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Exploring the Predictors of Accident Severity in Urban Ghana

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Abstract
Road traffic accidents involving adverse severe outcomes, injuries and fatalities in particular are among the major challenges facing Ghana. The present study investigates the underlying predictors of fatal and injury accidents in Kumasi, Ghana. A sample of 608 accident cases was systematically sampled from a large traffic police database. Data analysis was performed using the logit model with stepwise variable selection at 0.05 and deletion at 0.10. Of the entire sample, 56.6% were injury and 43.4% involved in at least one fatality. The model revealed that the significant predictors of severe accidents were mainly overcrowding, driver indiscipline on roads, driver fatigue, and design and conditions of roads with estimated odds ratio of 2.42, 3.83, 10.51 and 12.06 respectively. Other variables including speed, drunk driving, not using helmet, mechanical fault, over loading and indiscriminate use of roads by pedestrians were not significant predictors of severe accidents. Prevention strategies should target effective law enforcement, traffic regulations and safe road engineering.
Keywords: Road Traffic Accident, Fatality, Injury, Stepwise Logit Model

1. Introduction

Among the major challenges facing Ghana are the magnitudes of road traffic accidents, resulting injuries and fatalities. The National Road Safety Commission launched an information campaign using TV programs to educate professional drivers and to promote road safety in the country (Blantari et al. 2005). Moreover, in urban areas, speed limiting bumps are constructed on roads in order to reduce speed related accidents. Despite these road safety approaches, the rates of traffic accidents and related adverse outcomes on the roads of Ghana are very alarming. Evidence from 1994-1998 police data indicates that road traffic accidents are the leading cause of death and injuries in the country (Afukaar et al. 2003). Chen (2009) found that more than 100 people die in traffic crashes per 10,000 vehicles in Tanzania and Ghana, compared to the 1.7 fatalities per 10,000 vehicles in the US.

Most Ghanaians in urban areas use public transportation for daily routine activities. As passengers, they are exposed to the risks of accident, injury and fatality involving public buses. This risk is heightened by poor vehicle design, roadside hazard, and transportation conditions such as lack of seatbelts, overcrowding, and hazardous road environment. In one epidemiological study of transport related injuries in urban Ghana, Mock et al. (1999) found that the most common transport-related mechanisms were either to passengers involved in crashes of mini-buses or taxis (29%) or to pedestrians struck by these vehicles (21%).

For every vehicle accident, there are numerous factors contributing to its severity. Speed has been identified as a key risk factor in road traffic injuries, influencing both the risk of a road accident as well as the severity of the injuries that result from collisions. The Research and Innovative Technology Administration (RITA) of the U.S. Department of Transportation reports that vehicle speed as well as road way characteristics are major contributing factors of multi-vehicle (three or more) fatal crashes (Guarino and Champaneri 2010) . In Ghana, excessive vehicular speeds, inappropriate use of goods vehicles for passenger transport, excessive loading and inadequate trauma care are the key contributory risk factors to the high frequency of road traffic fatalities (Ackaah and Adonteng 2011). In another study, the main risk factors influencing pedestrian accidents on trunk roads in the country are daily pedestrian flow and vehicle kilometers travelled (Obeng and Salifu 2013). Moreover, driver fatigue, especially truck and bus driver fatigue are major issue, threatening transportation safety in the world at large (Adams-Guppy and Guppy 2003).

The studies of the causal relationship between traffic accidents or adverse outcomes of collisions and risk factors have extensively been considered within the framework of regression analysis. However, Jovanis and Chang (1986) discovered that accident data violates the homoscedasticity assumption of ordinary least squares regression (OLS), in that the variance of accident frequency increases with vehicular distance travelled in kilometers. Therefore, Poisson regression was applied as a means to predict accident. Moreover, Shankar et al. (1996) used nested logit model to analyze accident severity and suggested that environmental conditions, accident type, vehicle characteristics, highway design, and driver characteristics significantly influence accident severity. The multinomial logistic regression model has been used to study the associations between pedestrian injury and explanatory variables such as vehicular characteristics, temporal trends, and road environment (Damsere-Derry et al. 2010). The negative binomial model was used to investigate the effect of potential explanatory variables on traffic accident frequency for T and X-junctions in Ghana (Salifu 2004). In the same country, Ackaah and Salifu (2011) used the generalized linear model (GLM) with negative binomial error structure to study vehicular crashes occurring on the rural sections of the highways in the Ashanti region.

Though this subject has gained sufficient recognition within the context of regression analysis, additional studies within this framework are still needed due to differences in accident data, in particular variation in risk factors. Even in the same country, the key risk factors of traffic accidents and resulting adverse outcomes may vary across different sections of roads.

The objective of this study is to explore the key underlying determinants of fatal and injury accidents in urban Ghana, using Kumasi as the case study.

2.0 Materials and Methods

2.1 Data

The basis of statistical analysis of this paper is from data obtained from the Motor Transport and Traffic Unit (MTTU) of the Zongo police station in Kumasi, Ghana. The station is the headquarters of the ”B” District with jurisdiction covering highly populated areas like Central market, Asafo, Oforikrom, Manhyia and other areas. Extraction of data was done manually from a large police report of the period 2005-2009 using systematic sampling. Data was then classified as injury or fatal accident according to the following definitions: An accident was classified under fatal if the accident resulted into the death of at least one person; otherwise it was classified as injury. These were then recorded against circumstances surrounding the underlying cause of injury or fatality.

2.2 Method of Statistical Analysis

We performed binary logistic regression analysis, from which a logit model was formulated. To account for binary outcome, the response variable accident severity was artificially dichotomized into injury and fatal accidents. An accident is classified as fatal if it resulted to the death of at least one person, otherwise it is injury accident. In the coding scheme, the numbers 0 and 1 were used to indicate injury and fatal accidents respectively. For a dichotomous response variable Y taking on values 0 (i.e. injury accident) and 1 (i.e. fatal accident) with covariate vector

$X' = (x_1 \dots \dots \dots \dots \dots x_p)$ the logistic regression model for fatal outcome is written as

$$P\left(y = \frac{1}{x_1} \dots x_p\right) = \frac{exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)}{1 + exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)} \quad (1)$$

Where the $\beta_{j's}$ represent the regression coefficients which are estimated from data by the method of maximum likelihood estimation (MLE). Let the conditional probability of fatal outcome be denoted by

$$P\left(y = \frac{1}{x_1} \dots x_p\right) = \pi(x)$$

The expression in Equation 2 is called the odds.

$$\frac{\pi(x)}{1-\pi(x)} \quad (2)$$

Taking the natural logarithm of the odds gives the logit model $f(x)$ in Equation 3 which is a representation of the log transformation of the logistic regression model

$$f(x) = ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p) \quad (3)$$

The test of statistical significance was based on the p-values corresponding to the Wald statistic of the coefficient estimates ˆ/3j. The Wald statistic is obtained from the following vector-matrix algebra

$$\mathrm{W} = \beta'[\widehat{var}(\hat{\beta})]^{-1}(\hat{\beta}) \quad (4)$$

$$= (\hat{\beta})'(x\hat{v}x)\,\hat{\beta} \quad (5)$$

which is distributed as chi-square with p + 1 degrees of freedom under the hypothesis that each of the $p + 1$ coefficients is equal to zero (Hosmer et al. 2013). $x$is an n by $p + 1$ matrix containing the data for each subject and V is an n by n diagonal matrix with general element $\hat{\pi} \quad (1 - \hat{\pi}_i)$.

The stepwise selection method of model building was used. By this approach, variables with p-values less than 0.05 were selected into the model and those remaining significant at 0.10 were retained in the model by systematic approach.

The independent variables were measured on categorical scale and were given codes 0 or 1 to indicate the absence or presence of a risk factor respectively. The difference in logit for fatal accident with $x = 1$ and $x = 0$ was computed by

$$f(1) - f(0) = (\beta_0 + \beta_1 * 1) - (\beta_0 + \beta_1 * 0) = (\beta_0 + \beta_1) - (\beta_0) = \beta_1 \quad (6)$$

Moreover, the odds ratio, denoted OR, of fatal accident for the presence of a risk factor, $x = 1$ compared to the absence of the factor $x = 1$ was expressed by

$$\mathrm{OR} = \exp(\beta_1) \quad (7)$$

Comparison and the selection of the model which adequately fits the data was done by using the Akaike Information Criterion (AIC) ,the Schwarz Criterion (SC), and the deviance. The AIC is given by

$$AIC = -2logL + 2(p + 1) \quad (8)$$

where L is the likelihood of the fitted model and p is the number of regression coefficients estimated for nonconstant covariates. Also, the SC is given by

$$SC = -2logL + (k-1) + p)\log(\sum f_i) \quad (9)$$

Where the $f_i's$ are the frequency values of the ith observation and k is the number of levels of the dependent variable. The deviance is written as

$$D = -2logL \quad (10)$$

and so the AIC and SC penalize the log-likelihood by the number of predictors in the model. The model with the least AIC, SC and deviance is the preferred one. The analysis of these statistical techniques was computationally implemented using the SAS statistical software.

3. RESULTS

The methodologies discussed in the previous section are applied in this section to analyze road accident data. Of 608 accident cases sampled, 56.6% were injury whilst 43.4% were fatal accidents (Table 1). Design and condition of roads, driver fatigue, overcrowding, and driver indiscipline on roads are the factors accounting for high levels of injuries and fatalities.

Presented in Table 2 are the parameter estimates and their corresponding p-values of four different logit regression models for the association of risk factors and the outcome of road traffic accident fitted by the method of stepwise selection. Also, the goodness of fit statistics is given for each model.

Using the stepwise selection method, a significance level of 0.05 is required to allow a variable into the model, and a significance level of 0.10 is required for a variable to stay in the model. In this approach, an attempt is made to delete any insignificant variable from the model before adding a significant variable. Each addition or deletion of a variable to or from the model are listed as separate models as displayed in Table 2.

The variable overcrowding is selected into model 1 since it is significant ($p=0.007 <0.05$). The initial model that contains an intercept and overcrowding is fitted. Overcrowding remain significant ($p= 0.018 < 0.10$). The respective Values of Akaike's information criterion (AIC), Schwarz criterion (SC) and deviance for the resulting model are 29.82, 32.34 and 25.78.

Driver indiscipline on roads is added in model 2. The model then contains an intercept and variables overcrowding and driver indiscipline on roads. Both variables remain significant at 0.10 level; therefore neither overcrowding nor driver indiscipline on roads is removed from the model. The AIC and deviance decreased slightly to 29.78 and 23.78 respectively, whilst SC increased to 33.56.

The variable driver fatigue is added in model 3. The resulting model contains the intercept together with variables overcrowding, driver indiscipline on roads and driver fatigue. The respective values of AIC, SC and deviance are 29.76, 34.80, and 21.76.

Moreover, the variable design and condition of roads is entered in model 4. All the variables in this model remained significant at 0.10 level, as result none of them is deleted. Finally, none of the remaining variables meet the entry criterion and stepwise selection is terminated. Whilst model 4 has the highest SC of 35.52, the AIC of 29.23 and deviance of 19.23 are the least among the fitted models. Using these indicators simultaneously, we have no evidence to select the model which adequate fits the accident data. However, the likelihood ratio chi-square of 14.32 with corresponding p-value of 0.0055 suggests that model 4 fits significantly better than an empty model, compared to the other models (Table 3).

Table 4 presents results of the selected logit model. From the model, the intercept with p-value of 0.191 is statistically insignificant at0.10 level. However, the variables overcrowding, driver indiscipline on roads, driver fatigue, and design and conditions of roads with estimated odds ratio of 2.42, 3.83, 10.51 and 12.06 respectively are significantly associated with traffic fatalities. The odds ratio of 2.42 for overcrowding indicates that the odds being in a fatal accident at overcrowded sections of roads is 2.42 higher than non-overcrowded sections.

The variables speed, drunk driving, not using helmet, mechanical fault, excessive loading and indiscriminate use of roads by pedestrians are not significant predictors of accidents involving fatalities.

Moreover, dropping the insignificant variables we obtain the model logit (Odds) = 7.968 + 0.883X1 + 1.343X2 + 2.352X3 + 2.490X4 (11)

where X1, X2, X3 and X4 represent overcrowding, driver indiscipline on roads, driver fatigue, and design and condition of roads respectively.

3.1 DISCUSSION

Road traffic accidents and related adverse outcomes, particularly injuries and fatalities continue to be among the major challenges of all countries of the world. Despite numerous years of research, issues on traffic safety management still remain unresolved; moreover, resulting fatalities and injuries are understudy. Effective traffic safety management and control of adverse traffic outcomes requires a better understanding of the underlying factors associated with severe accidents. Findings from previous studies indicates that speed is a major contributing factor of traffic accidents (Guarino and Champaneri 2010; Ackaah and Adonteng 2011). On the contrary, results presented in this study indicate that speed is not a significant predictor of traffic fatalities and injuries in Kumasi. This may be due to the fact that the urban roads in Ghana are mostly overcrowded and does not provide room for inappropriate speeding. In line with this, we found that overcrowding is an important predictor of traffic fatalities and injuries. Moreover, driver indiscipline on roads, driver fatigue, and design and condition of roads emerged as significant predictors of traffic fatalities and injuries. Similar to the work of Adams-Guppy and Guppy (2003), driver fatigue are among the major factors threatening traffic safety in Africa. Existing findings have found road design to be a significant factor resulting to severe forms of traffic accidents (Shankar et al. 1996). Excessive loading is not significant predictor of traffic fatalities and injuries in urban Ghana, contrary to previous findings by Ackaah and Adonteng (2011). Furthermore, not using helmet, mechanical fault, drunk driving and indiscriminate use of road by pedestrian are not significant predictors of traffic fatalities in urban Ghana.

4. CONCLUSION

In this paper, we identified the significant underlying predictors of fatal and injury accidents in Kumasi using the logit model. The significant predictors found are overcrowding, driver indiscipline on roads, driver fatigue, and, design and conditions. Design and conditions of roads as well as driver fatigue were found to be the most threatening factor influencing traffic fatalities and injuries in the locality. Other factors including speed, drunk driving, not using helmet, mechanical fault, excessive loading and indiscriminate use of roads by pedestrians are not significant predictors. Prevention strategies should target effective law enforcement, traffic regulation and safe road engineering.

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Notes

Table 1: Distribution of Injury and Fatal accidents against Risk Factors

Variables	Injury Accident	Fatal Accident	Total
Design and condition of roads	78	64	142
Speed	27	18	45
Overcrowding	50	43	93
Drunk driving	14	9	23
Driver fatigue	72	51	123
Non using helmet	4	11	15
Driver indiscipline on roads	46	38	84
Mechanical faults	27	11	38
Excessive loading	7	5	12
Indiscriminate use of roads by pedestrians	19	14	33
Total	**344 (56.6%)**	**264 (43.4%)**	**608**

Notes

Table 1: Distribution of Injury and Fatal accidents against Risk Factors

Variables	Injury Accident	Fatal Accident	Total
Design and condition of roads	78	64	142
Speed	27	18	45
Overcrowding	50	43	93
Drunk driving	14	9	23
Driver fatigue	72	51	123
Non using helmet	4	11	15
Driver indiscipline on roads	46	38	84
Mechanical faults	27	11	38
Excessive loading	7	5	12
Indiscriminate use of roads by pedestrians	19	14	33
Total	**344 (56.6%)**	**264 (43.4%)**	**608**

Table 2: Logit Models with Stepwise Variable Selection for Accident Severity

Variables	Estimate	Entry p-value	Deletion p-value
Model 1			
Intercept	-3.659	0.008	0.008
Overcrowding	0.115	0.007	0.018
AIC	29.82		
SC	32.34		
Deviance	25.82		
Model 2			
Intercept	-5.662	0.008	0.010
Overcrowding	0.229	0.018	0.022
Indiscipline on roads	0.669	0.022	0.041
AIC	29.78		
SC	33.56		
Deviance	23.78		
Model 3			
Intercept	6.225	0.010	0.240
Overcrowding	0.369	0.022	0.022
Indiscipline on roads	1.339	0.041	0.080
Driver fatigue	1.116	0.033	0.031
AIC	29.76		
SC	34.80		
Deviance	21.76		
Model 4			
Intercept	7.968	0.240	0.191
Overcrowding	0.883	0.022	0.035
Indiscipline on roads	1.343	0.080	0.057
Driver fatigue	2.352	0.031	0.074
Design and condition of roads	2.490	0.044	0.077
AIC	29.23		
SC	35.52		
Deviance	19.23		

Table 3: Fit Statistics of the Logit Models for Injury and Fatal accidents

Model	Likelihood Ratio χ^2	p-value
Model 1	7.72	0.0082
Model 2	9.76	0.0076
Model 3	11.78	0.0064
Model 4	14.32	0.0055

Table 4: Selected Logit Model for Injury and Fatal Accidents

	Estimate	Std. Error	OR	p-value
Intercept	7.968	6.308	2887.1	0.191
Overcrowding	0.883	0.133	2.42	0.035
Indiscipline on roads	1.343	1.001	3.83	0.057
Driver fatigue	2.352	0.171	10.51	0.074
Design and condition of roads	2.490	2.675	12.06	0.077

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