. The specific objectives include: (1) Model the severity of road traffic accidents on Bamenda-Douala expressway using Poisson regression; (2) identifying significant predictors of RTA frequency; (3) evaluating the goodness-of-fit of the Poisson regression model; and (4) generating insights for targeted interventions (IRTAD, 2022; NHTSA, 2023)."

MATERIAL AND METHODOLOGY

We apply a Poisson regression model to the secondary data collected from the Accident data reports from the State Defense Secretariat (SED) in Cameroon. The Poisson regression models are universal linear models with logarithm as the link function. In statistics, the Generalized Linear Model (GLM) is a stretchy overview of usual linear regression that allows response variables that have error distribution models other than a normal distribution.

The method used for this study enlightened the theory behind the distributions and model for this application. The probability distributions of accident data and their possible regression model which may contain the Poisson distributions. This study considered accident data for ten-year period from 2011 to 2020. The number of people killed by road accident was used as the response variable in all models and the other variables such as age of casualty, the day and month the accident occurred which resulted in the death of the people, vehicle type and road user class as the explanatory variables.

Assumption of the Model

These assumptions are important to consider when conducting data analysis using the Poisson regression Model, as violating them can lead to biased or inaccurate results.

(i) The observations must be independent of each other

(ii) The relationship between the predictor variables and the response variable must be linear.

(iii) The variance of the response variable should be equal across different levels of the predictor variable

(iv) Outliers are observations that are significantly different from the rest of the data.

(v) The sample size should be large enough to ensure that the results of the analysis are reliable and accurate

The information from these reports were gathered and transferred into an Excel sheet. the comprehensive analysis of the data using statistical tools such as Poisson regression is to fit a model to the data set. This study is based on the data obtained from the (SED). The method used for this study enlightened the theory behind the distributions and model for this application. The probability distributions of accident data and their possible regression model which may contain the Poisson distributions.

The classic Poisson regression models for count data belong to the family of generalized linear models (Zeileis, Kleiber & Jackman, 2008).

Poisson regression is a non-linear regression analysis of the Poisson distribution, where the analysis is highly suitable for use in analyzing discrete data (count) if the mean equals the variance process.

In Poisson distribution models, the probability of the number of occurrences, X, of some random event, in an interval of time or space is given by

$$f(x) = \frac{e^{-\lambda}\lambda^{x},}{x!}, \quad x = 0, 1, \cdots, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

where $f(x)$ denote the probability that the outcome is x and $x! = x(x-1)\ldots$.3.2.1

The mean and variance of the Poisson probability distribution are:

Expectation

If $X \sim P(\lambda)$, we have

$$E(X) = \sum_{x=0}^{\infty} x\, P(X = x) = \sum_{x=1}^{\infty} x\, P(X = x)$$
$$= \sum_{x=1}^{\infty} x \frac{\lambda^x}{x!} e^{-\lambda} = \sum_{x=1}^{\infty} x \frac{\lambda^x}{x(x-1)!} e^{-\lambda}$$
$$= \sum_{x=1}^{\infty} \frac{\lambda^x}{(x-1)!} e^{-\lambda} = \lambda \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!} e^{-\lambda}$$
$$= \lambda \sum_{j=0}^{\infty} \frac{\lambda^j}{j!} e^{-\lambda} \text{ (putting } j = x-1)$$
$$= \lambda \sum_{j=0}^{\infty} P(X = x) = \lambda \ldots\ldots (2)$$

The variance is

$$E(X^2) = \sum_{x=0}^{\infty} x^2\, P(X = x) = \sum_{x=1}^{\infty} x^2\, P(X = x) = \sum_{x=1}^{\infty} x^2 \frac{\lambda^x}{x!} e^{-\lambda} = \sum_{x=1}^{\infty} x^2 \frac{\lambda^x}{x(x-1)!} e^{-\lambda}$$
$$= \sum_{x=1}^{\infty} x \frac{\lambda^x}{(x-1)!} e^{-\lambda} = \lambda \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!} e^{-\lambda} = \lambda \sum_{j=0}^{\infty} (j+1) \frac{\lambda^j}{j!} e^{-\lambda} \text{ (putting } j = x-1)$$
$$= \lambda \left[\sum_{j=0}^{\infty} j \frac{\lambda^j}{j!} e^{-\lambda} + \sum_{j=0}^{\infty} \frac{\lambda^j}{j!} e^{-\lambda} \right] = \lambda \left[\sum_{j=0}^{\infty} jP(X = j) + \sum_{j=0}^{\infty} P(X = j) \right]$$
$$= \lambda[E(X) + 1] = \lambda(\lambda + 1) = \lambda^2 + \lambda$$
$$Var(X) = E(X^2) - E(X)^2 = \lambda^2 + \lambda - \lambda^2 = \lambda \ldots\ldots (3)$$

Note that the variance is the same as the mean. Hence, if the number of trips follows the Poisson distribution and the mean number of store trips for a family with three children is larger than the mean number of trips for a family with no children, the variance of that distribution of outcomes for the two families will also differ. At times, the count response Y will pertain to different units of time or space, then Poisson probability distribution is expressed as follow:

$$f(x) = \frac{,(t\lambda)^x e^{(-t\lambda)}}{x!}, \quad x = 0, 1, \cdots, \ldots\ldots (4)$$

where λ denote the mean response for x for a unit of time or space (e.g. one month).

t denote the number of units of time or space to which Y corresponds.

x is the number of store trips during the month (e.g. Y is the number of store trips during one week where the unit time is one month) for a unit of time or space. Note: all response Y_i pertains to the same unit of time or space.

Poisson Regression Model:

Like any nonlinear regression model, can be stated as follows:

$$Y_i = E(Y_i) + \varepsilon_i \;; i - 0, 1, \ldots, \ldots\ldots (5)$$

The mean response for the ith case, to be denoted now by μ_i for simplicity, is assumed as always to be a function of the set of predictor variables $X_1, X_2, \ldots, X_{k-1}$. We use the notation $\mu(X_i, \beta)$ to denote the function that relates the mean response μ_i to X_i, the values of the predictor variables for case *i*, and β, the values of the regression coefficients. The commonly used functions for Poisson regression are:

$$\mu(X_i, \beta) = X'\beta \ldots\ldots (6)$$
$$\mu(X_i, \beta) = \exp(X'\beta) \ldots\ldots (7)$$
$$\mu(X_i, \beta) = \log_e(X'\beta) \ldots\ldots (8)$$

In all three cases, the mean response must be nonnegative. Since the distribution of the error terms ε_i for Poisson regression is a function of the distribution of the response which is Poisson regression model in the following form.

$$\mu_I = \mu(X_i, \beta) = X'\beta, \ldots\ldots (9)$$

where X_i are independent Poisson random variables with expected value μ_I. The most commonly used response function is $\mu_I = \exp(X'\beta)$, also used in this study.

Maximum likelihood Estimation

For Poisson regression model (3.38), the likelihood function is as follows:

$$L(\beta) = \prod_{i=1}^{n} f_i(X_i) = \prod_{i=1}^{n} \frac{\mu(X_i,\beta)^x exp(-\mu(X_i,\beta))}{X_i!} \ldots\ldots (10)$$

or

$$L(\beta) = \prod_{i=1}^{n} \frac{\mu(X_i,\beta)^x exp(-\mu(X_i,\beta))}{\prod_{i=1}^{n} X_i!} \ldots\ldots (11)$$

Once the functional form of $\mu(X_i, \beta)$ is chosen, the maximization of (10) or (11) produces the maximum likelihood of the likelihood function:

$\log_e L(\beta) = \sum_{i=1}^{n} X_i \log_e[\mu(X_i,\beta)] - \sum_{i=1}^{n} \mu(X_i,\beta) - \sum_{i=1}^{n} \log_e X_i\,!$ ……………… (12)

Numerical search procedures are used to find the maximum likelihood estimates $b_0,\ b_1,\dots,b_{k-1}$.

Iteratively reweighted least squares can again be used to obtain these estimates. We also rely on standard statistical software packages specifically designed to handle Poisson regression to obtain the maximum likelihood estimates. After the maximum likelihood estimates are been found, we can obtain the fitted response function and fitted values using Equation (13) and (14):

$$\left.\begin{array}{l} i)\ \hat{\mu} = \mu(X,b) \\ ii)\ \hat{\mu}_i = \mu(x_i,b) \end{array}\right\} \dots\dots (13)$$

From the three functions in (3.19) to (3.21), the fitted response functions and fitted values are:

$$\left.\begin{array}{l} i)\ \mu = (X',b): \hat{\mu} = (X',b);\ \hat{\mu}_i = \mu(X_i'\,b) \\ ii)\ \mu = exp(X',b): \hat{\mu} = exp(X',b);\ \hat{\mu}_i = exp(X_i'\,b);\ \hat{\mu}_i = exp(X_i',b) \\ iii)\ \mu = \log_e(X',b) : \hat{\mu} = \log_e(X',b)\,;\ \hat{\mu}_i = \log_e(X_i',b) \end{array}\right\} \dots\dots (14)$$

Model Development:

Model development for a Poisson regression model is carried out in a similar fashion to that logistic regression, conducting tests for individual coefficients or group of coefficients based on the likelihood ratio test Statistic G2 in (4) For Poisson regression model (12), the model deviance is as follows:

$$Dev(X_1,X_2,\dots,X_{k-1}) = -2\left[\sum_{i=1}^{n} X_i \log_e\left(\frac{\hat{\mu}_i}{X_i}\right) + \sum_{i=1}^{n}(X_i - \hat{\mu}_i)\right] \dots\dots (15)$$

Where µˆ*i* is the fitted value for the ith case according to (13(i)). The deviance residual for the ith case is:

$$dev_i = \pm\left[-2X_i \log_e\left(\frac{\hat{\mu}_i}{X_i}\right) - 2(X_i - \hat{\mu}_i)\right]^{-\frac{1}{2}} \dots\dots (16)$$

The sign of the deviance residual is selected according to whether $X_i - \hat{\mu}_i$ is positive or negative. Index plots of the deviance residuals and half-normal probability plots with simulated envelopes are useful for identifying outliers and checking the model fit. Note that if $X_i - 0$, the term $\left[X_i \log_e\left(\frac{\hat{\mu}_i}{X_i}\right)\right]$ in (15) and (16) equals 0.

Model Specification

Hence, two class of models (Poisson regression) are defined as Poisson regression model:

$\mu = \mu(X_i,\beta) = \exp\,(X_i',\beta)$ ……………………………………………………… (17)

where $\mu(X_i,\beta)$denotes the function that relates the mean response μ_i to X_i , the values of the predictor variables for case *i* , and β is the values of the regression coefficients.

For multiple Poisson regression model with more than one covariate, the probability event is

$\mu_i = \mu(X_i,\beta) = \exp(X_i',\beta) = exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k)$ ………………… (18)

we have $\beta_0 = constant$, $\beta_i = coefficients$, and $X = i^{th}$ predictors (or exponential of the ith predictors). To test whether several βk = 0, or relate to the response variables, the following techniques are employed; Likelihood ratio test statistic G^2, Odd ratio, Wald test (z-test) and Model selection criteria: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC):

Likelihood ratio test Statistic G^2

To test whether a subset of the X variables in a multiple logistic regression model can be dropped, that is, in testing whether the associated regression coefficients $\beta_k = 0$. The test procedure employed in this research is the general linear test procedure for Maximum likelihood estimation, the test is called the likelihood ratio test. It is based on comparison of full and reduced models. The full Poisson model with response function

$X'\beta_F = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_{k-1} X_{k-1}$ ………………………………………… (19)

Wald test (Z* - test)

A large-sample test of a regression parameter can be constructed based on the hypotheses, such that

$H_0: \beta_k = 0\ against\ H_0: \beta_k \neq 0$ ……………………………………………………… (20)

an appropriate test statistic is:

$Z^* - \frac{b_0}{S(b_k)}, k = 0,1,\dots,p$ …………………………………………………………….. (21)

and the decision rule is:

if $|Z^*| \leq Z_{\left(1-\frac{\alpha}{2}\right)}$ *accept* H_0, *otherwise reject* H_0 *where* Z is a standard normal random variable and $S(b_k)$ is the estimated approximate standard deviation of b_k obtained from Equation (3.51) and (3.52).

Criteria for Model Selection

The Model selection criteria considered in this research are (1) Akaike Information Criterions (AIC) and (2) Bayesian Information Criterions (BIC)

Akaike Information Criterions (AIC)

The general form for calculating AIC

$AIC = -2 \times In(Likelihood) + 2 \times p$ .... (22)

where

In is the natural logarithm (Likelihood) is the value of the likelihood P is the number of parameter in the model. AIC can be calculated using residual sum of squares from regression (Henry, 2010):

$AIC = n \times In(RSS/n) + 2 \times p$ .... (23)

where n is the number of data points (observations)

RSS is the residual sum of squares

AIC requires a bias- adjustment small sample sizes. If ratio of $\frac{n}{k} < 40$, then use bias – adjustment:

$AICC = n \times In\ (likelihood) + 2p + \frac{(2p(p+1))}{(n-p-1)}$ .... (24)

Note that the parameters are defined as above in Equation (3.56). Also, that as the size of the dataset, n, increases relative to the number of parameters, p; the bias-adjustment term on the right becomes very small. Therefore, it is recommended that we always use the small sample adjustment.

Bayesian Information Criterions (BIC)

The general form for calculating BIC

$BICC = n \times In(likelihood)) + n \times In(n) + [Inn] \times p$ .... (25)

Note: all parameters are defined as Equation (3.56); and the small values of BIC and AIC model will be chosen as the best model for the selected models (or selected as the suitable model among the selected models) [Schwarz, 1978].

Presentation of Data

The Table 1 below shows the total number of people in road accident along Bamenda-Douala expressway from 2011-2020 in years, with fatal cases, serious cases, minor cases, number of persons killed, number of persons injured, total cases and total casualty.

Table 1. Data on road traffic accidents from 2011-2020 along Bamenda-Douala expressway

Year	Fatal cases	Serious cases	Minor cases	Total cases	No. Of Persons Killed	No. Of Persons Injured	Total Casualty
2011	14	43	16	73	53	109	162
2012	9	39	14	62	42	101	143
2013	11	32	13	56	38	99	137
2014	13	44	17	74	41	102	143
2015	15	47	12	74	38	83	121
2016	9	27	7	43	19	93	112
2017	13	17	6	36	21	187	208
2018	28	124	17	169	49	451	500
2019	27	96	6	129	46	353	399
2020	29	92	19	140	54	465	519

Source: MINTP (Ministère des Travaux Publics.

Volatility and Trends: The data in Table 1exhibits considerable year-to-year variability, making it difficult to discern clear linear trends visually, especially for the early years. The trend from 2018 onward shows a marked increase compared to the years before 2018. There is a marked increase in fatal, serious, total cases, the number of persons killed and injured as well as total casualty after 2017. Fatal cases are relatively low compared to serious and minor cases, but their number of persons killed is high. This means more people die per fatal accident. This could be because many people were in each fatal accident. Follow a somewhat erratic pattern and a large value from 2018-2020. Relatively lower, with noticeable drops in 2016 and 2017, before experiencing a sharp rise in 2020. This could mean that there was less reporting of minor cases in the past. Reflect the trends of serious and minor cases, showing the highest values in 2018-2020. The Table also shows that the peak of the number of Persons Killed is in 2020, the trend follows total cases. There is a volatile higher number of persons injured at 2018, and again in 2020 whereas the total Casualties exhibit dramatic increases from 2018 to 2020.

RESULTS AND DISCUSSION

Table 2: Correlation of number of accidents: 2011, 2012, 2013,2014, 2015, 2016 ,2017, 2018, 2019 and 2020

	Year	Total cases	Fatal cases	Serious cases	Minor cases	Person killed	Person injured
Year	1	0.474 0.166	0.646 0.043	0.467 0.174	-0.055 0.880	0.164 0.650	0.612 0000
Total cases	0.474 0.166	1.000	0.841 0.002	0.985 0.000	0.578 0.080	0.759 0.011	0.565 0.089
Fatal cases	0.646 0.043	0.841 0.002	10.000.000	0.829 0.003	0.362 0.304	0.691 0.027	0.701 0.024
Serious Cases	0.457 0.174	0.985 0.000	0.829 0.003	1.000 0.000	0.445 0.197	0.711 0.21	0.515 0.128
Minor Cases	-0.055 0.886	0.578 0.080	0.362 0.304	0.445 0.197	1.000 0.000	0.673 0.033	0.366 0.298
Person killed	0.164 0.650	0.759 0.011	0.691 0.027	0.711 0.021	0.673 0.033	1.000 0.000	0.711 0.021
Person injured	0.6120.060	0.565 0.89	0.701 0.24	0.515 0.128	0.366 0.298	0.711 0.021	1.000 0.000

Table 2 displays the P-Value and the Pearson correlation value. A correlation coefficient measures the strength and direction of a linear relationship between two variables with values range from -1 to +1: Where +1 is perfect positive correlation (as one variable increases, the other increases proportionally) whereas -1 is perfect negative correlation (as one variable increases, the other decreases proportionally) while 0 mean no linear correlation. The closer the absolute value of the coefficient is to 1, the stronger the relationship. Generally, from 0.7 or higher: Strong correlation, 0.5 to 0.7: Moderate correlation, 0.3 to 0.5: Weak correlation and below 0.3: Very weak or negligible correlation

From Table 2 above shows that the Total Cases vs. Fatal Cases (Correlation = 0.841) is a strong positive correlation, suggesting that as the total number of accident cases increases, the number of fatal cases also tends to increase. Total Cases vs. Serious Cases (Correlation = 0.985) is a very strong positive correlation. This suggests that as the total number of accident cases increases, the number of serious cases also tends to increase. Total Cases vs. Minor Cases (Correlation = 0.578) is a moderate positive correlation, suggests that as the total number of accident cases increases, the number of minor cases also tends to increase. Fatal Cases vs. Person Killed (Correlation = 0.691) is a moderate positive correlation suggesting that as the number of fatal accident cases increases, the number of people killed also tends to increase.

Serious Cases vs. Person Injured (Correlation = 0.515) is a moderate positive correlation suggesting that as the number of serious accident cases increases, the number of people injured also tends to increase. Year vs. Total Cases (Correlation = 0.474) is a weak positive correlation. It suggests that there is a slight tendency for the total number of accident cases to increase over the years (2011-2020). However, the relationship isn't very strong, and other factors are likely more influential. Year vs. Person Killed (Correlation = 0.164) is a very weak positive correlation. It suggests that there is a very slight tendency for the number of people killed to increase over the years (2011-2020). However, the relationship isn't very strong, and other factors are likely more influential and Year vs. Minor cases (Correlation = -0.055) is a very weak negative correlation.

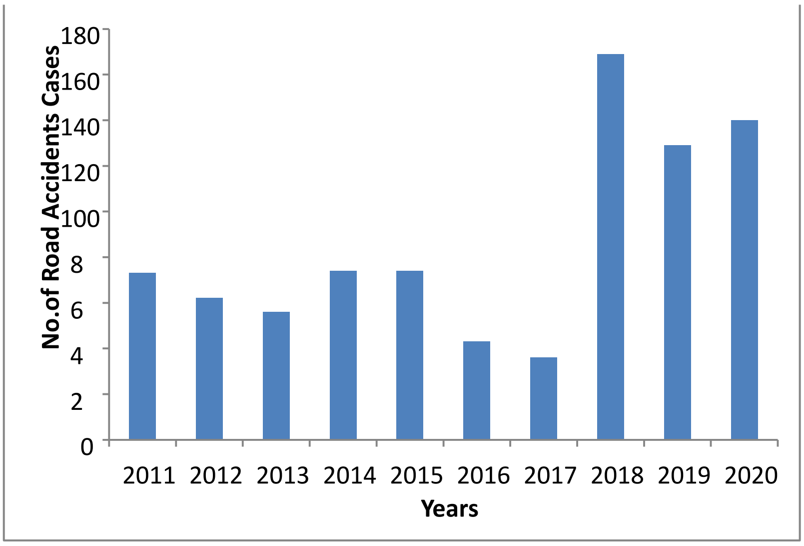

Figure 1: Graph showing number of total accidents cases along Bamenda-Douala expressway from 2011-2020.

It is interesting to observed from Figure 1 note from the graph of Figure 1 that the year 2018 has the highest number of road traffic cases of 169 persons followed by year 2020 and 2019 which is 140 and 129 respectively. This shows that road traffic accidents along Bamenda-Douala Road is on the increase.

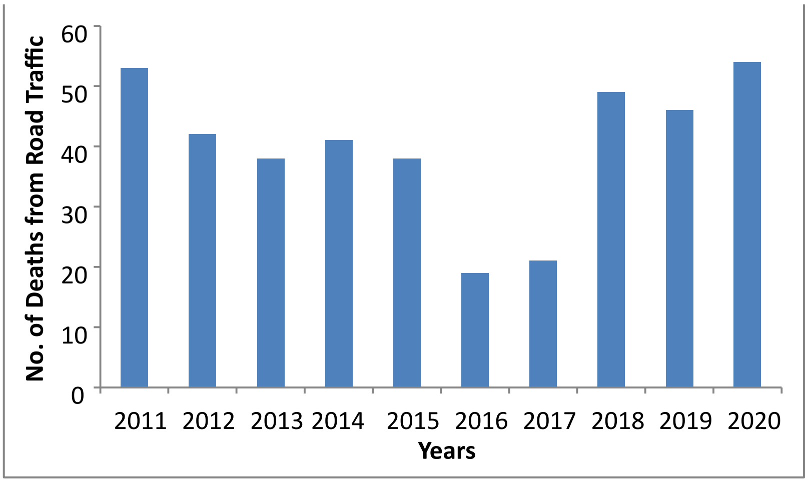

Figure 2: Graph showing number of death cases from 2011-2020 along Bamenda-Douala expressway.

In figure 2, it is observed that the death cases in year 2020 is the highest with 54 persons killed followed by 2011 and 2018 with 53 and 49 persons killed respectively.

Fitted Poisson Regression Model

Table 3: Estimated Coefficients, Wald Chi-Square and Significance Values Model

Parameter	Estimate	Std Error	Wald Chi-Square	Significance Value
(Intercept)	4516	0.1045	1865.79	0.000
Fatal Cases	-0.011	0.0164	0.436	0.509
Serious Cases	-0.001	0.0015	0.327	0.567
Minor Cases	-0.019	0.0076	6.047	0.014
Persons Killed	0.011	0.049	4.765	0.029
Persons Injured	0.004	0.0007	36.442	0.000

The fitted Poisson response function and the fitted values in Table 4 is expressed as;

$\text{Exp}(X_i', \beta) = exp(4516 - 0.011X_1 - 0.001X_2 - 0.019X_3 + 0.011X_4 + 0.004X_5)$

The table presents the results of a Poisson regression model, where the dependent variable is likely the number of road traffic accidents along Bamenda-Douala expressway. The table shows the estimated coefficients, standard errors, Wald Chi-Square statistics, and significance values (p-values) for each predictor variable included in the model. The intercept term is representing the log of the expected accident rate when all other predictor variables are zero. The extremely low p-value (0.000) indicates that the intercept is highly statistically significant.

The model identifies Minor Cases, Persons Killed, and Persons Injured as statistically significant predictors of the accident rate along the Bamenda-Douala expressway. The negative coefficients for Fatal Cases, Serious Cases, and Minor Cases suggests that an increase in the number of variables is associated with a decrease in the overall accident rate due to more care being taken. The positive and significant coefficients align with the expectation that more severe accidents are associated with a higher overall accident rate. The equation () is an expression representing the predicted rate of road traffic accidents. exp(...): The exponential function $e^{((4516-0.011X_1-0.001X_2-0.019X_3+0.011X_4+0.004X_5))}$ is used to transform the linear predictor into a rate (a positive value that can be interpreted as the expected number of accidents per unit of time or space). For instance, to obtain the expected number of the intercept

We exponentiate the coefficients and calculate the percentage changes, then interpret them in the context of the Cameroon road traffic accident analysis.

Table 4. Exponentiating Coefficients and Calculating Percentage Changes:

S/N	Parameter	Estimate	Exponentiated value	Percentage Change
1	(Intercept)	4516	5.74×10^{1961}	-
2	Fatal Cases	-0.011	0.989	1.1
3	Serious Cases	-0.001	0.999	0.1
4	Minor Cases	-0.019	0.981	1.9
5	Persons Killed	0.011	1.011	1.1
6	Persons Injured	0.004	1.004	0.04

The percentage in the table above are calculated as follows. For x_1 which represent fatal cases.

x_1 (Fatal Cases): Coefficient: -0.011, Exponentiated: $exp(-0.011) \approx 0.989$, Percentage Change: $(0.989 - 1) \times 100\% \approx -1.1\%$.

From the Table 5, the exponentiated value of the intercept is the baseline accident rate when all other variables are zero. For every one-unit increase in fatal cases, the predicted accident rate decreases by approximately 1.1%. For every one-unit increase in serious cases, the predicted accident rate decreases by approximately 0.1%. For every one-unit increase in minor cases, the predicted accident rate decreases by approximately 1.9% For every one-unit increase in persons killed, the predicted accident rate increases by approximately 1.1%. For every one-unit increase in persons injured, the predicted accident rate increases by approximately 0.4%.

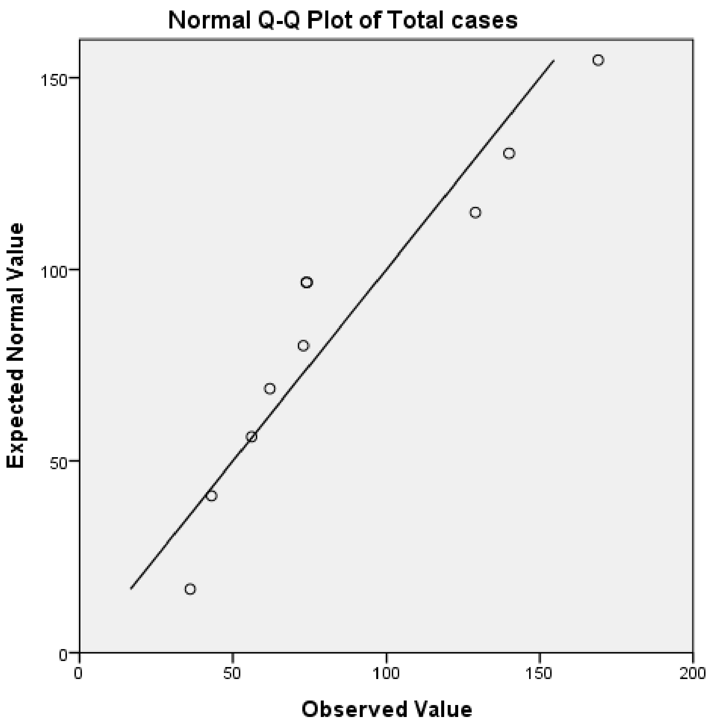

Figure 3 is a normal quantile-quantile plot comparing independent standard deviation Residuals on the vertical axis to a standard normal theoretical quantile on the horizontal axis. The linearity of the points suggests that the data are normally distributed.

CONCLUSION

This study concludes that there is a significant positive relationship between total cases and death from road accidents from 2011-2020 on Bamenda-Douala road. The project revealed significant negative trend in deaths from road accident from 2011-2020.

Policy Implications

1) The significant impact of "Persons Injured" suggests that interventions aimed at reducing the severity of accidents and minimizing injuries could be particularly effective.
2) The counterintuitive finding regarding "Fatal Cases" needs further investigation. It is crucial to understand why more fatal cases might be associated with a *lower* overall accident rate. This could reveal underlying factors that are not captured in the model.
Model Limitations: It's important to remember that this model only includes these specific variables. Other important factors (road conditions, weather, driver behavior, vehicle characteristics, etc.) might also be significant predictors of accidents and should be considered in a more comprehensive analysis.

Future Research

i) Explore the possible reasons for the negative coefficient on "Fatal Cases", "Serious Cases", and "Minor Cases".
ii) Consider adding other relevant predictor variables to the model to improve its explanatory power.
iii) Conduct further analysis to understand the interactions between different predictor variables.
v) Validate the model using a separate dataset or a different time period.
In conclusion, this table provides valuable insights into the factors associated with road traffic accidents on the Bamenda-Douala expressway. However, it's crucial to interpret the results cautiously, considering the potential limitations of the model and the need for further investigation to fully understand the complex dynamics of road safety in this region.

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