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Identification of Determinant Factors for Car Accident Levels Occurred in Mekelle City, Tigray, Ethiopia: Ordered Logistic Regression Model Approach

Hagazi Gebre Meles[1*], Desta Brhanu Gebrehiwot[2], Fireweini Gebrearegay[3], Gebretsadik Gebru Wubet[4], and Teodros Gebregergis[4]

[1]Department of Biostatistics, School of Public Health, College of Health Sciences, Mekelle University, Ethiopia

[2]Department of Economics, College of Business and Economics, Mekelle University, Ethiopia

[3]Department of Nutrition and dietetics, School of Public Health, College of Health Sciences, Mekelle University, Ethiopia

[4]Department of Statistics, College of Natural and Computational Sciences, Mekelle University, Ethiopia

(*hagazi.gebre@mu.edu.et)

ABSTRACT

The car accident injury level is known to be a result of a complex interaction of factors to drivers' behavior, vehicle characteristics, and environmental condition. Therefore, it is obvious that identifying the contribution of the factors to the accident injury is very critical. The objective of the study was to perform a descriptive analysis to see the characteristics of car accidents, and to assess the prevalence and determinants of road safety practices in Mekelle City, Tigray, Ethiopia. A random sample of data was extracted from the traffic police office from September 2014 to July 2017. An ordered logistic regression model was used to examine factors that worsen the car accident level. A total sample of 385 car accidents was considered in the study of which 56.7% were fatal, 28.6% serious, and 14.7% slight injury. The model estimation result showed that being experienced drivers (Coef. = 0.686; p-value< = 0.050) were found to increase the level of injury. On the other hand, being private vehicle (Coef. = -1.160; p-value <= 0.010), the type of accident of vehicle with pedestrian (Coef. = -2.852; p-value <= 0.010), being heavy truck (Coef. = -0.656; p-value <= 0.050), being a cross country bus (Coef. = -0.889; p-value <= 0.050) and being owner of vehicle is the driver himself (Coef. = -.690, p-value <= 0.050) were found to decrease the level of car accident injury severity. In conclusion, it is better to create continued awareness for those who are experienced drivers, who carelessly follow the traffic rules. Special attention is required for government-owned vehicle drivers, as they were found to increase the level of car accident injury through different short-term training.

Keywords: Car accident, Ordered Logistic Regression, Injury Level, Mekelle, Tigray, Ethiopia.

1. INTRODUCTION

In the world, 3400 people die from different injuries due to road traffic accident. Road traffic accident injuries are among the three leading causes of death for the age group 5-44 years as reported by World Health Organization (WHO, 2019). Unless immediate and effective action is taken, road traffic injuries are predicted to become the fifth leading cause of death in the world,

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resulting in an estimated. The economic costs of accidents are estimated at 1% of gross national product (GNP) in low-income countries, 1.5% for cumulative income countries and 2% for high-income countries. Generally taken, the economic consequences of motor vehicle crashes have been estimated between $518 billion a year, caused by damage to traffic accidents (Temjanovski and Arsova, 2019).

Worldwide, 1.2 million people are killedand up to 50 million injured each year (WHO, 2013). In 2020, road traffic injuries are projected to become the 3rd largest cause of disabilitiesin the world (Odero and Ayuku, 2003). Data suggest that road traffic deaths and injuries in low- and middle-income countries are estimated to cause economic losses of up 5% of GDP. Globally an estimated 3% of GDP is lost to road traffic deaths and injuries WHO (2019).

Current and projected trends in motorization indicated that the problem of RTAs will get worse, leading to a global public health crisis. It has been indicated that, accordingly, by 2020 traffic accident is expected to be the third major killer after HIV/AIDS and TB (Peden et al., 2004). Transportation is one of the necessities for the simple functioning of societies as its demand is greatly related to the movement of people from one place to another. Since every bustle of human being has its own consequences (positive or negative) transport is not an exception to this circumstance. In connotation to Rallis (1977) have stated that the constraints associated with transport include the risk of traffic mobbing, traffic coincidence, pollution, noise, and the like. Road Traffic Accidents (Demirtas, 2008) are among the most damaging environmental effects, which have caused from transportation development. Road safety, therefore, urges serious concern worldwide.

RTAs have turned out to be a huge global public health and development problem killing almost 1.2 million people a year and wounding or disabling about 20-50 million people more; the combined population of five of the world’s large cities (Goswami and Sonowal, 2009). The statistical profile reflects that in 2002, RTAs charged the global community about US $ 518 billion. In similar manner (WHO, 2013) reports that; Road traffic injuries are a major but neglected global public health disruptive, necessitating concerted sweats for actual and sustainable prevention. Of all the systems that people have to pact with daily, road transport is the most composite and the most dangerous. The catastrophe behind these figures regularly attracts less media courtesy than other, less recurrent but more unusual types of tragedy.

Most of the research in statistical modeling of accident data have demonstrated that the generation mechanism underpinning the no-injury and injury-involved traffic accidents may differ (Fountas and Rye, 2019).

1.1. Data

A cross sectional study was conducted for secondary data found from Mekelle Zone Traffic Police Office. Accidents are recorded by the traffic police on daily basis. This study was, therefore, based on a secondary data extracted from Mekelle Traffic Control and Investigation Department. The observations were random sample accidents that occurred over the recent three consecutive years (September 2014- July 2017). Mekelle City is in the northern part of Ethiopia in Tigray National Regional State, 783 km from Addis Ababa, Ethiopia.

The sample size was calculated using single population proportion formula by taking 20% prevalence of car accident for low-income countries (WHO, 2009), for there is no clear prevalence calculated for Mekelle city or for any other Ethiopia region. And with 95% confidence level for, 4% desired precision and accounted for one stage sampling, which is based on a biostatistics book (Gerald van Belle et al., 2004) identified the points to decide the precision based on how variable the data are, the chance that you are willing to tolerate concluding incorrectly that there is an effect when the treatments are equivalent, the magnitude of the effect to be detected and the certainty with which you wish to detect the effect. Accordingly, the calculation procedures and the sample size were calculated and selected respectively as follows:

$$\boldsymbol{n = \frac{(Z_{\alpha/2})^2 * P(1-P)}{d^2}}$$

Where,

$\mathrm{n} = \text{the required Sample size}$

Z= the standard score corresponding to 95% CI, and is equal to 1.96

P= the prevalence of car accident for low-income countries (20%)

d^2= margin of error which is taken as 4% (0.04) Using the above formula

$$n = \frac{\left(Z_{\propto/2}\right)^2 * P(1-P)}{d^2}$$

$$n = \frac{(1.96)^2 * 0.2(1-0.2)}{(0.04)^2}$$

$$n = 384.16 \cong 385$$

1.2. Sample Selection Procedure

Systematic sampling technique was used to select the study participants (accidents recorded). The total registered number of accidents in the office for the three consecutive years (Sept. 2014 – Aug. 2017) were 4500, then when we divide to the sample size (385), it became 11.69 approximately 12. Then we randomly select one accident from the total and then continued to select the next 12^{th} record, and then the next 12^{th} record, then ended up to the determined sample size (385). Data were collected from the daily registration book of the traffic police office. It was extracted by well-informed collectors under supervision of the authors. Training was provided to the data collectors for three consecutive days on the purpose of the study, the contents of the extraction sheet prepared by the authors, particularly on issues related to confidentiality of the office.

Operational definitions

Fatal accident: At least one person (driver, passenger, or pedestrian) died, within 30 days, from injuries received because of an RTC.

Severe Injury: At least one person was injured and admitted in hospital, but no deaths occurred.

Slight injury: At least one person required medical care, but no fatalities or injuries that required hospitalization occurred.

Property Damages: Collisions which did not result in injuries or deaths.

Ethical Approval: The office of research and community services office of Mekelle University, College of Natural and Computational Sciences approved the study protocol. Any personal name was not encoded; identifiers of the injured individuals were simply serial numbers.

2. METHODOLOGY

2.1. Ordered Logistic Regression

We use the Logistic Regression Model (LRM) whenever our response variable is a categorical (qualitative nominal type variable) or in short the response variable is binary or dichotomous furthermore the difference between logistic and linear regressions remains upon both the choice of parametric model and in the assumptions (Al-Ghamdi, 2002). Ordered logit model also known as ordered logistic regression or proportional odds model, is an ordinal regression model—that is, a regression model for ordinal dependent variables (McCullagh, 1980).

The proportional odds assumption is that the number added to each of these logarithms to get the next is the same in every case. In other words, these logarithms form an arithmetic sequence (McCullagh, 1980). The model states that the number in the last column of the table—the number of times that that logarithm must be added—is some linear combination of the other observed variables.

The coefficients in the linear combination cannot be consistently estimated using ordinary least squares. They are usually estimated using maximum likelihood. The maximum-likelihood estimates are computed by using iteratively reweighted least squares.

Examples of multiple ordered response categories include bond ratings, opinion surveys with responses ranging from "strongly agree" to "strongly disagree," levels of state spending on government programs (high, medium, or low), the level of insurance coverage chosen (none, partial, or full), and employment status (not employed, employed part-time, or fully employed)(McCullagh, 1980).

Suppose the underlying process to be characterized is

$$y^* = \mathbf{x}^{\mathsf{T}}\beta + \varepsilon,$$

Where,

$\mathbf{y}^*$is the exact but unobserved dependent variable (perhaps the exact level of agreement with the statement proposed by the pollster);

$X^T$is the vector of independent variables, ε is the error term, and β is the vector of regression coefficients which we wish to estimate.

Further suppose that while we cannot observe $\mathbf{y}^*$ we instead can only observe the categories of response

$$y = \begin{cases} 0 & \text{if } y^* \le \mu_1, \\ 1 & \text{if } \mu_1 < y^* \le \mu_2, \\ 2 & \text{if } \mu_2 < y^* \le \mu_3, \\ \vdots & \\ N & \text{if } \mu_N < y^* \end{cases}$$

Where, $\boldsymbol{\mu}_i$ are the externally imposed endpoints of the observable categories. Then the ordered logit technique will use the observations on *y*, which are a form of censored data on *y**, to fit the parameter vector β.

In ordinal logistic regression model, there are two classifications namely binary and multinomial. There are particular events when the scale of multiple category outcomes is not nominal but ordinal. In such setting, one could use the multinomial logistic regression. This analysis however would not take in to account the ordinal nature of the outcome and hence the estimated odds ratio may not address the questions asked of the analysis (Hosmer & Lemeshow, 2000a)

If an outcome variable $\boldsymbol{y}$ has $\boldsymbol{c}$ ordered categories ($c \geq 2$), which we arbitrarily refer to as $1, \ldots, c$. and there are k covariates $x_1, ---, x_k$ an ordinal regression model is defined by

$$\log\left[\frac{\Pr(y \leq j)}{\Pr(y \geq j+1)}\right] = \alpha_j + \beta_1 x_1 + \ldots + \beta_k x_k, \qquad \text{Where,} \quad j = 1 ---, c-1.$$

The regression coefficients $e^{\beta q}$ have a similar interpretation as for ordinary logistic regression. Specifically,

$$e^{\beta q} = \frac{(odds\ \ that\ \ y \leq j | x_q = x)}{odds\ \ that\ \ y \leq j | x_q = x-1)}$$

$$\boldsymbol{q = 1, \ldots, k}$$

$$\boldsymbol{j = 2, \ldots, k}$$

Odds ratio for $y \leq j$ given $x_q = xvsx_q = x - 1$ holding all other variables constant

If $c = 2$, then the ordinal logistic regression model reduces to ordinary logistic regression. In ordinal regression, $e^{\beta q}$ is assumed to be the same for each value. This type of ordinal regression model is called a cumulative odds or proportional odds ordinal logistic regression model (Rosner, 2010).

2.2. Assumptions of Logistic Regression Model

Inferences drawn from statistical modeling are valid when key assumptions of the statistical model are satisfied (Rosner, 2010).

In ordinal logistic regression models, there is an important assumption which belongs to ordinal odds. According to this assumption parameters should not change for different categories. In other words, correlation between independent variable and dependent variable does not change for dependent variable's categories; also, parameter estimations do not change for cut-off points. In an ordinal logit regression, when the assumption holds for $j-1$ logit comparison in a J categorized variable, α_{J-1}cut- off points and β_{J-1} .parameters are found. At this point ordinal logistic model differs from multinomial logistic regression.

Dependent variables which are analyzed in the majority of research and applied studies are generally in categorical and ordinal structure. Ordinal Logit Models that consider the ordinal structure of the dependent variable are used in case where the dependent variable has at least 3 categories with these categories ordinally arranged, i.e. severe of disease (mild, moderate, severe) or the educational level (elementary, high, university) (Hosmer & Lemeshow, 2000b).

Ordinal logistic regression describes the relationships between an ordered response variables and a set of predictor variables that can be continuous discrete, or a mixed of any of these. In ordinal logistic regression analysis, we have three types of commonly used model: the Adjacent category, the continuation ratio and proportional odds models.

There are various ordinal logit models to compare dependent variable categories. Easiest of these to apply or interpret are Cumulative Logit Models. Cumulative Logit Models are divided into 3 groups as Proportional Odds Model (POM), Non-Proportional Odds Model (NPOM) and Partial Proportional Odds Model (PPOM). Not like the Multinomial Logit Models, Cumulative Logit Models are work under the assumption of cumulative logit parallelity. But parallel lines assumption sometimes does not hold, in this case Proportional Odds Model gives incorrect results. Therefore, models that consider ordinal structure and relax the assumption are suggested. NPOM and PPOM are recently used for this purpose (Hosmer and Lemeshow, 2000a).

Like the other logit models, odds ratios are calculated to find cumulative probabilities in cumulative logit models. There is j – 1 ways to compare j categorized dependent variable Y. Equality shows odds ratio of dependent variable Y for (≥1, <1; ≥2, <2; … ≥−1, <−1) (Kleinbaum & Klein, 2010). We have used STATA version 12 for the analysis using enter model building method and finally we used wald test to see the statistical significance of the individual variables (Daniel and Cross, 2018).

3. RESULTS

3.1. Descriptive Statistics

The number of randomly selected accidents were 385, of which 56.7% of the injury was slight injury, 28.6% were serious injury, 14.7% of the accidents were fatal injury. The distribution of accident injury level by background characteristics are illustrated in table 1. In addition to the distribution, the association between the injury level and associated factors also shown in table 1 using the chi-square test of association. Years of experience, vehicle ownership (employed or self), vehicle type, and vehicle owner (private or governmental) are found to be significantly associated with the level of accident injury (Table 1).

Table 1. Distribution of vehicles' accident injury level from September 2014 –August 2017.

Variable	***Categories***	***Accident Injury Level Frequencies***				
		Fatal Injury 216 (56.7%)	***Serious Injury 109 (28.6%)***	***Slight Injury 56(14.7%)***	***Total 385(100%)***	***P-value<=***
Driver's age	<25 years	16(17.58%)	42(46.15)	33(36.26)	91(100%)	0.001***
	25-45 years	35(13.67%)	55(21.48%)	166(64.84%)	256(100%)	
	46-65 Years	4(12.90%)	11(35.48)	16(51.61%)	31(100%)	
	65+	2(28.57%)	1(14.28%)	4(57.14)	7(100%)	
Driver's Experience	<5 years	36 (16.14%)	72(32.29%)	115(51.57%)	223(100%)	0.229
	50-10 years	8(10.53%)	16(21.05%)	52(68.42%)	76(100%)	
	>10 years	12(14.63%)	21(25.61%)	49(59.76%)	82(100%)	
ownership	Employed	45(13.68%)	82(24.92%)	202(61.40%)	329(100%)	0.001***
	Own(self)	11(21.15%)	27(51.92)	14(26.92)	52(100%)	
Vehicle Type	Automobile	16(10.88%)	35(23.81%)	96(65.31%)	147(100%)	0.001***
	Heavy Tracks	13(16.25)	15(18.75%)	52(65.00%)	80(100%)	
	Taxi	2(5.56%)	17(47.22%)	17(47.22%)	36(100%)	
	Bajaj	11(24.44)	21(46.67%)	13(28.89%)	45(100%)	
	Bus	9(16.98%)	12(22.64%)	32(60.38%)	53(100%)	
Ownership type	Government	2(3.33%)	11(18.33%)	47(78.33)	60(100%)	0.001***
	private	54(16.62%)	98(30.53%)	169(52.65)	321(100%)	
Road partition	One way	9(10.00%)	27(30.00%)	54(60.00%)	90(100%)	0.381
	Two way	47(16.15%)	82(28.18%)	162(55.67%)	291(100%)	
Road Condition	Dry	55(14.55%)	108(28.57%)	215(56.88%)	378(100%)	0.598
	Wet	2(28.57%)	3(48.86%)	2(28.57%)	7(100%)	
Light	Day	42(14.29%)	76(25.86%)	176(59.86%)	294(100%)	0.053
	Night	14(16.09%)	33(37.93%)	44(448.35%)	91(100%)	
Accident Type	Vehicle-Vehicle	11(5.67%)	36(18.56%)	147(75.77%)	194(100%)	0.001***
	Vehicle-Other	6(9.09%)	6(9.09%)	54(81.82%)	66(100%)	
	Vehicle-Pedestrian	39(32.77%)	67(56.30%)	13(10.92%)	119(100%)	

Note: *** = significant at 1% level of significance.

We can also see by using bar chart to simply observe the injury level within age group. Accordingly, 76.85 % of slight injuries are under the driver's age group of 26-45 years old while the rest 23.15% of the slight injury were committed by the other categories. The highest proportions of fatal injury (63.64%) were also recorded by the drivers' age category i.e. from 26-45 years old.

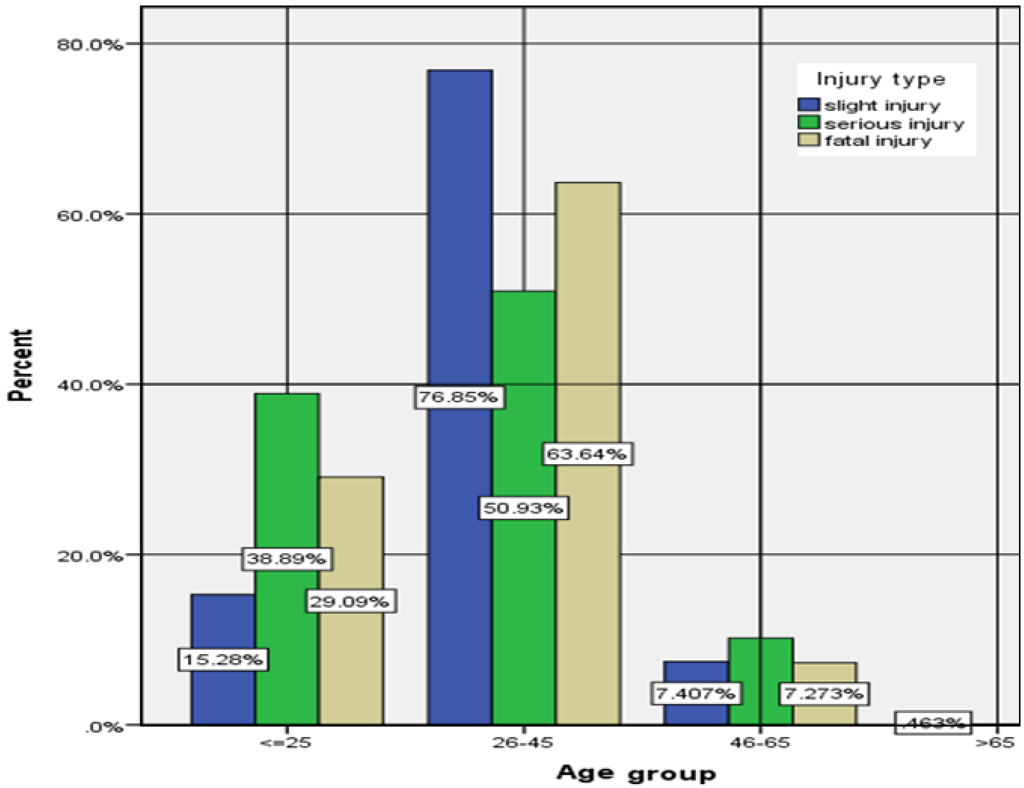

Figure 1. The distribution of car accident injury level by age of sample data from Mekellle Traffic Police Office, Tigray, Ethiopia, 2017.

3.2. Ordered Logistic Regression Analysis

This section focused on regression analysis undertaken to test the relative predictive power of socio-demographic and environmental covariates with severity of car accident injury. In this study ordinal logistic regression is selected for analyzing the car accident data using the explanatory variables associated with the dependent variable. Accordingly, Age (Age of driver), Educational Background of driver, Experience of driver, Service time of vehicle, type of accident (crash with what object), Light condition during accident (day or night), Road pavement (Asphalt, coble stone, aggregate), Road Partition (one way, two way), and vehicle type (bajaj, taxi, heavy trucks, cross country bus) are included in the model.

The log odds of fatal injury level for drivers with age group of 5-10 years age group is increased by 0.686. The estimated odds ratio (OR = 1.986) indicates that the odds of fatal injury (as opposed to moderate injury or slight injury) for older age drivers is 98.6% higher than young age drivers (<5 years' experience), as the odds of moderate or slight injury (as opposed to fatal injury), holding other variables constant. The confidence interval for odds could be as minimum as 1.002 and as maximum as 3.934 with 95% confidence and shows that it is statistically significant as it doesn't include one. This result seems contradictory with the experience level, but it could be due to the greater confidence of experienced drivers which may lead to carelessly follow the ethics of driving like driving more than the allowed speed, not using seat belt, and talking mobile phone calls while driving.

The log odds of fatal injury for drivers who have privately own the vehicles is found to deceased by 1.160 as compared to the vehicles owned by the government. The estimated odds ratio (OR = 0.313) shows that the odds of fatal injury (as opposed to moderate or slight injury) for drivers who drive private owned vehicles is lower than those drivers who have driven governmental vehicles is decreased by 68.7%. The 95% confidence interval also suggests that odds could be as minimum as 0.137 and as maximum as 0.714.

The log odds of fatal injury for accident type; Vehicle with pedestrian is deceased by 2.852. The estimated odds ratio (OR =0.058) shows that the odds of fatal injury (as opposed to moderate or slight) for vehicle with pedestrian accident is lower than those accidents vehicle with vehicle by 94.2%. The 95% confidence interval also suggests that odds could be as minimum as 0.031 and as maximum as 0.106.

The log odds of fatal injury for vehicle type; heavy track is deceased by 0.656. The estimated odds ratio (OR =0.519) shows that the odds of fatal injury (as opposed to moderate or slight) for heavy track accident is lower than those by automobile by 48.1%. The 95% confidence interval also suggests that odds could be as minimum as 0.263 and as maximum as 1.023.

The log odds of fatal injury for vehicle type; cross country bus is deceased by 0.899. The estimated odds ratio (OR =0.411) shows that the odds of fatal injury (as opposed to moderate or slight) for heavy track accident is lower than those by automobile by 58.9%. The 95% confidence interval also suggests that odds could be as minimum as 0.189 and as maximum as 0.894.

The log odds of fatal injury for vehicle owner; Vehicle owned driver is decreased by 2.852.692 as compared to vehicle is owned by employer. The estimated odds ratio (OR =0.502) shows that the odds of fatal injury (as opposed to moderate or slight) for vehicle owned driver is lower than those accidents with driver employed by 49.8% (Table 2).

Table 2. Factors affecting Car Accident Injury Level: Ordered Logistic Regression result.

Variables	***Category***	***Coefficient***	***Odds ratio***	***Stand. error***	***z-value***	***P-value<=***
Driver's Age	<25 years (ref)					
	25-45 years	.437	1.548	.318	1.37	0.170
	46-65 Years	-.104	.901	.530	-0.20	0.844
	65+	11.555	104329.3	714.387	0.02	0.987
Driver's Experience	<5 years (ref)					
	5-10 years	.686	1.986	.349	1.97	0.049**
	>10 years	.249	1.283	.357	0.70	0.485
Vehicle service	Vehicle service	-.001	.999	.002	-0.61	0.542
Ownership type	Governmental (ref)					
	Private	-1.160	.313	.420	-2.76	0.001***
Light condition	Day (ref)					
	Night	.145	1.556	.305	0.48	0.634
Accident type	Vehicle-Vehicle (ref)					
	Vehicle-Other	.408	1.503	.413	0.99	0.323
	Vehicle-pedestrian	-2.852	.058	.317	-8.98	0.001***
Vehicle Type	Automobile (ref)					
	Heavy track	-.656	.519	.346	-1.89	0.050**
	Taxi	.303	1.354	.439	0.69	0.491
	Bajaj	-.115	.892	.420	-0.27	0.785
	Cross country bus	-.889	.411	.396	-2.24	0.025**
Vehicle owner	My employer (ref)					
	My self	-.690	.502	.373	-1.85	0.044* *
/cut1		-6.056		1.009		
/cut2		-3.792401		.966		
Model Summary	Number of obs.	344				
	Log likelihood	-244.113				
	LR chi2(15)	162.82				
	Prob > chi2	0.0000				
	Pseudo R2	0.2501				

Note: *** = significant at 1%, ** = significant at 5%.

4. DISCUSSION

In this study, age of driver was not found statistically significant in explaining the severity of injury from car accident, but a study conducted in USA (Pour-Rouholamin et al., 2016) has shown that age was found statistically significant in explaining the severity level of the car accident. In this study (Pour-Rouholamin et al., 2016), drivers at the age of 25 to 64 (middle-aged) were used as the reference group, the study found that adult drivers (less than 24) and older drivers (65 years and above) significantly affect the pedestrian injury severity but with contradictory effects. Pedestrian–vehicle crashes caused by adult drivers were more likely to result in severe crashes, whereas those caused by older drivers were more likely to result in no/possible injuries.

In this study, light condition is not found to be statistically significant (Coef. = .145; p-value >= 0.050); whereas according to (Huang et al., 2008) nighttime driving was resulted a more serious injury outcome (Coef. = 0.3920; p-value <= 0.050) than daytime driving. From vehicle type heavy truck (Coef. = -.656, p-value>= 0.050) and cross-country bus (Coef. = -.889, p-values<= 0.05) were found to be statistically significantly decreasing the severity of accident injury, which shows similar results with (Huang et al., 2008). The time of accident was classified as day and night to indicate light and in this study; it was not found statistically significant whereas studies conducted by (Huang et al., 2008; Simomcic, 2001) showed that accidents happened during the night increase the level of accident as compared to accident happened in the day time and the magnitude is similar with the result of this study regardless of its significance i.e. (Coef. = .145; p-value >= 0.100). Vehicle type in this study is categorized as automobile, taxi, heavy truck, Cross country buss and Bajaj. The accidents occurred due to heavy truck and cross-country buss were found to be decreasing the level of accident (Coef. = -.656; p-value <= 0.050) and (Coef. = -.889; p-value <= 0.050) respectively. This may be due to the drivers are highly skilled and experienced. Specially, for the heavy truck, since they are large in size and have at most two persons (the driver and his assistant) it is less likely to get a fatal injury. This is because they may skip of the accident by just jumping from the vehicle. This finding was supported by (Levine et al., 1999) who found that every 454 kg increase in vehicle weight was equivalent to the driver’s ability to resist front impact car accident of 10 more kph before being fatally injured.

5. CONCLUSION

An ordered logistic regression model was used to examine factors that worsen the car accident level. A total sample of 385 car accidents were considered in the study of which 56.7% were fatal, 28.6% serious and 14.7% slight injury. The model estimation result showed that, being experienced drivers (Coef. = 0.686; p-value <= 0.050) were found to increase the level of injury. On the other hand, being private vehicle (Coef. = -1.160; p-value <= 0.010), the type of accident of vehicle with pedestrian (Coef. = -2.852; p-value <= 0.010), being heavy truck (Coef. = -0.656; p-value <= 0.050), being a cross country buss (Coef. = -0.889; p-value <= 0.050) and being owner of vehicle is the driver himself (Coef. = -.690, p-value <= 0.050) were found to decrease the level of car accident injury severity. Therefore, it is better to create continued awareness to those who are experienced drivers, who carelessly follow the traffic rules. Special attention is required to government owned vehicle drivers, as they were found to increase the level of car accident injury through different short-term trainings.

Generally, this study exerts an important effort to under-stand the effects of various interdependent factors on car accident injury level. However, the study was forced to be limited to show variation in the interaction of factors across different scenario of collision due to the small sample, because the data were not in softcopy rather in hard copy. Therefore, it was very difficult to consider more samples in this situation. So, we recommend the traffic police office of Mekelle city to develop a data base on car accident in order to investigate more results using different statistical models.

Based on these findings some interventions can be developed to minimize the level of cara accident in Mekelle City, Ethiopia. Prevention strategies applied to reduce injuries and fatalities from car accident should focus on continued awareness creation to experienced drivers, government employed driver on speeding, and driving at nighttime. Therefore, implementing better driver licensing and road safety awareness campaign on safe driving practices can play a pivotal role in road safety improvement. In addition, strict police enforcement also applied for those frequent offenders. Most importantly, it is needed to prepare a huge data base that includes driver alcohol used or not, road characteristics at time of accident, road speed limit for further investigation.

6. ACKNOWLEDGEMENTS

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7. CONFLICT OF INTERESTS

No conflict of interests.

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