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ORIGINAL ARTICLE

A generalized ordered logit analysis of risk factors associated with driver injury severity

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Abstract

Aim Road traffic crashes remain a major public health issue and have been the subject of debate in many studies due to their effect on society. This study contributes to the discussion by investigating the risk factors that significantly contribute to driver injury severity sustained in traffic crashes.

Subject and methods Using the crash data from the Greater Accra region of Ghana, spanning a 3-year period (2014–2016), a generalized ordered logit (GOL) model was estimated to determine the effect of a wide range of variables on driver injury severity outcome.

Results The results suggest that, in the event of a crash, more severe driver injury was influenced by multiple factors including driver's gender, driver's action (e.g., turning, overtaking, going ahead), number of vehicles involved, day of week of the crash, vehicle size, and road width.

Conclusion The findings of this study highlight the need to further study risk factors significantly influencing driver injury severity.

Keywords Driver injury severity · Ordered response · Generalized ordered logit model · Accra

Introduction

Road traffic crashes have been the subject of discussion in many studies due to increasing incidence rates year after year and the fatalities associated with the crashes (WHO 2015). Road traffic crashes are claimed to cause significant cost to society in terms of human casualties (death and disability), economic losses, emotional burden, and transportation problems (Chen et al. 2016d; Lee and Li 2014). They have been described as the leading cause of deaths and serious injuries in both developed and developing countries (Tay and Rifaat 2007). In Ghana, the annual road crash statistics depict that fatalities due to road traffic crashes in 2016 increased by 15.6% and resulted in 2084 deaths (Agyeman et al. 2017). Thus, the improvement of road safety in Ghana requires an in-depth understanding of the factors contributing to injury severity in other to develop appropriate countermeasures.

Due to the health consequences of traffic crashes, most of the literature on traffic safety has focused on how to minimize their occurrence and, particularly, to identify factors influencing the severity of injury sustained by the casualties (Chen et al. 2016d). Previous studies have identified a wide range of factors that potentially influenced injury severity of casualties involved in road traffic crashes; these include roadway characteristics, occupant/pedestrian characteristics, vehicle characteristics, and weather and environmental conditions (Amoh-Gyimah et al. 2016; Aziz et al. 2013; Chen and Chen 2011). The findings from these studies have contributed to reducing the rate of incidence and severity of injury sustained by casualties.

Although several studies on injury severity have been conducted in Ghana, little attention has been given to factors influencing vehicle occupant injury severity. However, understanding such aspects can help improve the safety of all road users. The objective of this study was to identify factors that significantly influence driver injury severity in the event of a crash. Such analysis is important to provide useful insights for road safety policies in Ghana.

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The use of statistical models for crash injury severity analysis has become an increasingly important topic within road safety science (Savolainen et al. 2011; Ye and Lord 2013). One obvious use of models is for assessing the risk factors associated with road crash severity and aiding design issues in roadway travel (Chang and Chien 2013; Kockelman and Kweon 2002; Ye and Lord 2013). Such studies are important for developing effective countermeasures to reduce the risk of crash and the associated severities (Chen et al. 2016d). A wide range of statistical models has been implemented to identify factors that influence injury severity associated with road casualties (Savolainen et al. 2011; Ye and Lord 2013). The commonly used injury severity models can be grouped into nominal (e.g., multinomial logit, nested logit and mixed multinomial logit) and ordinal (e.g., ordered logit/probit and GOL). Since injury severity is considered as an ordinal response variable, i.e., it descends from the highest injury (fatal) to the least serious (no injury), the use of an ordinal model is appropriate to account for the ordering nature of the variable (Abdel-Aty 2003; Wang and Abdel-Aty 2008). In this study, a GOL model was implemented. The choice of this model was influenced by its ability to handle proportional odds assumptions associated with a conventional ordered logit/probit approach (Williams 2006). Not only that, this model is also recommended as the best alternative to a multinomial logit model for ordinal response variables (Eluru 2013).

Material and methods

Model specification

This study implemented a GOL model to analyse driver injury severity. The GOL model extends the traditional ordered logit model to overcome proportional odds assumption associated with the former (Williams 2006). That is, the GOL model allows the parameters to vary across the categories of the response variable. Given a response variable y with J injury severity levels, the probability of a driver injury severity for a given crash can be defined as:

$$p(y>j)=\frac{\exp\left(\alpha_j-X_i\beta_j\right)}{1+\exp\left(\alpha_j-X_i\beta_j\right)},\quad j=1,\ \ldots,\mathrm{J}{-}1$$

where j represents an injury severity category, α_j represents the cut-off point for the j^{th} cumulative logit, β_j is a vector of model parameters, and $X_i$is a vector of observed explanatory variables (Williams 2006). In practice, the proportional odds assumption may be violated by one or several variables (Michalaki et al. 2015; Wang and Abdel-Aty 2008). In such a situation, some of the parameters of variables satisfying the proportional odds assumption may be redundant (Quddus et al. 2010; Williams 2006). Hence, a gamma parameterized form of the GOL model proposed by Peterson and Harrell (1990) is commonly used. The gamma parameterized GOL model is commonly known as the partially constrained GOL or partial proportional odds model. The partially constrained GOL model is defined as:

$$p(y>j)=\frac{\exp\left[\alpha_j-\left(X_i\beta_j+T_i\gamma_j\right)\right]}{1+\exp\left[\alpha_j-\left(X_i\beta_j+T_i'\gamma_j\right)\right]}$$

where T_i represents a subset of explanatory variables for which the proportional odds assumption is violated and γ_j is a vector of parameters associated with T_i (Wang and Abdel-Aty 2008). The gamma coefficients represent deviations from proportionality. If all gammas are equal to zero, the model reduces to the traditional ordered logit model. The parameters of the model are estimated using the maximum likelihood procedure (Williams 2006).

Data description

In this study, driver injury severity data for the Greater Accra region of Ghana, spanning a 3-year period from 2014 to 2016, were used. The Greater Accra area is the most populous region in Ghana. The capital city of Ghana, Accra, is located here. The region has the highest number of vehicle fleets and records the highest number of road traffic crashes (Agyeman et al. 2017). tThe data were extracted from the National Road Traffic Accident Database hosted by the Building and Road Research Institute of the Council for Scientific and Industrial Research, Ghana. The data contain detailed information about crashes and vehicle and driver characteristics, including time of the crash, location, number of vehicles involved, vehicle type, weather conditions, environmental conditions, roadway geometric characteristics, driver injury severity, driver demographic characteristics, and so on. The frequency and percentage distribution of the variables considered in this study are presented in Table 1. All the independent variables were categorical with different levels. The response variable—driver injury severity—was categorized into three levels: killed or seriously injured (KSI), minor injury, and no injury. KSI describes a situation where the driver died within 30 days of the crash event or was hospitalized for at least 24 h for medical attention. Minor injury describes a situation where the driver sustained little injury after the crash, requiring no or less than 24 h of hospital treatment, and no injury described a situation where the driver sustained no injury after the crash. In all, there were 14,603 observations over the study period, with missing or incomplete records for some variables. Out of the 14,603 vehicles involved in road traffic crashes over the study period, 3.4% of the drivers were killed or sustained serious injury, 10.7% were recorded as having minor injuries, and 86% were recorded as uninjured (Table 1). After screening out incomplete records, 14,548 observations were ultimately used for model

Table 1 Frequency and percentage distribution of all the variables considered in this study

Variable	Frequency	Percentage
Driver injury severity		
Killed or seriously injured (KSI)	490	3.36
Minor injury	1556	10.66
No injury	12,557	85.99
Driver gender		
Male	13,614	93.34
Female	971	6.66
Driver age		
< 26	1246	8.56
26–60	12,844	88.22
60+	469	3.22
Driver error		
At fault	9265	63.49
Not at fault	5328	36.51
Driver action		
Turning	639	4.38
Overtaking	243	1.66
Going ahead	12,561	86.03
Other	1157	7.92
Vehicle type		
Car	10,094	69.15
Medium-sized vehicles	2138	14.65
Large vehicle	2356	16.20
Vehicle defective		
Yes	1823	12.51
No	12,751	87.49
Number of crash vehicles		
Single	2722	18.64
Multiple	11,881	81.36
Day of week		
Weekday	10,293	70.49
Weekend	4310	29.51
Time of collision		
AM peak	2325	15.38
PM peak	3072	20.15
Off-peak	9808	64.47
Weather		
Clear	12,671	86.77
Other	1932	13.23
Light conditions		
Day	9887	67.71
Night-no lights	1397	9.57
Night-lights on	3319	22.73
Road description		
Straight and flat	14,290	97.87
Other	311	2.13
Road surface type		
Paved	15,099	99.33
Unpaved	104	0.67
Road separation		
Median	9327	63.87
No median	5276	36.13
Road surface condition		
Dry	14,505	99.33
Wet	98	0.67
Road works		
Yes	40	0.27
No	14,563	99.73
Location type		
At junction	4788	37.72
Not at junction	5537	62.08
Traffic control		
Signalized	6601	45.21
Non-signalized	8001	54.79
Road width		
6 m and less	9020	61.77
More than 6 m	5583	38.23
Collision type		
Head-on	858	5.88
Rear-end	6619	45.33
Right-angle	1239	8.48
Side-swipe	2473	16.93
Hit objects	2841	19.45
Run-off-road	573	3.92

development. It is important to state that under-reporting, comprising non-reporting and under-recording, has not been accounted for in this study.

Results and discussion

To determine the potential factors influencing driver injury severity level, a GOL model was fitted to the data. The estimated parameters of the fitted model are presented in Table 2. Since all the independent variables considered in the model are categorical, the inclusion of a variable in the model was based on the 90% significance level of at least one category of the same factor (Tay et al. 2011). The overall significance of the model relative to the null model (i.e., model with constant terms only) was found to be satisfactory as suggested by the p values of the likelihood ratio test, reported as goodness of fit in Table 2. Out of the 20 variables considered in the study, 13 were found to be significant (10% alpha level), representing factors that influence driver injury severity in the event of a crash. Whilst other studies have shown that driver age, driver error, driver action, road description, road surface type, road surface condition, and road works significantly influence driver injury severity, they were found not to be significant risk factors at the 10% alpha level in our study. The interpretation of the model parameters was according to the following sub-headings: driver characteristics, vehicle characteristics, temporal characteristics, environmental characteristics, and roadway characteristics.

Driver characteristics

While exploring driver characteristics, this study found that the gender of the driver significantly influenced the severity of the injuries they sustained during a crash. The results suggest that female drivers were more likely to be severely injured compared to males when involved in a crash. This finding is congruent with conclusions from other studies (Abay et al. 2013; Chen and Chen 2011). The variation in injury severity between males and females may be influenced by the fact that males are more likely to take evasive action that will prevent

Table 2 Generalized ordered logit model estimation results

Variable	Coefficient	Standard error	*P* value
Beta			
Driver gender (*Ref: Male*)			
Female	0.400	0.093	0.000
Driver action (*Ref: Other*)			
Turning	0.569	0.160	0.000
Overtaking	1.132	0.194	0.000
Going ahead	0.536	0.116	0.000
Vehicle type (*Ref: Car*)			
Medium-sized vehicle	0.056	0.073	0.440
Large vehicle	−0.305	0.075	0.000
Vehicle defective (*Ref: Yes*)			
No	−0.750	0.068	0.000
Number of crash vehicles (*Ref: Single*)			
Multiple	1.212	0.142	0.000
Day of week (*Ref: Weekday*)			
Weekend	0.105	0.054	0.055
Time of collision (*Ref: Off-peak*)			
AM peak	−0.167	0.078	0.033
PM peak	−0.119	0.066	0.071
Weather (*Ref: Other*)			
Clear	−0.149	0.084	0.077
Light conditions (Ref: Night–no lights)			
Day	−0.300	0.088	0.001
Night–lights on	−0.290	0.089	0.001
Road separation (*Ref: Median*)			
No median	−0.119	0.056	0.034
Traffic control (*Ref: Non-signalized*)			
Signalized	−0.109	0.054	0.047
Road width (*Ref: 6 m and less*)			
More than 6 m	0.108	0.052	0.036
Collision type (*Ref: Run-off-road*)			
Head-on	−1.762	0.176	0.000
Rear-end	−3.291	0.168	0.000
Right-angle	−2.959	0.185	0.000
Side-swipe	−3.455	0.178	0.000
Hit objects	−2.887	0.123	0.000
Gamma			
Clear weather	−0.266	0.108	0.013
Signalized traffic control	−0.474	0.096	0.000
Rear-end	−0.445	0.103	0.000
Alpha			
Constant 1	0.623	0.179	0.000
Constant 2	−0.562	0.197	0.004
Goodness-of-fit statistics			
Number of observations	14,548		
Log-likelihood at convergence	−6288		
Log-likelihood	−7043		
P value	0.000		
Pseudo R^2	0.105		

severe injury. According to Chen and Chen (2011), such differences are likely to be influenced by a combination of physiological and behavioural factors.

With respect to driver action, the results show that the driver's actions significantly influence the severity of the injury they sustained when involved in a crash. The results indicated that drivers turning, overtaking, or going ahead were more likely to sustain severe injury when involved in a crash compared to other actions, such as reversing, sudden stops and parking off road. This finding is consistent with other existing studies (Paleti et al. 2010; Wu et al. 2014) and may be explained by different factors. For instance, the effect of going ahead and overtaking may be influenced by excessive speeding, which increases the impact of vehicle damage and driver injury severity when there is a crash (Yasmin et al. 2014). High injury severity due to driver turning may be explained by the fact that turning drivers are more likely to have have disregarded traffic signals, leading to conflicting situations and high impact in the event of a crash (Wang and Abdel-Aty 2008). In addition, turning drivers have lower visibility and less time and space to respond to emergent situations.

Vehicle characteristics

The effect of vehicle type on driver injury severity revealed that in the event of a crash, the injuries sustained by medium-sized vehicle drivers were not significantly different from car drivers. However, drivers of larger vehicles were less likely to sustain severe injury compared to car drivers. This finding is in agreement with conclusions in other existing studies (Abay et al. 2013; Chen et al. 2016a) and may be explained by the fact that larger vehicles are able to better tolerate crash impact because of their body size and weight, leading to low driver injury severity.

In comparison with non-defective vehicles, defective vehicles were more likely to be associated with severe injury of the driver in the event of a crash. This result is consistent with existing findings (Kashani et al. 2012; Yamamoto and Shankar 2004) and may be influenced by the fact that defective vehicle parts such as tires, brakes, and suspensions may cause the driver to lose control of the vehicle, leading to high crash impact and severity.

With respect to number of vehicles, the results reported show that drivers were more likely to sustain severe injury when the crash involved multiple vehicles. The positive relationship between number of vehicles and injury severity may be influenced by the fact that crashes involving several vehicles lead to multiple collisions and larger impact, thereby increasing the likelihood of the driver to sustain severe injury (Chen et al. 2016b). In contrast, other studies (Chen et al. 2015; Chen and Chen 2011) have argued that drivers, particularly truck drivers, are less likely to sustain severe injury when involved in multi-vehicle crashes because of the large body size and high weight of their vehicle.

Temporal characteristics

In comparison with weekday crashes, drivers who were involved in crashes during weekends were more likely to sustain severe injury. This finding was expected (Kim et al. 2013) and could be explained by the behaviour of the drivers and traffic intensity. During weekdays, drivers are less likely to speed or be intoxicated because of high traffic volume or the presence of police respectively, leading to less driver injury in the event of a crash. On the other hand, drivers are more likely to not be sober during weekends because of more social functions, leading to careless and aggressive driving behaviour. Furthermore, unqualified drivers are more likely to drive during weekends than weekdays.

While exploring the effect of time of collision, the results of our study showed that drivers involved in crashes during AM and PM peaks were significantly less likely to sustain severe injury compared to off-peak periods. This finding is in agreement with the conclusions made in previous study (Huang et al. 2008) and may be explained by the fact that drivers are less likely to speed during peak periods compared to off-peak period because of high traffic intensity, leading to lower crash impact and injury severity in the event of an actual crash.

Environmental characteristics

The results from our analysis showed that weather conditions significantly influence injury severity of drivers when involved in a traffic crash. It has been found that drivers are less likely to sustain severe injury when the weather conditions are good. The positive effect of clear weather conditions may be due to high visibility (Chen et al. 2016c; Kim et al. 2013). That is, during adverse weather conditions (rain, fog, smoke, etc.), drivers usually have low visibility which can affect their ability respond to emergency situations requiring braking or maneuvering, leading in turn to more severe impact and injury when involved in a crash (Kim et al. 2013).

Light conditions were also found to affect driver injury severity during traffic crashes. Drivers were less likely to sustain severe injury when involved in crashes during day time or night time when it was light, compared to dark night times. This finding can be explained by lack of visibility during night-time driving, particularly affecting older drivers and resulting in high impact and injury severity in the event of crash. The result trend is consistent with existing studies from other countries (Huang et al. 2008; Kim et al. 2013; Wu et al. 2014).

Roadway characteristics

With regard to road separation, the results of our study showed that drivers were less likely to sustain severe injury when involved in a crash on roads without median barrier (such as cable barrier or wire rope). This result may be explained by the absence of median barriers enabling drivers to maneuver in an emergency situation, leading to less impact and injury severity. In addition, our results may be influenced by the fact that concrete median barriers are common in Ghana, and this median type increases the probability of more severe crash outcomes (Hu and Donnell 2010). In contrast, other studies have argued that the presence of median barriers reduces the risk of exposure to oncoming traffic and possible head-on collisions (Hu and Donnell 2010; Khorashadi et al. 2005), leading to lower impact and injury severity. Chen and Chen (2011) have also argued that the presence of median barriers may encourage drivers to drive more cautiously.

Roads with traffic controls/signals also significantly influence the injury severity of a driver when involved in a crash. Drivers were less likely to sustain severe injury when involved in a crash on roads with traffic signals compared to non-signalized roads. This finding may be explained by the fact that drivers are more likely to reduce speed when approaching signalized intersections, leading to less impact and injury severity in the event of a crash (Liu 2007).

With respect to road width, our results showed that roads with a width of 6 m and more were associated with severe injury in the event of crash. This result confirms existing findings (Yuan et al. 2017) and may be influenced by the fact that roads wider than 6 m are usually multi-lane highways and such roads are known to be associated with severe injury in the event of a crash due to the high levels of speed on found on them.

Collision type was identified as a significant variable that influences the injury severity of a driver when involved in a crash. Compared to run-off-road crashes, all other collision types were less likely to cause drivers to sustain severe injury when involved in a crash. This result is in agreement with existing studies which found that run-of-road crashes account for the majority of fatalities (Gong and Fan 2017; Shawky et al. 2015).

Conclusion

Based on the crash data of the Greater Accra region of Ghana spanning a 3-year period, this study explored the risk factors that contribute to driver injury severity in the event of a crash. Using a GOL model, multiple potential variables including driver, vehicle, temporal, environmental, and roadway characteristics were explored in the analysis. From the estimated models, the variables that significantly increase the likelihood of a driver to sustain severe injury include driver gender, driver action (e.g., turning, overtaking, going ahead), number of vehicles involved, weekend driving, vehicle size, and road width.

This study sheds some light on these factors in relation to the situation in the Greater Accra Region, Ghana. The findings suggest several policy directions relating to driver injury severity. For instance, education programs on driving and road safety should be intensified. Such schemes should explain the need for motorists to drive within posted speed limits, or even slower during adverse weather conditions, at weekends, and in dark areas. The installation of lighting systems on road segments where visibility is low would go a long way to minimizing severe crashes and also help to diminish the risk associated with other more vulnerable road users. Equipping un-signalized roads with traffic signals/control devices would be useful to avoid multi-vehicle crashes, particularly at intersections.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Informed consent Since this study used a data set that is available online in the public domain, there was no need to seek consent to publish the results.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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