Road Traffic Fatalities in Malawi: The Role of Pedestrian Behaviour Factors

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Key Findings

- The negative binomial regression model was found to be the best fitting model or the model that better agrees with the data.
- Pedestrian behaviour factors of walking on roads, crossing outside pedestrian crossings, crossing carelessly, and other forms of negligence demonstrated a positive relationship with road-related fatalities.
- Behaviour factors of being under the influence of alcohol demonstrated zero influence and crossing at pedestrian crossings exhibited a small negative influence.
- There was a 1% increase in the number of crash deaths for every additional fatal crash involving pedestrians walking on a road.

Abstract

Pedestrian behaviour is one of the major contributors to road fatalities. The negative binomial regression model was found to better agree with road fatality data, and this study used this model to assess the influence of pedestrian behaviour factors on road fatalities in Malawi. The data used in this analysis were crash reports of pedestrian behaviour factors and observed fatalities for the period 2000–2015 obtained from the national database, except for the 2013 data, which were disregarded because they appeared to be incomplete. Whereas pedestrian behaviour factors of walking on roads, crossing outside pedestrian crossings, and other negligent and careless behaviours were found to be positively correlated with road deaths, indicating that road-related fatalities increased with increasing input data, factors of being under the influence of alcohol and crossing at pedestrian crossings demonstrated negligible influence. The study also found that there was a 1% increase in the number of crash deaths for every additional fatal crash involving pedestrians walking on roads. Moreover, an additional 0.5% increase in the number of fatalities was recorded for every fatal crash involving a pedestrian behaviour factor of crossing outside the pedestrian crossing or other negligent behaviour. An increase of 0.3% in the number of the fatalities was seen for every extra fatal crash caused by crossing carelessly or factors other than pedestrian behaviour. Despite coefficient values being small in all variables, which is a major limitation of this study, enforcement can prioritise those variables that increase road-related fatalities or even couple them with other risk factors such as speed.

Keywords

Road Fatalities, Pedestrian Behaviour Factors, Count Data, Poisson Regression Models, Malawi

Introduction

Pedestrians are among the most vulnerable road users in almost all regions of the world, according to the World Health Organization (WHO), with Africa being the most severely affected (WHO, 2015). The recent WHO report on the global status of road safety indicates that pedestrians represented 39% of all crash deaths that occurred in Africa (WHO, 2015). Some reported studies have shown that the highest proportion of crash-related deaths reported in many African countries involve pedestrians. For example, an analysis of 2010 crash reports in Malawi showed that pedestrians accounted for 48% of all road deaths (Kuotha et al., 2016). An analysis of crash reports in Malawi for the period 2000–2015 also shows that the rate of road-related pedestrian fatalities remained high, at 47% (Table 1). Odero et al. (2003) reported that, in Kenya, pedestrians alone represented 42% of all crash victims killed between 1971

Table 1. Distribution of road fatalities in Malawi by road user class (2000–2015)

Road user category	Killed	Proportion (%)
Bicyclist	1891	16.4
Driver	1044	9
Motorcyclist	163	1.4
Pedestrian	5373	46.5
Passenger	3092	26.7
Total	11563	100

Source: National crash database

and 1990. Similarly, pedestrians accounted for 55% of all road traffic deaths in Mozambique in the period 1993–2000 (Romão et al., 2003) and 46% of all crash deaths reported in Ghana in the period 1994–1998 (Afukaar et al., 2003). Unlike in Malawi, in Ghana in 2016, road-related pedestrian fatalities were reported to have decreased to 22% (National Road Safety Commission, 2016); nevertheless, they remained high, being the second most common category of road-related deaths.

In addition to the high numbers of pedestrian deaths from exposure to road traffic (Odero, 1995; Khayesi, 1997, 1999; Said, 2000; Nantulya & Muli-Musiime, 2001), they also belong to the most disadvantageous social-economic group, particularly in Africa (Nantulya & Muli-Musiime, 2001). Road-related pedestrian fatalities in Africa are on the increase, and equivocal evidence points to contributions from pedestrian behaviour. For example, Ahmed (2016) showed that the probability of being involved in a fatal pedestrian crash increases with increasing road speed limit, increasing number of lanes, lack of designated crosswalks, and pedestrians crossing at mid-block sections, on rural roads, and in dark locations. Another study found that older pedestrians' road-crossing behaviour in complex traffic situations was less safe than that of their younger counterparts while, in less complex situations, older pedestrians' behaviour was more like that of younger pedestrians (Oxely et al., 1995). Poudel-Tandukar et al. (2007) found that there is no significant association between road behaviours such as 'looking both ways along the road before crossing' or 'playing in the road or sidewalks' and pedestrian injury. Further, Praveen et al. (2018) found that pedestrians with technological and social distractions were more prone to road traffic injuries. In observing the complexity of understanding the influence of pedestrian behaviour on fatalities, Mako and Szakoyi (2016) suggested that there should be a stronger contribution from human and engineering fields to realise more positive change in the safety of vulnerable road users. This study aims to assess the influence of pedestrian behaviour factors on road fatalities in Malawi. The study is a contribution towards addressing the growing problem of road traffic injuries through enhancing the understanding of the contributory factors towards pedestrian-related traffic fatalities. This study will help ensure that already scarce resources mainly in low-income countries (Lagarde, 2007) such as Malawi are properly targeted, thereby improving peoples' well-being.

Methodology

Archived crash data were analysed to establish the influence of pedestrian behaviour factors on road fatalities in Malawi. The following discusses mainly the data sources and methods used for collecting and analysing the data. The conceptual framework for the methodology used in this study is presented in Figure 1.

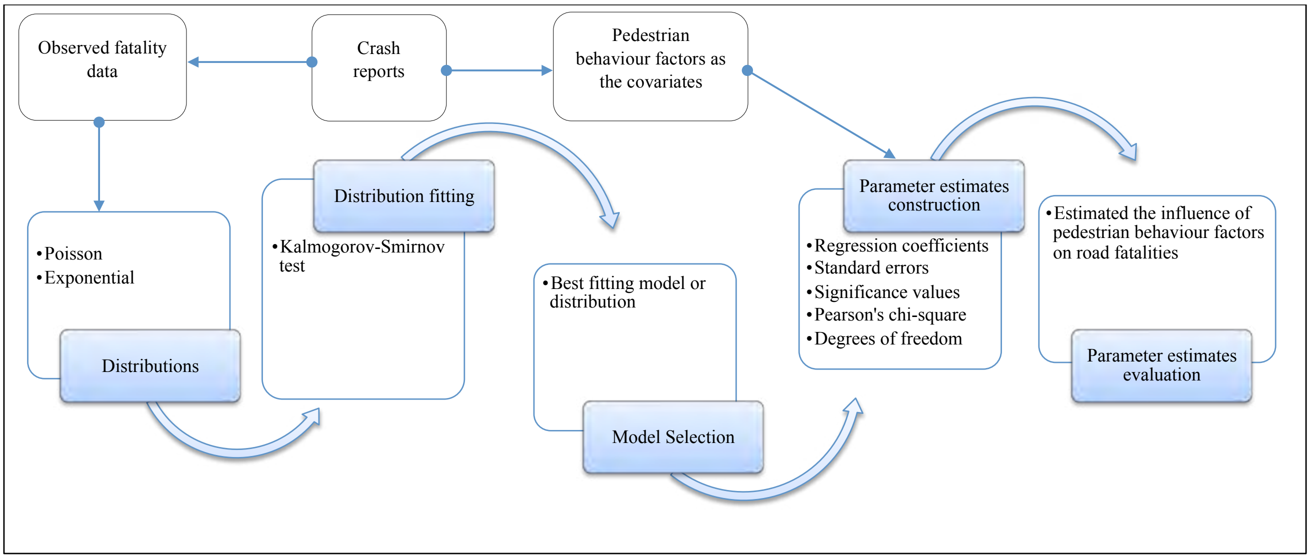

Figure 1. Process undertaken to assess the influence of pedestrian behaviour factors on road fatalities in Malawi

Data Sources and Type

Police are the only source of crash data in Malawi and routinely collect data on road crashes, personal injuries (minor, serious, and fatal), and property damage. Accident report forms are used for recording crash details to provide consistency in reporting. Apart from the data being used for court prosecution and insurance compensation by police, they are also sent to the Malawi Directorate of Road Traffic & Safety Services (DRTSS) for processing, storage, and reporting to state authorities and the general public. In Malawi, a death is considered a result of a road accident if the victim dies instantly or within 30 days of the crash ("Road Traffic Act," 1997; WHO, 2013).

The data used in this analysis, which are crash reports for pedestrian behaviour factors and fatalities, are presented in Table 2. These data were obtained from the national database of annual crash reports kept and managed by DRTSS. They cover the period from 2000 to 2015, except for the 2013 data, which were disregarded because they appeared to be incomplete. The restructuring of DRTSS in 2013 affected data recording in that year. However, statistics and trends of the observed data (Table 2) show that data entry became normal again in 2014 and subsequent years.

Model Identification

Studies in the past have generally suggested the use of regression count models such as Poisson regression (PR) and negative binomial regression (NBR) models (Cameron & Trivedi, 1998; Wulu et al., 2002; Surhone et al., 2010; Sarani et al., 2012) and autoregressive (AR) and autoregressive integrated moving average (ARIMA) (Lana et al., 2018) time series models for estimating road traffic fatalities. Because crash deaths are data counts in positive integers and generally small in sample size, PR or NBR models have generally been favoured as powerful tools for making reliable predictions in road safety (Cameron & Trivedi, 1998; Wulu et al., 2002; Surhone et al., 2010; Sarani et al., 2012. Further, as the intent of this study is to establish the influences of pedestrian behaviour factors on road traffic fatalities, PR models were deemed appropriate as they use multivariate data to establish the relationship between the influencing factors and outcome data (Sarani et al., 2012).

Apart from the fact that data must be count data, they should also meet the distribution assumption for purposes of using PR models for statistical analyses. To satisfy this assumption, the observed traffic fatality data (Table 2) were tested for Poisson and exponential distributions. These distributions were tested using the Kalmogorov–Smirnov (K-S) test. One of the advantages of the K-S test is that it

Table 2. Annual distribution of road crashes by pedestrian behaviour factors

Year	BUI	Crossing at pedestrian crossing	Crossing carelessly	Crossing outside pedestrian crossing	Nothing noted	Walking on road	Other	Traffic fatalities
2000	7	2	60	2	39	5	1	342
2001	9	0	55	7	54	9	4	321
2002	10	0	90	6	107	15	3	453
2003	10	3	82	2	57	16	8	432
2004	5	7	30	0	58	12	39	283
2005	11	3	124	1	267	21	42	1027
2006	8	2	124	0	218	25	17	930
2007	15	1	118	1	257	9	18	841
2008	23	3	103	1	308	22	28	942
2009	17	6	64	2	200	19	52	863
2010	15	5	88	0	324	20	22	976
2011	11	5	75	3	230	15	28	784
2012	17	8	102	3	144	9	143	880
2013	4	2	28	1	126	11	20	416
2014	14	0	42	1	378	13	17	1068
2015	17	0	67	5	341	18	24	1068

Source: National crash database

does not depend on adequate sample size for the test results to be valid (Croarkin et al., 2002); hence, it is ideal for this study because the observed datasets are not long enough (n = 15). In this case, the distribution that showed better agreement with the data could be used for determining the influence of pedestrian behaviour factors on road traffic fatalities.

Mathematical structures for PR and NBR models recommended for estimating crash data are expressed in the following.

Poisson regression model

Suppose Y is a discrete random variable such as crash deaths having independent response variables $y_1, y_2, \ldots, y_n$ that follow a Poisson distribution (Wulu et al., 2002). The density function of a PR model of a random count Y given x_i (Cameron & Trivedi, 1998; Wulu et al., 2002; Surhone et al., 2010; Sarani et al., 2012) may be defined as follows:

$$f(Y = y_i \mid x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \qquad y_i = 0,1,2,\ldots, \tag{1}$$

where μ_i is the mean incidence rate of events for an observation i which are crash deaths; and μ_i is also the called exponential mean or linear parameter of the PR model. Therefore,

$$\mathrm{E}[y_i \mid x_i] = \mu_i = \exp\left(\beta_0 + X_i^{'}\beta_i\right) = \exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni}) \tag{2}$$

Taking the natural logarithm of the linear parameter (μ_i) gives

$$\ln\mathrm{E}[y_i \mid x_i] = \ln\mu_i = \ln[\exp\left(\beta_0 + X_i^{'}\beta_i\right)]$$

$$= \ln[\exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni})],$$

$$f(Y = y_i \mid x_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} \tag{3}$$

where $y_i = \mu_i$ is the incidence rate of events for an observation i that follows a Poisson distribution, which are the crash deaths; $\beta = \beta_1, \beta_2, \ldots, \beta_n$ are the regression coefficients for the explanatory variables of pedestrian behaviour factors of walking on the road, crossing outside pedestrian crossings, other negligent behaviour, crossing carelessly, being under the influence (BUI) of alcohol, and crossing at pedestrian crossings estimated from a set of crash data; $X = X_{1i}, X_{2i}, \ldots, X_{ni}$ are a set of n explanatory variables of the above-mentioned pedestrian behaviour factors; and β_0 is a constant (intercept).

Equation (3) is referred to as a PR model. The assumption is that the mean and variance are equal and this model describes a set of count data as equidispersed. Hence, PR models are ideal for handling equidispersion (Wulu et al., 2002).

Negative binomial regression model

The negative binomial distribution is a mixture of Poisson and gamma distributions (Surhone et al., 2010; Hilbe, 2011). Suppose Y is a discrete random variable such as crash deaths having independent response variables $y_1, y_2, \ldots, y_n$ that follow a negative binomial distribution (Wulu et al., 2002). The density distribution of an NBR model of a discrete random count Y given θ_i (Cameron & Trivedi, 1998) is as follows:

$$f(Y = y_i \mid \theta_i) = \frac{\exp(-\theta_i)(\theta_i)^{y_i}}{y_i!}, \; y = 0, 1, \ldots, \tag{4}$$

where $\theta_i = \mu_i v_i$.

Suppose the parameter θ_i has a random intercept term and that the random term enters the conditional mean function multiplicatively (Cameron & Trivedi, 1998), that is,

$$\theta_i = \mu_i v_i = \exp\,(\beta_0 + X_i^{'}\beta_i + \varepsilon_i) = \text{linear parameter}$$
$$= e^{X_i^{'}\beta_i} e^{\beta_0 + \varepsilon_i}, \tag{5}$$

where $\exp(\beta_0 + \varepsilon_i)$ is interpreted as a random intercept, $\mu_i = e^{(\beta_0 + X_i^{'}\beta_i)}$ is the mean incidence rate of events for an observation i, which are crash deaths, and $v_i = e^{\varepsilon_i}$ is the NBR model error term.

Taking the natural logarithm of the linear parameter ($\theta_i = \mu_i v_i$) gives

$$\ln(\theta_i = \mu_i v_i) = \ln\,[\exp\,(\beta_0 + X_i^{'}\beta_i + \varepsilon_i)]$$
$$= \beta_0 + X_i^{'}\beta_i + \varepsilon_i,$$

where

$$X_i^{'}\beta_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni}.$$

Therefore,

$$f(Y = y_i \mid \mu_i, v_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} + \varepsilon_i, \tag{6}$$

where $y_i = \mu_i$ is the incidence rate of events for an observation i that follows a negative binomial distribution, which are the crash deaths; $\beta = \beta_1, \beta_2, \ldots, \beta_n$ are the regression coefficients for the same explanatory variables as explained in the PR model; $X = X_{1i}, X_{2i}, \ldots, X_{ni}$ are a set of n explanatory variables of the same pedestrian behaviour factors as described in the PR model; β_0 is a constant (intercept); and ε is the NBR model error term.

Equation (6) is referred to as an NBR model. The assumption is that the variance is greater than the mean and this model describes a set of count data as overdispersed. Therefore, NBR models are ideal for handling overdispersion (Wulu et al., 2002).

The parameter estimates for these models (PR and NBR) can be constructed using these equations, i.e., Eq. (3) for the PR model and Eq. (6) for the NBR model. However, performing analyses using this approach (equations) could be too tedious and overwhelming; therefore, any appropriate statistical software can be used.

For this study, the parameter estimates for the model (PR or NBR) that demonstrated better agreement with the observed fatality data were constructed using SPSS software. The constructed parameter estimates were mainly regression coefficients (β), standard errors (SEs), two-tailed significance (ρ), Pearson's chi-square, and degree of freedom (DF). The regression coefficients were used for defining the level of influence of pedestrian behaviour factors on road fatalities, and Pearson's chi-square and DF were used for testing data characteristics.

Results and Discussion

To assess the influence of pedestrian behaviour factors on road fatalities in Malawi, data on crash reports as presented in Table 2 have been considered. The analyses were conducted in two stages:

i. A goodness-of-fit test was undertaken for different distributions to identify a best-fit distribution or a model that best agrees with the data to ensure that valid results or estimates are obtained.

ii. Unknown parameter estimates of the best-fit distribution or model identified in (i) were constructed. This will be the model to use for determining the influence of pedestrian behaviour factors on road traffic fatalities in Malawi.

Goodness-of-Fit Test for Different Distributions

The results of a series of K-S tests performed on the observed traffic fatalities are presented in Table 3. At a significance level of 0.05, values of $p \leq 0.05$ rejected the null assumption that data followed a specified distribution and accepted the alternative hypothesis. The results show that the K-S tests rejected the supposition that data were Poisson distributed as the p value ($p = 0.000$) was < 0.5 and failed to reject the exponential assumption ($p = 0.096$). The exponential family also comprises distributions such as gamma, Poisson, and negative binomial. Studies recommend PR and NBR models as the ideal tools for analysing crash data and the Poisson distribution has been rejected (Table 3), demonstrating the appropriate use of the NBR model.

Table 3. Distribution fitness statistics

Distribution	K-S test		
	Statistic	***N***	**Significance level**
Poisson	2.322	15	0.000
Exponential	1.231	15	0.096

Parameter Estimates

Using SPSS software for count models, the NBR model was run to assess the influence of pedestrian behaviour factors (see Table 2) on road fatalities in Malawi and its parameter estimates are presented in Table 4. The results of the Omnibus test show that the model was statistically better over its null model (without predictors), a statistically significant result, with $p = 0.000 < 0.05$. Another way of stating this is to say that the model was not statistically different from its null model. The results further show that pedestrian behaviour factors of walking on the road (β = 0.009), crossing outside pedestrian crossings (β = 0.003), other negligent behaviours (β = 0.004), and crossing carelessly (β = 0.003) were positively correlated with road fatalities. This indicates that the rate of road-related fatalities increases with increasing input data of these variables, hence providing an important development in road safety. Despite this, the coefficient values in all variables were negligible, indicating that these behaviour factors had an insignificant influence on road fatalities, which is a major limitation of this study. However, with more input data in the future, the influence of these variables could intensify and become detrimental to road safety.

Because pedestrian behaviour factors have been demonstrated to make an insignificant contribution to the risk of road fatalities in the country, other factors rather than these variables must play a major role in the risk of road-related pedestrian fatalities observed in Table 1 and the total number of road fatalities. One such factor could be speed. This assumption is supported by much of the literature. As stated earlier, research has shown that the rate of fatal pedestrian crashes increases with increasing speed limit (Ahmed, 2016). Studies have also indicated that the large proportion of road traffic deaths for vulnerable road users mainly in African countries (Odero et al., 2003; Romão et al., 2003; Afukaar et al., 2003; WHO, 2015) is explained by the traffic mix (of pedestrians, bicyclists, motorcyclists, cars, trucks, and buses), which exposes road users with the least degree of protection to high-speed traffic (Tiwari et al., 1998; Peden et al., 2004; Lagarde, 2007).

Even though these variables have been shown to have an insignificant influence on road fatalities, these findings can still contribute to road safety. BUI was found to have no influence (β = 0.000) on road fatalities and crossing at pedestrian crossings was negatively correlated (β = –0.008) (Table 4), supporting the literature. Because income is positively associated with alcohol-related deadly crashes (Peden et al., 2004; Vecino-Ortiz et al., 2014), it should not be surprising for this study to find that the factor of pedestrians BUI has no influence on road fatalities because pedestrians are generally economically underprivileged in developing countries (Nantulya & Muli-Musiime, 2001). The numbers of fatal pedestrian crashes should also be minimal at pedestrian crossings because most pedestrian crossings, particularly in public built-up areas such as schools and markets, are mostly constructed with speed humps or rumble strips or a combination of both, which automatically forces drivers to reduce approaching speed and saves lives (Afukaar, 2003; Forjuoh, 2003).

Lastly, it can be seen that the value of Pearson's chi-square (0.152) divided by degrees of freedom (7) did not yield a value equal or close to 1.0 (being 0.0217) (Table 4). This suggests that the observed fatalities were not overdispersed and hence the NBR model performed the same as an

Table 4. Parameter estimates

Variable	Negative binomial regression		
	β	Standard error	Significance level at 95% confidence interval
Intercept	5.366	0.2238	0.000
BUI	0.000	0.0133	0.981
Crossing at pedestrian crossing	-0.008	0.0342	0.826
Crossing carelessly	0.003	0.0018	0.065
Crossing outside pedestrian crossing	0.003	0.0282	0.912
Nothing noted	0.003	0.0007	0.000
Walking on road	0.009	0.0100	0.386
Other form of negligence	0.004	0.0024	0.090
	Value	Value/DF	
DF	7		
Pearson's chi-square	0.152	0.0217	
Omnibus (*p*)	0.000		

ordinary PR model could have done. The NBR model handles overdispersed data by offering an improvement in the parameter estimates of the PR model (Cameron & Trivedi, 1998; Wulu et al., 2002; Lord & Mannering, 2010).

Percentage Change in Fatalities Resulting from Pedestrian Behaviours

From the analysis of the data in Table 2, it was found that there was a 1% increase in the number of crash deaths for every additional fatal crash involving pedestrians walking on a road. Moreover, an additional 0.5% increase in the number fatalities was recorded for every fatal crash involving the pedestrian behaviour factor of crossing outside pedestrian crossings or other negligent behaviour. An increase of 0.3% in the number of fatalities was seen for every extra fatal crash caused by pedestrians crossing carelessly or factors other than pedestrian behaviours.

Conclusions

The study found that, between 2000 and 2015, there was a 1% increase in the number of crash deaths for every additional fatal crash involving pedestrians walking on the road. An additional 0.5% increase was recorded for every fatal crash involving the pedestrian behaviour factor of crossing outside pedestrian crossings or other negligent behaviour. Further, a 0.3% increase was noted for every extra fatal crash caused by pedestrians crossing carelessly or factors other than pedestrian behaviours.

An NBR model was developed to estimate the influence of pedestrian behaviour factors on road fatalities in Malawi, and these factors are listed in Table 2. Through their coefficient values, it was found that the covariates such as 'Being under the influence of alcohol,' even including other factors, possibly have minimal effect on road safety in Malawi, as the coefficients have very small values, but this was a major limitation of this study.

However, with the availability of more input data in the future, meaningful results may be obtained in assessing the key covariates. Because of the general concern over pedestrian fatalities, it is important that these covariates be considered when conducting public awareness campaigns and law enforcement. DRTSS regularly conducts awareness campaigns to educate pedestrians about the safety benefits of observing traffic rules that govern their movements on roads. These campaigns should be maintained.

Another limitation of this study was the use of police-recorded data. These data are often underreported by gross margins (Liren, 1996; Jacobs et al., 2000; Gururaj et al., 2000; Mackay, 2003; Peden et al., 2004). Therefore, the findings of this study may not reflect the true influence of the covariates. Malawi needs to establish more data sources to be used for comparison with data reported by police.

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References

Afukaar, F. K. (2003). Speed control in developing countries: issues, challenges and opportunities in reducing road traffic injuries. *INJURY CONTROL AND SAFETY PROMOTION, 10*(1-2), 77-81.

Afukaar, F. K., Antwi, P., & Ofosu-Amaah, S. (2003). Pattern of road traffic injuries in Ghana: implications for control. *INJURY CONTROL AND SAFETY PROMOTION, 10*(1/2), 69-76.

Ahmed, M. S. (2016, October 16-20, 2016). *Pedestrian Safety and Road Crossing Behaviour: A Case Study of Abu Dhabi.* Paper presented at the 2nd IRF Asia Regional Congress, Kuala Lumpur, Malaysia.

Cameron, A. C., & Trivedi, P. K. (1998). *Regression analysis of count data*. Cambridge, UK: Cambridge university press.

Croarkin, C., Tobias, P., & Zey, C. (2002). *Engineering statistics handbook*: NIST iTL.

Forjuoh, S. N. (2003). Traffic-related injury prevention interventions for low-income countries. *INJURY CONTROL AND SAFETY PROMOTION, 10*(1-2), 109-118.

Gururaj, G., Thomas, A. A., & Reddi, M. (2000). *Underreporting of road traffic injuries in Bangalore. Implications for road safety policies and programmes.* Paper presented at the Proceedings of the 5th world conference on injury prevention and control.

Hilbe, J. (2011). *Negative Binomial Regression* (2nd ed.). New York: Cambridge University Press.

Jacobs, G., Aeron-Thomas, A., & Astrop, A. (2000). Estimating global road fatalities (Vol. 1-35). Crowthorne: U.K.: Transport Research Laboratory.

Khayesi, M. (1997). Livable streets for pedestrians in Nairobi: The challenge of road traffic accidents. *World Transport Policy and Practice, 3*(1), 4-7.

Khayesi, M. (1999). *An analysis of the pattern of road traffic accidents in relation to selected social-economic dynamics and intervention measures in Kenya* (Ph.D. dissertation), Kenyatta University.

Kuotha, W. S., Ngwira, G. M., & Ngoma, I. (2016). *Road Traffic Injuries in Malawi: Their Magnitude, Major Causes and Action for Intervention.* Paper presented at the 3rd International Conference on Transportation in Africa (ICTA2016), Ramada Resort, Accra, Ghana.

Lagarde, E. (2007). Road traffic injury is an escalating burden in Africa and deserves proportionate research efforts. *PLoS medicine, 4*(6), 170.

Lana, I., Del Ser, J., Velez, M., & Viahogogianni, E. I. (2018). Road traffic forecasting: recent advances and new challenges. *IEEE Intelligent Transportation Systems Magazine, 10*(2), 93-109.

Liren, D. (1996). *Viewing china road traffic safety and the countermeasures in accordance with international comparison. Beijing research in traffic engineering.* Paper presented at the Proceedings of the Second Conference in Asian Road Safety.

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. *Transportation Research Part A: Policy and Practice, 44*(5), 291-305.

Mackay, M. (2003). *National differences in European mass accident data bases.* Paper presented at the Proceedings: Contemporary Injury Severity and Outcome Issues, RCOBI Annual Conference, Lisbon, Portugal.

Mako, E., & Szakoyi, P. (2016). Evaluation of human behaviour at pedestrian crossings. Transportation Research Procedia. *Transportation Research Procedia, 14*(2016), 2121-2128.

Nantulya, V. M., & Muli-Musiime, F. (2001). Kenya: uncovering the social determinants of road traffic accidents. *Challenging inequities in health: from ethics to action*, 211-225.

National Road Safety Commission. (2016). Ghana 2016 National Road Traffic Crash Statistics Report. Kumasi: CSIR – Building and Road Research Institute.

Odero, W. (1995). Road traffic accidents in Kenya: An epidemiological appraisal. *East African Medical Journal, 75*(5), 299-305.

Odero, W., Khayesi, M., & Heda, P. M. (2003). Road traffic injuries in Kenya: Magnitude, causes and status of intervention. *INJURY CONTROL AND SAFETY PROMOTION, 10*(1-2), 53-61.

Oxely, J., B., F., Ihsen, E., Day, R., & Charlton, J. (1995). An investigation of road crossing bahaviour of older pedestrians. Victoria, Australia: Monash University Accident Research Centre.

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., & Mathers, C. (2004). *World report on road traffic injury prevention*. Geneva, Switzerland: World Health Organisation (WHO).

Poudel-Tandukar, K., Nakaraha, S., Ichikawa, M., Poudel, K. C., & Jimba, M. (2007). Risk perception, road behaviour, and pedestrian injury among adolescent students in Kathmandu, Nepal. *Injury prevention, 13*, 258-263.

Praveen, K. N., Nandini, C., Saranya, R., & Sridevi, N. H. (2018). Impact of pedestrian crossing behaviour at intersections on road traffic accidents in Shivamogga, Karnataka: an observational study. *International Journal of Community Medicine and Public Health, 5*(6), 2437-2441.

Road Traffic Act, Road Traffic Directorate, Malawi (1997).

Romão, F., Nizamo, H., Mapasse, D., Rafico, M. M., José, J., Mataruca, S., . . . Bicho, J. M. M. (2003). Road traffic injuries in Mozambique. *INJURY CONTROL AND SAFETY PROMOTION, 10*(1-2), 63-67.

Said, S. H. (2000). *The care burden and severity profit of road trauma admissions at Kenyatta National Hospital.* (M.Med.), University of Nairobi, Nairobi, Kenya.

Sarani, R., Rahim, S., Marjan, J. M., & Wong, S. (2012). Predicting Malaysian Road Fatalities for Year 2020. *Kuala Lumpur: Malaysian Institute of Road Safety Research (MIROS)*.

Surhone, L. M., Timpledon, M. T., & Marseken, S. F. (2010). *Ncss (Statistical Software)*: VDM Publishing.

Tiwari, G., Mohan, D., & Fazio, J. (1998). Conflict analysis for prediction of fatal crash locations in mixed traffic streams. *Accident Analysis & Prevention, 30*(2), 207-215.

Vecino-Ortiz, A. I., Bishai, D., Chandran, A., Bhalla, K., Bachani, A. M., Gupta, S., . . . Hyder, A. A. (2014). Seatbelt wearing rates in middle income countries: A cross-country analysis. *Accident Analysis & Prevention, 71*, 115-119.

WHO. (2013). *WHO global status report on road safety 2013: supporting a decade of action*. Geneva, Switzerland: World Health Organization.

WHO. (2015). *Global status report on road safety 2015*. Geneva, Switzerland: World Health Organization.

Wulu, J., Singh, K., Famoye, F., & McGwin, G. (2002). Regression analysis of count data. *Journal of the Indian Society of Agricultural Statistics, 55*(2), 220-231.