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Effect of Temporal Instability of Factors Contributing to Single-Vehicle Crash Severity--a Mixed Logit Approach

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EFFECT OF TEMPORAL INSTABILITY OF FACTORS CONTRIBUTING TO SINGLE-VEHICLE CRASH SEVERITY--A MIXED LOGIT APPROACH

THESIS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering in the College of Engineering at the University of Kentucky

By

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ABSTRACT OF THESIS

This study investigates the factors associated with single-vehicle crash injury severity using five years (2014 – 2018) of crash data from Kentucky, USA, using a mixed (random-parameter) logit model. We also explore the temporal heterogeneity of the correlated factors across different times of the day. Most crash-severity models assume that the estimated parameters remain temporally stable. For instance, the effect of light conditions on crash severity may differ based on the time of the crash occurrence—noon vs. dusk. The temporal instability of the factors due to the time-of-day variation can lead to (under) overestimating the parameters that influence the development and implementation of safety countermeasures—crash modification factors and safety performance functions.

To account for the temporal variations and associated instability, we estimated crash severity models for five periods of the day: 12 am – 5 am, 5 am – 9 am, 9 am – 2 pm, 2 pm – 7 pm, and 7 pm – 12 am. Each model considers five crash injury-severity outcomes: (a) fatal, (b) suspected serious injury, (c) suspected minor injury, (d) possible injury, and (e) property-damage only (as defined by the Kentucky State Police). Log-likelihood tests confirm the statistical validity of the time-of-day grouping of the crash severity models. The Chi-Square test-statistic indicates the significance of using five different models instead of a single aggregate model for the dataset. The used dataset is a collection of police crash investigation reports, and these reports were prepared after the crashes have occurred. So, data on traffic volume/ADT/AADT were not used for this study.

Further, the pseudo direct elasticity values are estimated to find the sensitivity of the explanatory variables—how much change in the probability of different injury outcomes. Explanatory variables such as age, gender, and lighting condition are incorporated into the models to examine the associated effects. Results show that being a female driver increases the probability of fatal injury by 76.85% for crashes occurring in the 5 am to 9 am window. Also, being a driver within the age-group of 50 years or more increases fatality probability by 49.07% for crashes occurring from 2 pm to 7 pm. Alcohol-involvement significantly increases the probability of fatal and severe injury in all the models (five-time periods). Further, our estimated results indicate that icy road surface, losing control of vehicles, and oversteering have a temporally stable effect (do not change across different time-of-the-day models) and are found to have a positive correlation with fatality and severe injury severity outcomes. On the other hand, variables such as drivers younger than 25 years, male drivers, streetlights turned on exhibit varying influence on the injury-severity outcome at different times of a day.

The findings of this research can be used to develop (and calibrate) Safety Performance Functions (SPF) and Crash Modification Factors (CMF) for the State of Kentucky. The time-of-day analyses will make the SPFs and CMFs more robust and flexible by accommodating temporal heterogeneity in the factors correlated with single-vehicle crash severity.

KEYWORDS: *Single Vehicle Crashes, Injury-Severity, Time of Day, Temporal Instability, Logit Model*

A M Hasibul Islam

(Name of Student)

[12/03/2020]

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CHAPTER 1. INTRODUCTION

1.1. Background and Motivation

Despite extensive efforts in research, countermeasures, and education, thousands of people lose their lives due to traffic crashes every year. In 2018, fatality due to traffic crashes was 36560 in the USA alone; from these deaths, 724 were in Kentucky [1]. Among 724 fatalities on the roads of Kentucky, 387 deaths, or 52.85% of total fatal crashes were caused by single-vehicle crashes It shows that single-vehicle crashes constitute a large portion of the fatal crashes and steps should be taken to reduce fatality and improve the situation for road users.

Traffic crash injury-severity data plays an important role in worldwide roadway crash studies and safety policies. These data allow us to study the fundamental factors associated with crashes and to build crash injury prediction models, severity prediction models and crash frequency prediction models. Over the years, a significant number of studies have been undertaken for analyzing traffic crashes, the resulting injury-severity towards drivers and passengers, and the variables which influence the injury-severity outcome. One key element that has often been overlooked in many injury-severity studies is the temporal variation of parameters. Mannering [2] showed that human behavior changes with the time of day, that is the action of people in the same scenario changes with variation in time. According to Behnood and Mannering [3], this temporal variation could also be a function of the urban nature of data, the change in variable reporting in police crash investigation reports, the development of new safety measures and improved technology, and/or the effect of the macroeconomic situation. They used single-vehicle crash data of Chicago from 2004 to 2012 to build separate models for different years and found that model specification and estimated parameters exhibit temporal instability for the driver crash injury models, showing the effect of change in years. Pahukula [4] estimated separate injury severity models for different times of a day for large truck crashes and found that the effects of the explanatory variables varied from one time of a day to another. Behnood and Mannering [5] found differences in the influence of variables with different times of a day (morning and afternoon). Dabbour [6] also found temporal variations of variables by creating separate models for different years. All these studies point in one direction: time does cause variation in many variables and affects crash outcomes. The time can be long (year to year change), or short (week, month, day, or even hours). Most studies showed temporal variation by creating year-to-year models, but studies showing temporal variations of variables in a shorter duration (different hours of a day) are less common.

Moreover, many undocumented factors, such as visibility or driver characteristics may play an important role in injury severity outcomes and vary by time of day. As the parameters of statistical analysis are considered temporally stable over time, performing analysis without knowing the effect of time variation on the factors might lead to an erroneous outcome.

The stability of factors is important for accident data analysis especially in assessing the safety countermeasures. If a safety countermeasure is deployed, and the influences of the variables of crash injury severity are unstable, or any significant temporal change is not considered, it will be difficult to assess the change in crash injury severity; it will be unclear whether safety countermeasure or temporal instability is causing the change. For example, we can think about before-after study on implementing seatbelts for drivers. Before seatbelt, driving was less safe, and people used to take less risks on road. After the seatbelt, though drivers are provided with added safety, there is also a temporal change in decision making. Which is, drivers may find it compelling to take more risks on roads than before. While assessing the effect of this countermeasure, we can clearly see that not accommodating this temporal shift will lead to erroneous result. Moreover, the reduction of speed limit may have a different impact at different times of the day—morning and evening peak hours vs off-peak hours.

We have not found any study from Kentucky yet, which tried to find out the parameters to be most influential for fatal and serious injuries and how these parameters show temporal instability. Such study will help to understand the factors behind single vehicle crash injury-severity and their temporal instability might dictate future safety countermeasures.

1.2. Objectives

The objectives of this research can be summarized as below:

A. To Investigate the potential determinants of injury outcomes for single-vehicle crashes for the roads of Kentucky.
B. To evaluate the variation in the influence of these determinants at different times of a day
C. To account for potential unobserved heterogeneity, which might be unavailable in the dataset for analysis by using random parameters logit modeling approach.

1.3. Organization of the dissertation

Chapter 1 provides a brief background, motivation, necessity, and objectives of the research; Chapter 2 provides a review of the previous studies on temporal instability and effect of time on variables of crash injury-severity; Chapter 3 shows the general methodology followed in this research and shows brief description on random parameters logit model, log-likelihood ratio tests and elasticity analysis; Chapter 4 shows a complete description of the data used which includes variables present in the dataset, the number of incidents of each variable concerning five different injury-severity levels, mean and standard deviation of each variable for both urban and rural roads and also before cleaning-after cleaning statistics of the dataset; Chapter 5 shows the results and discussions for each model and Chapter 6 discusses the shortcomings of the research, future scope of the research and a brief conclusion.

CHAPTER 2. LITERATURE REVIEW

In the past studies of injury severity, it has been found that the effect of variables of injury-severity of different vehicles such as large trucks, passenger cars, motorcycles, etc. changes with time variation, which include a variation of time in a single day or variation by year [5] [4][7]. It is also found out that the environment setting also influences the injury-severity outcome. For example, it is found from the study [8] that rural crashes of large trucks bring out more fatal outcomes than urban large truck crashes which might be because of the slower response time of EMS, differences in geometric and environmental condition, and traffic flow and lighting condition. Based on the review of the previous studies, the variables being studied before in injury-severity analysis of different vehicle types and their influence on injury-severity can be summarized as follows:

1. Driver Characteristics and driver actions:
   Age:
   Truck drivers younger than 31 years old were found to be much more likely involved in a serious crash [9][10], which is contradicting with the findings from [11] which indicates that young drivers will have less severe injury outcome due to having much more physiological strength than older drivers. Drivers aged 65 and over experienced much severe injury outcomes than other age groups [12] [11] [13], contradicting the finding of [10]. Young motorcyclists had much more probability of being involved in no injury crash [14][15]. Older female drivers having multiple occupants produced more severe injury outcomes [16].
   Gender:
   Male truck drivers were found to be involved in severe injuries during the morning [9]. Female drivers were found to experience more no injury outcomes than male drivers [17][12], contradicting the findings of [18] which says female drivers are more prone to severe injuries in low-risk segments. Male motorcyclists are subjected to less severe injury outcomes than their female counterparts [15]. Male drivers were found to experience no injury outcome, except for the years 2007-2009 [3]. Male drivers were found to be involved in more fatal injury crashes than female drivers [11].
   Drunk Driving/Driving under influence of drugs:
   Alcohol or illicit drugs are found to increase fatality/ severe injury outcomes [19][20] [3] [6] [8][10], though this result was not consistent in some years of the data [3]. Alcohol-impaired driving caused less severe injuries for male drivers less than 31 years old but caused severe injury for the female of the same age group and had no significant effect on drivers over 31 years old [16].
   Race:
   Black truck drivers were involved in less severe injuries and Hispanic drivers were involved in more severe injuries during morning and afternoon time [9]. The proportion of black and Hispanic groups are found to have a positive correlation with crash occurrences [23].

Driver Actions:
Stopped before collision and backing resulted in a less severe crash for truck drivers [9]. Making a left turn in the afternoon period resulted in a much severe crash outcome [9]. Changing lanes was found to be statistically significant only during the mid-day period [21].
Driver at fault:
Drivers violating the right of way are mostly involved in minor injuries in the afternoon period but hit and run produced minor injuries during the morning period [9]. Truck drivers at fault produced less severe or no injury outcomes for the truck drivers [9]. Truck driver at fault produces higher severity probability than passenger car driver at fault on urban roads but produces lower injury/severity of truck drivers on rural roads [8].
Driver's apparent physical condition:
Fatigue, the effect of medication, reduced visibility due to aging, falling asleep/fainted are found to produce severe injury outcomes [21] [11] [3] [10].
Distracted driving:
Cellphone usage slightly increases fatal injury outcomes [12]. Distracted driving produced fatal injury outcome in two latent classes, but produced less severe outcome in one, which might be due to drivers slowing down while having distraction [16].
Speeding:
Speeding is found to increase fatal crash injury across all ages and genders [12] [15] [10], also increased the probability of large trucks being involved in severe crashes [21].

2. Geometric and Roadway condition:
   Median width between 51 and 75 ft variable was found to be statistically significant during the mid-day period, increasing minor injury probability [21]. Wide shoulder width was found to increase the possibility of fatal injury [21]. Two-lane highways increase the probability of fatality [10]. Concrete median barriers reduced the probability of severe injury/fatality significantly [8]. Single vehicle collision increases fatality probability in a rural setting [8][10]. Dry road surface conditions produced no injury [9] [21] and severe injury [9] [13] outcomes for truck drivers during the morning period. Contradicting to that, drivers under 45 years experienced a decrease in no injury and severe injury probability on wet surface and snowy surface but higher probabilities of minor/severe injury on the dry surface [22]. Wet surface reduced the risk of fatal injury, but increased the probability of no injury or minor injury [12]. Dry road surface increased severe injury outcome for motorcyclists, which might be related to over-confidence and risk-taking perception, but produced a decreased probability of severe injury crash in horizontal curves [14] [15]. Dry road surface increases fatal injury outcomes for passenger cars [13].

3. Weather and lighting condition:
   Older drivers are found to avoid driving in adverse conditions [12]. Cloudy weather significantly produced fatal injury outcomes [12]. Snowy, cloudy [21], stormy, rainy weathers [21] are found to produce severe injury outcomes [11]. Clear weather increases the probability of severe [21] [13] and no injury outcome [21].

Daylight reduce severe crash injury outcome except for days where the morning time is short (winter and fall) [9]. Darkness without adequate streetlight increased the probability of severe injury outcome, but this effect was reduced with streetlight [12] [11] [13]. Daylight conditions increased the probability of no visible injury for motorcyclists [14]. Darkness was found to increase fatality in [10].

4. Roadway design attributes:
   Traffic control devices and stop/yield signs produced a lower probability of severe injury outcomes due to a reduction in speed [11]. Unpaved roads are found to produce less severe injury outcomes [11].

5. Vehicle Characteristics:
   Vehicle Type:
   Motorcyclists are prone to more severe accident outcomes than car/truck drivers because of exposure to the crash without an energy-dissipating structure [14]. Drivers of panel vans are found to experience less severe injuries than other vehicle types due to the large body and better protection in high-risk segments, whereas station wagons and utility vehicles produced less injury severity for low-risk segments [11]. Commercial vehicles produced no injury and severe injury outcome in most of the years of study, while passenger cars increased the probability of no injury and decreased the probability of severe injury outcome [3]. Light-duty vehicles excluding passenger cars produced severe injury probability [13][10]. Tractor with or without trailers increases severe injury/fatality probability both in urban and rural roads [8].
   Vehicle Age:
   Truck age was found to be statistically significant in different time periods without producing temporally stable results [9]. Older drivers driving older vehicles (vehicle age 11 years or above) faced much fatal injury in single-vehicle crashes [12]. Younger drivers driving newer vehicles faced many fatal injury outcomes [12]. Older vehicles are found to produce fatal injury outcomes in all the models [13][10].
   Multiple Occupants:
   Having no passenger except the driver in the vehicle produced no injury outcome and having multiple occupants produced mixed results, which is not conclusive [16] [3].

6. Safety Countermeasures:
   Seat Belt:
   Seat belt use significantly decreased severe injury outcomes [22][12][16] for the morning period but surprisingly increased severe injury outcomes for the afternoon period, which might be due to darkness and traffic patterns, and temporal shift in the perception of risk-taking [21]. Helmet usage decreased the probability of severe injury outcomes for motorcyclists [14] [15] [11]. Seatbelt use decreased severe injury probability in all the models [13].
   Air Bag:
   Airbag deployment decreases the probability of severe injury, though it increases severe injury probability for older female drivers [16].

7. Effect of Time:
   Weekday mornings produced less severe injury outcomes than weekends, but weekday evenings produced more severe injury outcomes than weekends [9]. Weekends crash showed an increase in the probability of severe injury outcomes [12]. Motorcyclists riding from May through July experienced increased probability of no injury or minor injury [15].

8. Miscellaneous:
   Stop sign-controlled intersection increases the probability of severe injury, but intersection with some sort of control for pedestrians produces much less injury severity outcome [11]. Collision with a fixed object increases fatal injury probability for motorcyclists [15].

Following key points and gaps in studies can be summed up from the above discussion:

Different variables, such as age, gender, vehicle type, weather condition, roadway geometry, speed limit, a driver under influence of alcohol/drug/medication, economic downturn, etc. are found to influence the injury-severity outcome of crashes. It is also evident that some variables provided a stable influence in some studies while the same variables provided varying influence. Example: The increased speed limit is found to be influential in some studies[15][11] while a few studies found no significant influence of it on injury-severity outcome [24].

Temporal stability of accident data is significantly important for crash prediction models, injury severity models, and traffic safety countermeasures. Several elements have been mentioned by researchers that are suspected to cause temporal instability of variables. It is also suspected that time variation or passage of time plays a key role in causing temporal instability. Passage of time is an important factor that has been overlooked in many studies. With the passage of time, people's perspectives about risk perception, decision making on road, driving behavior, and many other human and environmental characteristics change. Without incorporating the contribution of this highly significant factor, any study or result should not be fully accurate or precise. The stability of the factors with varying time should be tested to better understand these variables.

Most of the data analysis papers discussed above-used data for an urban area or urban roadway, because of the better availability and frequency of data. But rural roadways are also significantly important for our roadway system. They should be considered for modeling as well to better understand if there is any trend for temporal instability for varying geography. Due to advancement in technology and skill development, recorded crash data are now more detailed and descriptive. It provides analysts the opportunity to look for the effect of various unobserved factors. Random parameters logit models with its variances are found to be better in incorporating these variables into the models and see how it affects the injury severity outcome.

Time of day analysis can provide a good basis for studying the effect and stability of factors. It is evident from the above reviews that a single variable may have a varying effect over different times of a day. As a day can be divided into different time periods, also as we can model using groups of different numbers of years or months or days, it provides a good opportunity to analyze the effects of different explanatory variables associated with a crash for different scenarios. This way, any specific dataset can be studied more precisely and rigorously for the existence and effect of temporal instability of the factors. Time of day study involving single-vehicle crashes will provide analysts the better opportunity to study complex human and driver behavior than multi-vehicle crashes, as specific personality traits can be studied with ease.

In summary, the contribution of this thesis can be stated as below:

Firstly, this thesis identifies the factors which influence different injury outcomes for single-vehicle crashes. Various factors are considered, and the most influential ones are identified.

Secondly, it concludes how these factors influence injury outcomes at varying times. It also accounts for any unobserved heterogeneity in the dataset.

Finally, this thesis discusses the temporal heterogeneity of the various determinants. The effects of various influential determinants are discussed from the perspective of temporal heterogeneity and time of day is considered to be the prominent factor behind this variation.

CHAPTER 3. METHODOLOGY

For studying driver-injury severities in single-vehicle crashes, injury severity is divided into five distinct groups: fatality, suspected serious injury, suspected minor injury, possible injury, and property damage only. From the past studies, it is found that these crash injury severities have been modeled using the following modeling approaches: multinomial logit model, latent class model, mixed logit model, ordered probit/logit model, random parameters ordered probit model, nested logit model, heteroskedastic ordered probit model, Bayesian binary logit model, Markov switching model. As most of the collected data is subjected to unobserved heterogeneity, it is a common practice nowadays to use heterogeneity models-models that capture potential unobserved heterogeneity that exists in the dataset. Some common heterogeneity models being used today are random parameters or mixed logit models, latent class models, Markov switching models, and latent class with random parameters within class models.

In this study, random parameters multinomial logit model [25]–[27] will be used to study the effect of time change on the variables of injury severity. The model begins by defining a probability function as follows:

$$S_{in} = \beta_i X_{in} + \varepsilon_{in}$$

Where $S_{in}$is a function that determines the probability of driver injury outcome *i* in crash *n*, β_i is a vector of estimable parameters for injury-severity outcome *i*, X_{in} is a vector of the observable characteristics that impact the injury severity for observation n, and ε_{in} is an error term that is extreme value distributed. The outcome probabilities of a random parameters logit model which takes into consideration unobserved heterogeneity in the data can be written as below:

$$P_n(i) = \int \frac{EXP(\beta_i X_{in})}{\sum_{\forall K} EXP(\beta_i X_{in})} f(\beta|\varphi) d\beta$$

Where $P_n(i)$ is the probability of observation n having injury-severity outcome *i*, $f(\beta|\varphi)$is the density function of β with φ referring to the vector of parameters (mean and variance) of that density function, and all other terms have a definition as before.

To statistically verify whether injury-severities of single-vehicle crashes were significantly different across different times on a day, a series of likelihood ratio tests will be conducted. The formulation for this is as below:

$$\chi^2 = -2[LL(\beta_{m_2 m_1)} - LL(\beta_{m_1})]$$

Where $LL(\beta_{m_2 m_1)}$ is the log-likelihood at the convergence of a model containing converged parameters of time of day data m_2, while using data from the period m_1, and $LL(\beta_{m_1})$ is the log-likelihood at the convergence of the model using time of day data m_1, with the same explanatory variables but with parameters no longer restricted to the converged parameters of time of day data m_2. For simulation, 200 Halton draws will be used. A total of four types of distribution will be used for the distribution of random parameters: a) Normal b) log-Normal c) Triangular and d) Uniform Distribution.

Direct pseudo-elasticity of the probability concerning the explanatory variables will be calculated using the elasticity equation for each of the variables for each model. The equation is as below [12]:

$$E_{x_{nk}}^{P_{ni}} = \frac{P_{ni}[given\ x_{nk}=1] - P_{ni}[given\ x_{nk}=0]}{P_{ni}[given\ x_{nk}=0]}$$

CHAPTER 4. DATA DESCRIPTION

We will use five years of police crash data (from 2014 to 2018) collected from Kentucky Traffic Safety Data Services, a program of Kentucky Transportation Center (KTC).

From the literature review, a table is prepared to show the variables previously used for crash injury severity analysis and the available variables in our dataset, which is provided in appendix 2. One of the issues with the dataset was that it had a lot of null values. This is something that the police department of Kentucky can look into in the future because more complete data collection would have provided a much larger sample size to work on. After removing all the null values from the dataset, the resulting values for each variable are compared with the variables before cleaning, which can be found in Tables 1 to 9 of Appendix 1.

After cleaning the dataset, cross-tabulation data was generated for roadway characteristics, roadway conditions, weather conditions, lighting conditions, driver age, and driver gender, concerning injury severity. Outcomes are shown below:

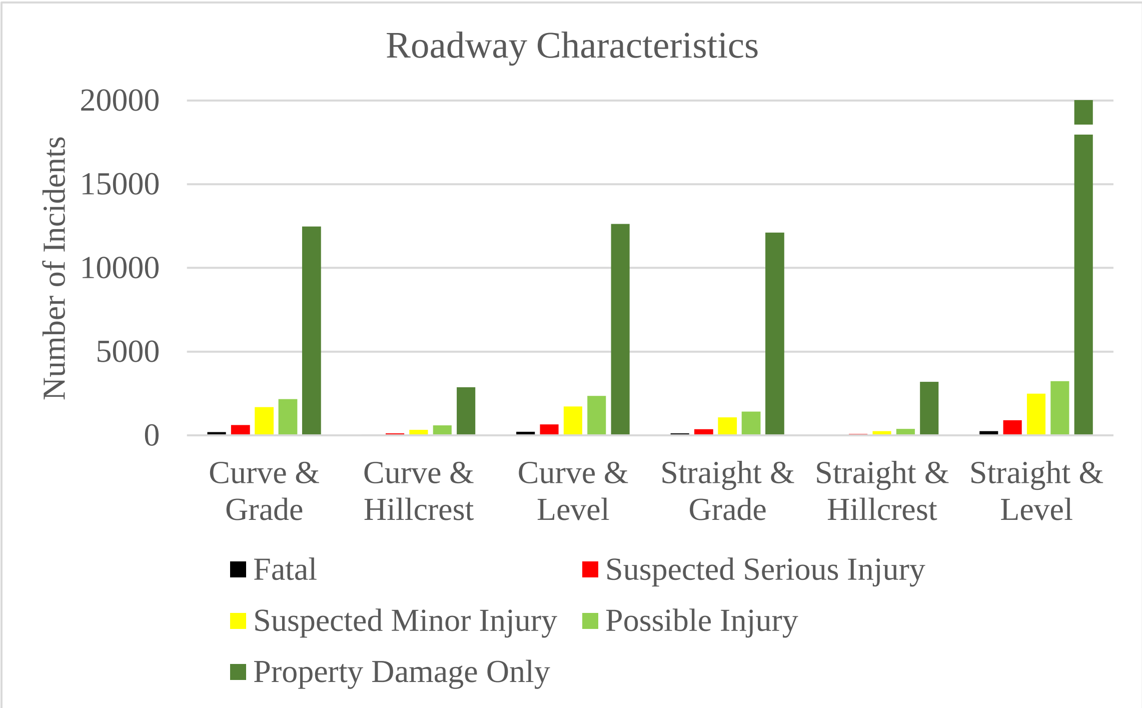

Figure 1: Cross-tabulation data for roadway characteristics and injury severity

Figure 1 shows the cross-tabulation data for injury severity outcomes against roadway characteristics. Straight and level roads produced the greatest number of crashes. Also, curve and grade, curve and level, and straight and grade roads produced a significant number of crashes.

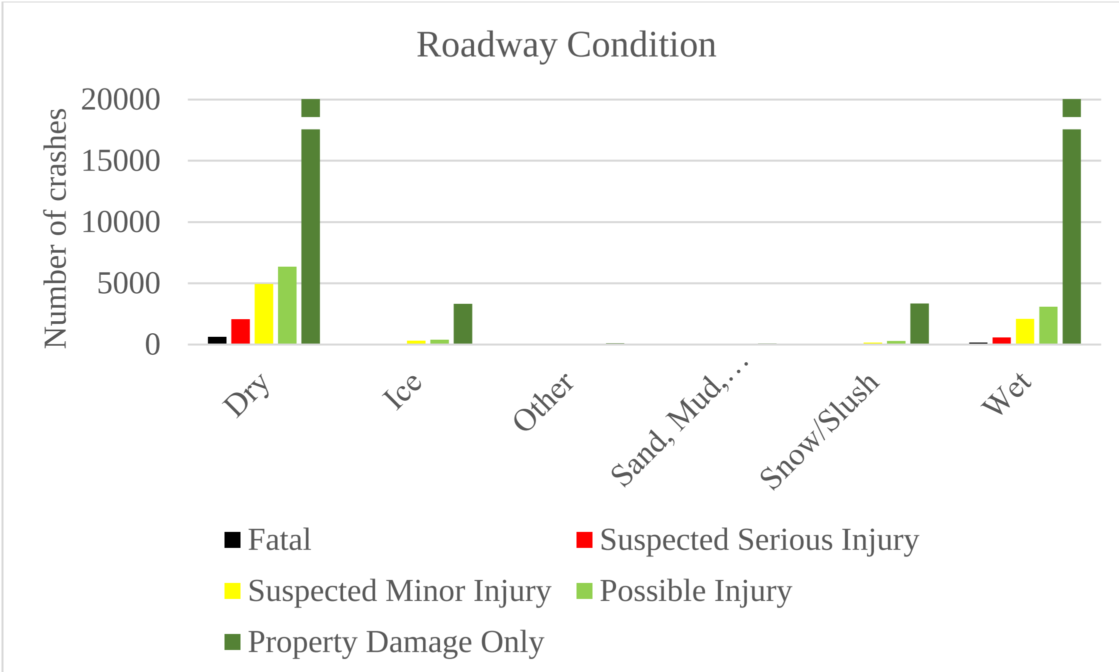

Figure 2: Cross-tabulation data for roadway condition and injury-Severity

Figure 2 shows the cross-tabulation data for injury severity outcomes against roadway conditions. Dry and wet roads produce the maximum number of crashes and dry roads produce the maximum number of fatal and suspected serious injuries.

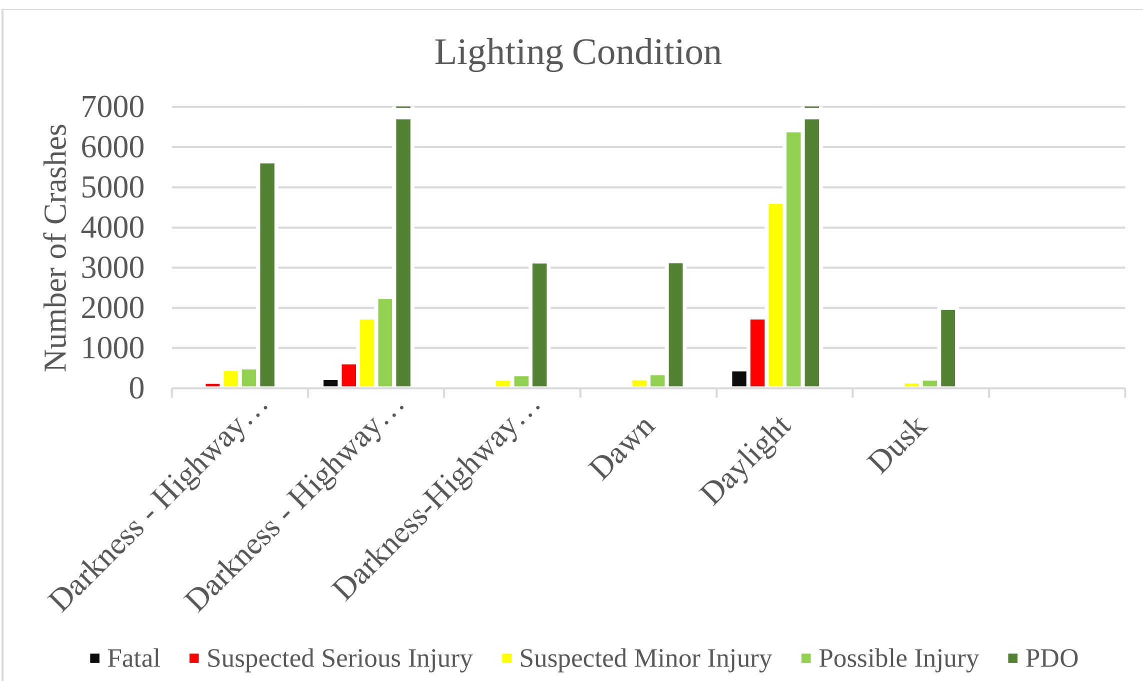

Figure 3: Cross-tabulation data for lighting condition and injury severity

Figure 3 shows the cross-tabulation data for injury severity outcomes against lighting conditions. It is found that most of the crashes occurred during daylight. Darkness with highway not lighted caused the second most amount of crashes.

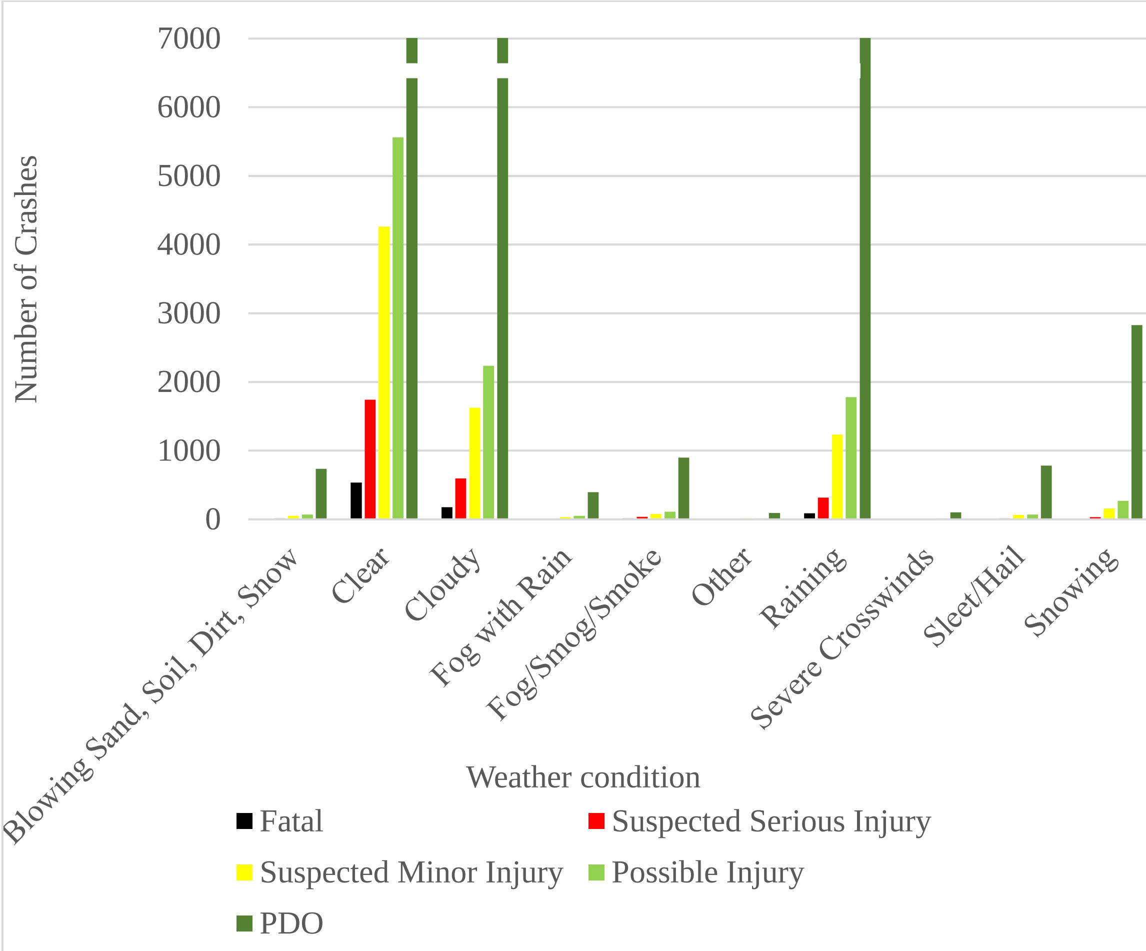

Figure 4: Cross-tabulation data for weather condition and injury severity

Figure 4 shows the cross-tabulation data for injury severity against weather conditions. Clear, cloudy, and raining conditions consist of the greatest number of crashes. Among them, clear condition incorporates the greatest number of crashes which is because most of the time weather is clear.

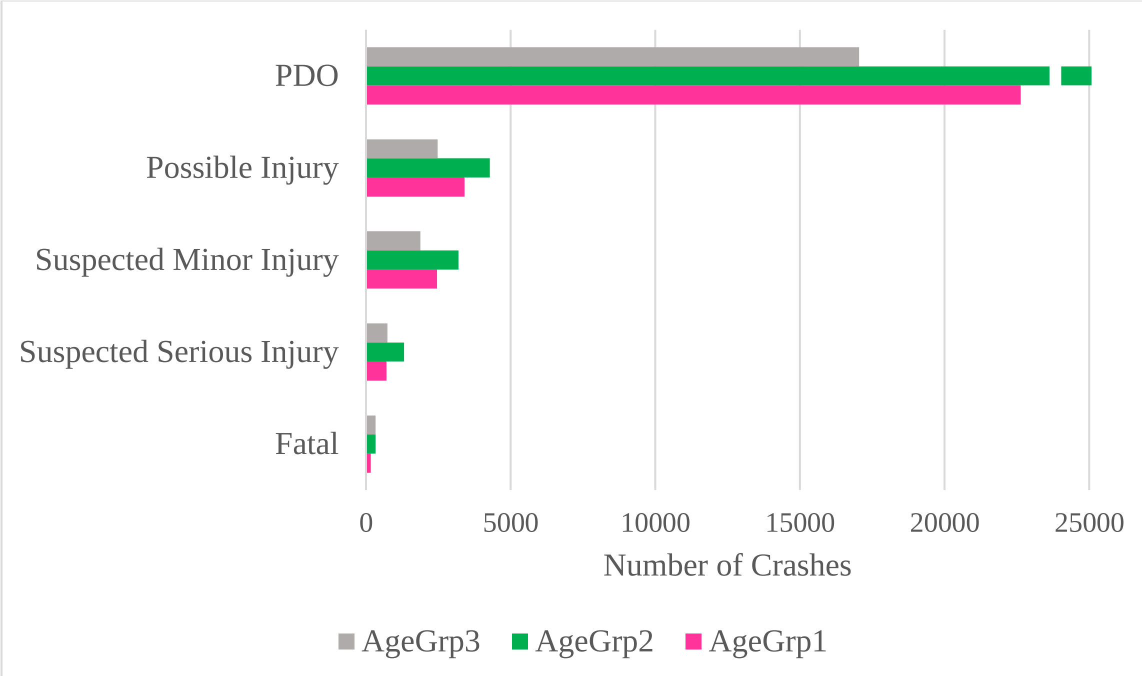

Figure 5: Cross-tabulation data for Age Group and injury severity

Figure 5 provides the cross-tabulation chart Driver age and injury severity. One thing to notice here is that younger people (AgeGrp1) were involved in fatality almost half of that than the other two age groups. Also, for every injury severity type, AgeGrp 2 people dominated the chart. Compared to other injury outcomes, older people (AgeGrp 3) were involved in much more serious injuries (suspected serious injury and fatal injury) than the younger drivers (AgeGrp 1).

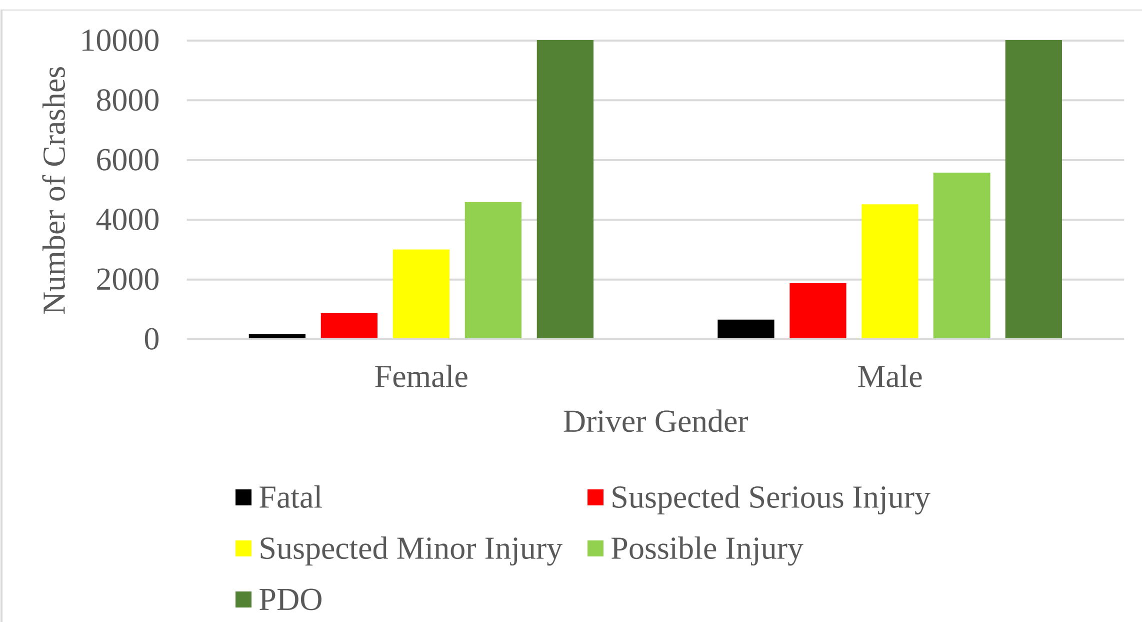

Figure 6: Cross-tabulation data for Driver Gender and Injury Severity

Figure 6 presents cross-tabulation data for driver gender and injury severity. It is found that male drivers were involved in more crashes than female drivers in all the injury severity outcomes. Fatality and serious injuries are also high for male drivers compared to female drivers.

Next, the whole dataset was divided into two groups: urban roads and rural roads. Five times of day as proposed before were used and descriptive statistics were calculated for both urban and rural roads. The outcome is shown below in Table 1.

Table 1: Descriptive statistics of variables for urban and rural roads on different time periods

Variable (1 if present, 0 otherwise)	Time: 12am-5am		Time: 5am-9am		Time: 9am-2pm		Time: 2pm-7pm		Time:7pm-12am		Time: Whole day	
	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural
Roadway Characteristics												
Curve & Grade	0.1305	0.1487	0.1406	0.1968	0.1590	0.2234	0.1470	0.1972	0.1468	0.1581	0.1461	0.1888
Curve & Hillcrest	0.0275	0.0355	0.0289	0.0447	0.0302	0.0497	0.0290	0.0480	0.0339	0.0391	0.0301	0.0445
Curve & Level	0.1813	0.1673	0.1741	0.1829	0.1621	0.2065	0.1532	0.2001	0.1453	0.1822	0.1611	0.1907
Straight & Grade	0.1210	0.1692	0.1629	0.1724	0.1513	0.1577	0.1358	0.1581	0.1455	0.1597	0.1441	0.1622
Straight & Hillcrest	0.0286	0.0487	0.0324	0.0437	0.0281	0.0392	0.0373	0.0440	0.0322	0.0451	0.0321	0.0437
Straight & Level	0.5111	0.4307	0.4612	0.3595	0.4693	0.3234	0.4978	0.3527	0.4963	0.4158	0.4864	0.3702
Roadway Condition												
Dry	0.6855	0.7024	0.5514	0.5647	0.6118	0.5817	0.6514	0.6288	0.6460	0.6933	0.6281	0.6288
Ice	0.0351	0.0381	0.1011	0.1039	0.0326	0.0366	0.0195	0.0229	0.0334	0.0263	0.0423	0.0436
Other	0.0011	0.0010	0.0020	0.0020	0.0005	0.0019	0.0006	0.0012	0.0020	0.0011	0.0012	0.0014
Sand, Mud, Dirt, Oil, Gravel	0.0008	0.0001	0.0014	0.0012	0.0024	0.0020	0.0008	0.0018	0.0007	0.0011	0.0013	0.0014
Snow/Slush	0.0378	0.0257	0.0627	0.0486	0.0554	0.0568	0.0308	0.0349	0.0332	0.0273	0.0434	0.0394
Wet	0.2397	0.2325	0.2814	0.2797	0.2974	0.3210	0.2968	0.3104	0.2847	0.2509	0.2838	0.2854
Weather Condition												
Blowing Sand, Soil, Dirt, Snow	0.0122	0.0063	0.0137	0.0098	0.0118	0.0106	0.0083	0.0091	0.0064	0.0076	0.0102	0.0089
Clear	0.6134	0.6070	0.4626	0.4793	0.4868	0.4990	0.5363	0.5394	0.5639	0.6099	0.5285	0.5423
Cloudy	0.1740	0.1767	0.2451	0.2393	0.2528	0.2412	0.2080	0.1995	0.1792	0.1782	0.2138	0.2086
Fog with Rain	0.0031	0.0099	0.0031	0.0071	0.0022	0.0028	0.0014	0.0044	0.0035	0.0073	0.0026	0.0058
Fog/Smog/Smoke	0.0080	0.0370	0.0120	0.0410	0.0012	0.0019	0.0010	0.0012	0.0040	0.0061	0.0046	0.0138
Other	0.0008	0.0013	0.0040	0.0018	0.0007	0.0010	0.0006	0.0009	0.0015	0.0014	0.0015	0.0013
Raining	0.1481	0.1237	0.1798	0.1611	0.1983	0.1940	0.2118	0.2055	0.1936	0.1521	0.1905	0.1742
Severe Crosswinds	0.0000	0.0013	0.0017	0.0012	0.0007	0.0016	0.0004	0.0016	0.0007	0.0017	0.0007	0.0015
Sleet/Hail	0.0092	0.0094	0.0109	0.0139	0.0029	0.0086	0.0058	0.0089	0.0149	0.0101	0.0085	0.0101
Snowing	0.0313	0.0275	0.0670	0.0455	0.0427	0.0392	0.0263	0.0294	0.0324	0.0255	0.0393	0.0335
Lighting Condition												
Darkness - Highway Lighted/On	0.6137	0.0977	0.1781	0.0194	0.0041	0.0009	0.0621	0.0117	0.4700	0.0636	0.2321	0.0315
Darkness - Highway not Lighted	0.2824	0.7900	0.0910	0.2133	0.0031	0.0129	0.0520	0.1458	0.2713	0.7018	0.1262	0.3227
Darkness-Highway Lighted/Off	0.0863	0.0912	0.0312	0.0280	0.0007	0.0019	0.0166	0.0201	0.0866	0.0881	0.0401	0.0404
Dawn	0.0027	0.0053	0.1824	0.2022	0.0024	0.0054	0.0033	0.0035	0.0015	0.0022	0.0353	0.0421

Variable (1 if present, 0 otherwise)	Time: 12am-5am		Time: 5am-9am		Time: 9am-2pm		Time: 2pm-7pm		Time:7pm-12am		Time: Whole day	
	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural
Daylight	0.0038	0.0113	0.5102	0.5271	0.9887	0.9780	0.8257	0.7728	0.1156	0.0939	0.5415	0.5369
Dusk	0.0111	0.0044	0.0072	0.0099	0.0010	0.0008	0.0404	0.0461	0.0550	0.0504	0.0248	0.0264
Unit Type												
Bus	0.0004	0.0004	0.0023	0.0016	0.0034	0.0010	0.0021	0.0013	0.0005	0.0000	0.0018	0.0009
Emergency Vehicle in Response	0.0057	0.0046	0.0023	0.0007	0.0022	0.0012	0.0010	0.0015	0.0020	0.0031	0.0023	0.0020
Emergency Vehicle Non-Response	0.0164	0.0152	0.0074	0.0042	0.0036	0.0027	0.0050	0.0030	0.0111	0.0087	0.0080	0.0057
Farm Tractor and/or Farm Equipment	0.0000	0.0001	0.0003	0.0001	0.0002	0.0012	0.0006	0.0010	0.0000	0.0002	0.0003	0.0006
Go-Cart	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001
Hit & Run/Unknown	0.0008	0.0006	0.0003	0.0001	0.0000	0.0001	0.0008	0.0002	0.0015	0.0001	0.0007	0.0002
Lt. Truck	0.2496	0.3373	0.3255	0.3957	0.3204	0.3616	0.3022	0.3587	0.2673	0.3544	0.2959	0.3632
Military Vehicle	0.0000	0.0001	0.0006	0.0006	0.0002	0.0003	0.0006	0.0003	0.0002	0.0003	0.0004	0.0003
Motor Home/Recreational Vehicle	0.0004	0.0009	0.0009	0.0006	0.0010	0.0023	0.0002	0.0014	0.0007	0.0015	0.0006	0.0014
Motor Scooter or Motor Bicycle	0.0004	0.0005	0.0009	0.0001	0.0024	0.0008	0.0064	0.0016	0.0022	0.0008	0.0028	0.0009
Motorcycle	0.0153	0.0072	0.0092	0.0062	0.0197	0.0270	0.0310	0.0367	0.0290	0.0200	0.0220	0.0221
Other	0.0004	0.0015	0.0009	0.0004	0.0002	0.0008	0.0006	0.0021	0.0005	0.0020	0.0005	0.0014
Other Public Owned Vehicle	0.0011	0.0008	0.0006	0.0006	0.0012	0.0009	0.0006	0.0008	0.0002	0.0007	0.0007	0.0008
Passenger Car	0.6500	0.5449	0.5875	0.5178	0.5365	0.4946	0.5701	0.5295	0.6304	0.5664	0.5896	0.5299
Passenger Car & Trailer	0.0008	0.0019	0.0009	0.0021	0.0043	0.0035	0.0033	0.0033	0.0027	0.0030	0.0026	0.0029
School Bus	0.0000	0.0000	0.0029	0.0021	0.0005	0.0008	0.0010	0.0012	0.0000	0.0002	0.0009	0.0009
Taxicab	0.0015	0.0003	0.0009	0.0001	0.0007	0.0001	0.0002	0.0000	0.0012	0.0001	0.0008	0.0001
Truck & Tractor	0.0088	0.0163	0.0129	0.0122	0.0266	0.0214	0.0205	0.0126	0.0124	0.0105	0.0171	0.0143
Truck Tractor & Semi-Trailer	0.0393	0.0564	0.0315	0.0376	0.0484	0.0470	0.0356	0.0286	0.0309	0.0225	0.0372	0.0357
Truck-Other Combination	0.0031	0.0016	0.0011	0.0021	0.0038	0.0042	0.0014	0.0021	0.0012	0.0011	0.0021	0.0023
Truck Single Unit	0.0061	0.0093	0.0115	0.0151	0.0247	0.0284	0.0166	0.0139	0.0057	0.0043	0.0137	0.0145
Age Group												
AgeGrp1:0-25 years	0.3924	0.3529	0.2797	0.2949	0.2832	0.2807	0.2937	0.3000	0.3347	0.3341	0.3110	0.3081
AgeGrp2:26-50 years	0.4844	0.4794	0.5107	0.4916	0.4400	0.4193	0.4515	0.4350	0.4661	0.4551	0.4674	0.4518
AgeGrp3: Over 50 years	0.1233	0.1677	0.2096	0.2135	0.2767	0.3000	0.2548	0.2650	0.1993	0.2107	0.2216	0.2401
Driver Gender												
Female	0.2805	0.2888	0.4091	0.3990	0.4216	0.4142	0.3937	0.4059	0.3567	0.3849	0.3793	0.3893

Variable (1 if present, 0 otherwise)	Time: 12am-5am		Time: 5am-9am		Time: 9am-2pm		Time: 2pm-7pm		Time:7pm-12am		Time: Whole day	
	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural	Mean Urban	Mean Rural
Male	0.7191	0.7112	0.5909	0.6009	0.5784	0.5856	0.6063	0.5939	0.6431	0.6151	0.6206	0.6106
Unidentified	0.0004	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0002	0.0002	0.0001	0.0001	0.0001
Human Characteristics												
Alcohol Involvement	0.2111	0.1263	0.0186	0.0153	0.0132	0.0166	0.0342	0.0401	0.0938	0.0778	0.0635	0.0479
Cell Phone	0.0137	0.0063	0.0052	0.0041	0.0062	0.0061	0.0072	0.0072	0.0089	0.0062	0.0079	0.0061
Disregard Traffic Control	0.0031	0.0046	0.0026	0.0021	0.0058	0.0018	0.0031	0.0020	0.0037	0.0036	0.0037	0.0026
Distraction	0.0477	0.0257	0.0218	0.0203	0.0312	0.0355	0.0323	0.0325	0.0369	0.0228	0.0332	0.0279
Drug Involvement	0.0344	0.0281	0.0100	0.0109	0.0211	0.0173	0.0253	0.0225	0.0319	0.0281	0.0242	0.0210
Emotional	0.0099	0.0049	0.0020	0.0015	0.0048	0.0026	0.0035	0.0038	0.0062	0.0051	0.0050	0.0035
Exceeded Stated Speed Limit	0.0496	0.0214	0.0112	0.0088	0.0132	0.0111	0.0221	0.0135	0.0292	0.0160	0.0234	0.0135
Failed to Yield Right of Way	0.0027	0.0004	0.0020	0.0003	0.0026	0.0004	0.0025	0.0005	0.0007	0.0001	0.0021	0.0004
Fatigue	0.0366	0.0308	0.0186	0.0203	0.0072	0.0087	0.0058	0.0088	0.0079	0.0064	0.0131	0.0127
Fell Asleep	0.0618	0.0665	0.0487	0.0544	0.0209	0.0225	0.0151	0.0227	0.0134	0.0151	0.0285	0.0316
Following Too Close	0.0027	0.0008	0.0057	0.0011	0.0067	0.0014	0.0087	0.0022	0.0025	0.0007	0.0056	0.0013
Improper Backing	0.0015	0.0010	0.0014	0.0005	0.0048	0.0008	0.0019	0.0007	0.0017	0.0007	0.0023	0.0008
Improper Passing	0.0008	0.0003	0.0026	0.0012	0.0010	0.0017	0.0027	0.0023	0.0020	0.0011	0.0019	0.0015
Inattention	0.1378	0.1080	0.1134	0.1013	0.1453	0.1506	0.1455	0.1419	0.1319	0.1028	0.1357	0.1237
Lost Consciousness/Fainted	0.0073	0.0065	0.0157	0.0067	0.0252	0.0188	0.0209	0.0129	0.0119	0.0054	0.0171	0.0106
Medication	0.0015	0.0015	0.0034	0.0010	0.0043	0.0019	0.0050	0.0030	0.0042	0.0021	0.0039	0.0020
Misjudge Clearance	0.0172	0.0106	0.0338	0.0159	0.0671	0.0271	0.0528	0.0227	0.0329	0.0166	0.0434	0.0197
Not Under Proper Control	0.2126	0.1865	0.2419	0.2024	0.2782	0.2785	0.2606	0.2487	0.2213	0.1828	0.2462	0.2248
Overcorrecting/Oversteering	0.0679	0.0793	0.0696	0.0852	0.0873	0.1141	0.0807	0.1008	0.0696	0.0699	0.0760	0.0914
Physical Disability	0.0023	0.0013	0.0029	0.0010	0.0041	0.0028	0.0060	0.0026	0.0027	0.0009	0.0038	0.0018
Sick	0.0050	0.0030	0.0066	0.0027	0.0115	0.0061	0.0112	0.0054	0.0040	0.0026	0.0080	0.0042
Too Fast for Conditions	0.0916	0.0592	0.1268	0.0839	0.1096	0.0921	0.0898	0.0768	0.0948	0.0557	0.1022	0.0748
Turning Improperly	0.0019	0.0018	0.0026	0.0006	0.0036	0.0015	0.0039	0.0016	0.0050	0.0008	0.0036	0.0012
Weaving in Traffic	0.0027	0.0000	0.0014	0.0003	0.0007	0.0008	0.0010	0.0008	0.0030	0.0005	0.0017	0.0006
Other	0.0473	0.0314	0.0736	0.0347	0.0887	0.0438	0.0714	0.0424	0.0421	0.0282	0.0661	0.0369
None Detected	0.3248	0.4745	0.3576	0.4964	0.2731	0.3591	0.3347	0.4100	0.4134	0.5513	0.3407	0.4543

CHAPTER 5. DISCUSSION OF ESTIMATION RESULTS

5.1 Statistical Testing:

The null hypothesis for the log-likelihood ratio test is that the combined model including all time frames of a day does not have significantly lower log-likelihood than the separate models built for different times of a day, which in turn indicates a lack of significant difference between the combined model and separate models. The test statistics is χ^2 distributed with n degrees of freedom (in our case, *DF* =35+43+41+39+32-55 = 135). Following the method described in Section 3, test statistics for log-likelihood ratio tests for our models can be written as below:

$$LR = -[LL(\beta_{all}) - LL(\beta_1) - LL(\beta_2) - LL(\beta_3) - LL(\beta_4) - LL(\beta_5)]$$

Where,

$LL(\beta_{all})$= Log-likelihood value for all time of day model = -70785.15

$LL(\beta_1)$ = Log-likelihood value for 12am to 5am model = -7736.47

$LL(\beta_2)$ = Log-likelihood value for 5am to 9am model = -12384.77

$LL(\beta_3)$ = Log-likelihood value for 9am to 2pm model = -16520.1

$LL(\beta_4)$ = Log-likelihood value for 2pm to 7pm model = -20145.69

$LL(\beta_5)$ = Log-likelihood value for 7pm to 12am model = -13722.51

Putting these values in the equation:

$$\text{LR} = -2[-70785.15 + 7736.74 + 12384.77 + 16520.1 + 20145.69 + 13722.51]$$

$= 550.68 > 191.52 = \chi^2_{135,99.99\%}$

The above result shows that we can reject the null hypothesis. It means that models built for different times of a day instead of a single model including all time frames are justified.

5.2 Roadway Characteristics and Roadway Condition:

Three tables are prepared for showing outputs for our models. Table 2 shows the output for fatal injury and serious injury, table 3 shows the output for minor injury and possible injury, and table 4 shows the output for property damage only crashes for all the models. From table 2, hilly roads with curves are found to positively influence the probability of a fatal crash at the 12 am to 5 am timeframe but decrease the probability of a fatal crash at the 9 am to 2 pm timeframe. This contradicting finding might be due to the availability of daylight during daytime and drivers being more cautious and aware during daytime than nighttime, which supports the finding of [9]. This variable is found to be random for the combined model for possible injuries (table 3) with a mean of -1.21 and a standard deviation of 2.03. Using these values in a normal distribution curve, it can be found that for 72.44% of the sample, the probability is lower for possible injury, and for the rest of the sample, the probability is higher for possible injury. From table 3, this variable is also found to decrease the probability of possible injury for the 12 am to 5 am model and the 9 am to 2 pm model.

Straight and at-grade roads increase the probability of fatal crashes for both the combined model and 5 am to 9 am model. This variable is insignificant for possible injury and minor injury outcomes for all the models.

Dry road surface has a significant positive correlation with fatal injury, serious injury, or both for all the models. This finding is supported by the findings of [9] and [19], where it is shown that truck drivers experience fatal/serious injury on dry roads during morning time [9] and passenger cars experience severe injury [13].
Roads with ice increase the probability of fatal injury and serious injury outcome for the combined model and 9 am to 2 pm model. This variable also increases serious injury probability for the 2 pm to 7 pm model. This finding is in line with the finding of [21] where the researchers showed that snowy roads increase the probability of serious injury. From table 3, this variable is found to increase the possibility of possible injury for all the models, except the 12 am to 5 am model.

5.3 Weather Condition:

Cloudy weather is found to increase the probability of severe injury crashes for the combined model, 9 am to 2 pm model and 7 pm to 12 am model. This finding matches the finding of [12] where it is shown that cloudy weather significantly increases fatal/serious injury. This variable is found as random for serious injury outcomes for the 5 am to 9 am model with a mean value of -2.16 and a standard deviation of 2.49. Using these values on a normal distribution curve, it is found that for 51.76% of the sample, the probability is lower for serious injury and higher for the rest of the 48.24% sample. This variable also increases the probability of possible injury outcome for the combined model, 12 am to 5 am model and 7 pm to 12 am model.

5.3 Lighting Condition:

From Table 2, it is found that crashes during daylight have increased the probability of fatal injury for the combined model, 2 pm to 7 pm model and 7 pm to 12 am model but decreased the probability of fatal injury for the 9 am to 2 pm model. This can be explained by [13] where the researchers showed that daylight reduces severe crash injury outcomes except for days where the morning time is short (winter and fall). From table 3, daylight is found to increase possible injury outcomes for the combined model, 5 am to 9 am model, 2 pm to 7 pm model and 7 pm to 12 am model.

Darkness with streetlights turned on produced different injury outcomes. From table 2, it is found that this variable increases fatal injury outcomes in the combined model, 12 am to 5 am model and 7 pm to 12 am model; it also has a significant positive correlation with serious injury outcomes in the 12 am to 5 am model. However, this variable is found to negatively impact serious injury outcomes for the combined model, 2 pm to 7 pm model, and 7 pm to 12 am model. This result is contradictory with the findings from [12], [11], and [13] where it is shown that darkness without adequate streetlight increased the probability of severe injury outcome, but this effect was reduced with streetlight. From table 3, this variable is found to decrease minor injury probability for the combined model, 9 am to 2 pm model, 2 pm to 7 pm model and 7 pm to 12 am model.

When roads are not lighted, it also produced differing outcome than previous studies, as from table 2 it is found to negatively influence the probability of serious injury outcome for the combined model, 2 pm to 7 pm model and 7 pm to 12 am model, which contradicts the findings of [12], [11], and [13]. From table 3, it is found to have a negative correlation with minor injury and possible injury for all the models.

Table 2: Model outputs for all the models for fatal Injury and Serious injury outcome

Explanatory Variables	*Whole day Model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
Constants	-4.49 (-17.78)	-2.41 (-21.54)	-4.05 (-12.68)	-2.47 (-13.97)	-4.78 (-13.98)	-1.99 (-23.09)	-3.44 (-5.16)	-2.32 (-10.48)	-4.51 (-11.64)	-2.48 (-8.53)	-3.68 (-14.96)	-2.65 (-13.33)
Roadway Characteristics and Conditions												
Curve & hill (1 if roadway characteristics is curve & hill; 0 otherwise)	0.21 (2.01)		0.76 (2.67)		0.99 (3.45)		-0.54 (-2.53)					
Straight & grade (1 if roadway characteristics is straight & grade; 0 otherwise)	0.34 (3.47)				1.24 (4.53)							
Dry (1 if roadway condition is dry; 0 otherwise)	0.92 (4.28)	0.66 (6.38)		0.41 (2.81)	0.89 (3.43)		1.62 (2.75)	0.55 (2.7)	0.71 (3.11)	1.19 (4.19)		0.39 (2.68)
Ice (1 if roadway has ice; 0 otherwise)	0.55 (2.44)	0.38 (3.51)					1.53 (2.55)	0.5 (2.36)		0.78 (2.69)		
Weather Condition												
Cloudy (1 if the weather condition is		0.17(3.2)				-2.16 (-1.12)		0.2 (2.05)				0.22 (1.53)

Explanatory Variables	*Whole day Model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
cloudy; 0 otherwise)												
Standard Deviation – Normal Distribution						2.49 (2.05)						
Lighting Condition												
Day (1 if daylight; 0 otherwise)	0.48 (3.87)						-1.17 (-3.58)		1.05 (3.74)		0.8 (2.81)	
Lighton (1 if highway is lighted and light is on; 0 otherwise)	0.47 (3.6)	-0.19 (-7.54)	0.84 (2.85)	0.27 (2.14)						-0.49 (-6.2)	0.48 (2.25)	-0.17 (-2.74)
No light (1 if the highway has no light; 0 otherwise)		-0.5 (-5.51)								-1.28 (-2.84)		-0.45 (-2.5)
Driver Age												
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)	-2.17 (-2.59)	-0.31 (-6)		-0.28 (-2.26)				-2.18 (-1.31)	-1.05 (-4.16)	-0.59 (-6.66)	-2.13 (-1.4)	-0.29 (-2.33)
Standard Deviation – Normal Distribution	2.01 (3.92)							2.26 (1.98)			1.85 (1.95)	
Age group 3 (1 if driver age is	-1.17 (-1.86)	0.12 (2.41)			-0.25 (-0.24)		1.14 (7.52)	0.37 (4.06)	-1.5 (-1.32)		-0.99 (-0.65)	

Explanatory Variables	*Whole day Model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
over 50 years; 0 otherwise)												
Standard Deviation – Normal Distribution	2.2 (5.26)				1.75 (2.26)				2.6 (3.54)		1.89 (1.8)	
Gender												
Male (1 if the driver is male; 0 otherwise)		-0.04 (-0.19)						0.18 (2.05)		0.22 (2.88)		-0.008 (-0.02)
Standard Deviation – Normal Distribution		0.76 (2.52)										1.03 (2.22)
Female (1 if driver is female; 0 otherwise)	-1.59 (-3.29)		-3.86 (-2.47)		-19.11 (-2.05)		-1.28 (-2.26)		-3.91 (-2.75)		-0.77 (-3.65)	
Standard Deviation – Normal Distribution			2.73 (3.42)		9.13 (2.5)		1.24 (2.65)					
Human Characteristics												
Oversteering (1 if the driver has done oversteering; 0 otherwise)		-1.2 (-1.96)		0.66 (3.47)		0.61 (3.59)		0.64 (5.48)		0.4 (3.74)		-0.52 (-0.61)
Standard Deviation –		2.3 (4.93)										2.18 (2.98)

Explanatory Variables	*Whole day Model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
Normal Distribution												
Control (1 if vehicle is not under proper control; 0 otherwise)	1.29 (14.17)	0.88 (18.78)	-6.1 (-1.35)		1.51 (6.46)	0.62 (5.16)	0.89 (5.78)	0.77 (8.25)	0.51 (0.79)	0.84 (11.28)	1.44 (7.92)	-1.21 (-1.31)
Standard Deviation – Normal Distribution			5.52 (2.16)						1.62 (3.14)			2.87 (4.11)
Alcohol (1 if driver was found driving drunk; 0 otherwise)	1.42 (12.65)	1.23 (17.54)	0.64 (0.53)	1.28 (10.3)	1.76 (4.49)	1.29 (4.95)	1.05 (3.22)	0.66 (2.85)			1.4 (6.83)	1.78 (10.8)
Standard Deviation – Normal Distribution			1.75 (1.69)									
Too Fast (1 if the vehicle was moving too fast; 0 otherwise)			0.95 (2.6)									
Asleep (1 if the driver fell asleep; 0 otherwise)				0.91 (4.92)								

Table 3: Model outputs for all the models for Minor injury and Possible Injury outcome

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Roadway Characteristics and Conditions												
Curve & hill (1 if roadway characteristics are curve & hill; 0 otherwise)		-1.21 (-4.48)		-0.25 (-2.16)				-0.13 (-1.74)				
Standard Deviation – Normal Distribution		2.03 (6.65)										
Ice (1 if the roadway has ice; 0 otherwise)		0.21 (6.76)				0.11 (1.83)		0.39 (5.95)		0.22 (3.69)		0.22 (3.14)
Weather Condition												
Cloudy (1 if the weather condition is cloudy; 0 otherwise)		0.1 (3.1)		0.19 (2.01)								0.13 (1.81)
Lighting Condition												
Day (1 if daylight; 0 otherwise)		0.24 (10.64)				0.19 (3.82)				0.27 (6.16)		0.27 (3.81)

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Lighton (1 if the highway is lighted and light is on; 0 otherwise)	-0.14 (-4.85)						-1.18 (-2.66)		-0.73 (-7.21)		-0.14 (-2.46)	
Nolight (1 if highway has no light; 0 otherwise)	-0.21 (-4.13)	-0.29 (-5.6)		-1.07 (-1.43)		-0.22 (-1.67)			-1.22 (-4.28)	-0.35 (-1.93)	-0.29 (-3.36)	-0.31 (-4)
Standard Deviation – Normal Distribution				1.51 (1.86)								
Driver Age												
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)	-0.18 (-5.74)				-1.43 (-2.43)	-0.3 (-4.64)			-0.23 (-3.81)			
Standard Deviation – Normal Distribution					1.94 (3.43)							
Age group 2 (1 if the driver's age was in the range of 26-50; 0 otherwise)	-0.16 (-5.72)				-0.31 (-4.96)		-0.43 (-1.69)		-0.16 (-3.1)			
Standard Deviation – Normal Distribution							0.75 (1.65)					

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Gender												
Male (1 if the driver is male; 0 otherwise)			-0.11 (-1.71)									
Female (1 if driver is female; 0 otherwise)	0.14 (5.43)	0.33 (14.46)		0.29 (3.98)	0.36 (5.79)	0.37 (7.33)	0.16 (3.08)	0.03 (0.11)		0.27 (6.96)		0.21 (4.31)
Standard Deviation – Normal Distribution								1.24 (2.65)				
Human Characteristics												
Oversteering (1 if the driver has done oversteering; 0 otherwise)	0.29 (7.98)				0.29 (2.9)		-0.48 (-0.61)		-2.4 (-1.31)		0.18 (2.13)	
Standard Deviation – Normal Distribution							1.72 (1.71)		3.92 (2.13)			
Control (1 if vehicle is not under proper control; 0 otherwise)	0.22 (7.8)	-0.08 (-2.96)		-0.29 (-3.34)		-0.18 (-2.87)	0.22 (3.82)		0.39 (7.11)		0.2 (3.37)	
Inattention (1 if driver demonstrated inattention; 0 otherwise)	-0.26 (-4.23)	-0.28 (-4.74)	-0.8 (-4.61)	-0.59 (-3.43)			-0.15 (-2.08)			-0.17 (-3.13)	-0.47 (-3.07)	-0.41 (-2.76)

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Parameters (Z Score)		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*		*Parameters (Z Score)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Too Fast (1 if the vehicle was moving too fast; 0 otherwise)			-0.43 (-3.02)									
None (1 if no specific driver characteristic was identified; 0 otherwise)	-1.07 (-32.83)	-1.06 (-36.55)	-1.49 (-16.31)	-1.28 (-14.5)	-1.2 (-16.03)	-0.98 (-17.11)	-0.82 (-11.81)	-0.68 (-11.5)	-0.66 (-10.92)	-0.9 (-19.42)	-1.48 (-20.71)	-1.26 (-22.46)

Table 4: Model outputs for all the models for Property Damage Only (PDO) Crashes

Explanatory Variables	*Whole day model*	*12 am-5 am*	*5 am-9 am*	*9 am-2 pm*	*2 pm-7 pm*	*7 pm-12 am*
	Parameters (Z Score)	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*
Constant	2.18 (66.85)	1.76 (22.53)	2.11 (38.78)	2.3 (36.24)	2.32 (36.14)	2.06 (29.91)
Roadway Characteristics and Conditions						
Curve & grade (1 if roadway characteristics is curve & grade; 0 otherwise)	0.15 (6.67)	0.17 (2.58)		0.12 (2.58)	0.18 (4.38)	
Curve & hill (1 if roadway characteristics is curve & hill; 0 otherwise)	-0.3 (-9.99)	-0.3 (-3.15)	-0.23 (-4.44)	-0.36 (-5.6)	-0.3 (-6.59)	
Straight & grade (1 if roadway characteristics is straight & grade; 0 otherwise)	-0.29 (-11.86)	-0.35(-4.55)	-0.25 (-4.76)	-0.35 (-6.68)	-0.29 (-6.23)	
Dry (1 if roadway characteristics is dry; 0 otherwise)	-0.24 (-8.07)			-0.48 (-7.8)	-0.37 (-6.37)	
Weather Condition						
Cloudy (1 if the weather condition is cloudy; 0 otherwise)						
Blowing (1 if weather condition is blowing/sand/slit; 0 otherwise)	-0.18 (-6.52)	-0.11 (-2)	-0.18 (-4.26)	-0.1 (-1.95)	-0.17 (-3.9)	

Explanatory Variables	*Whole day model*	*12 am-5 am*	*5 am-9 am*	*9 am-2 pm*	*2 pm-7 pm*	*7 pm-12 am*
	Parameters (Z Score)	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*	*Parameters (Z Score)*
Human Characteristics						
Inattention (1 if driver demonstrated inattention; 0 otherwise)	-0.14 (-2.58)	-0.5 (-3.43)				

5.4 Driver Age:

From Table 2, it is found that crashes involving young drivers less than 26 years old (Age Group 1) produced a decreased probability of fatal or severe injury or both for all the models. This finding contradicts the findings from[9] and [10] which showed that crashes involving truck drivers younger than 31 years old produced much more serious crashes. However, this finding supports the finding of [11] which indicates that crashes involving young drivers will have less severe injury outcomes due to having much more physiological strength than older drivers. This variable is found as random for the combined model (mean -2.17, standard deviation 2.01) and for the 7 pm to 12 am time period (mean -2.13, standard deviation 1.85) and found as random for severe injury for the 9 am to 2 pm period (mean -2.18, standard deviation 2.26). From table 3, this variable is found to have a decreasing probability of minor and possible injury outcome in three models and found as random for the 5 am to 9 am model for minor injury outcome.

Age Group 2 variable represents the driver being in the range of 26 to 50 years. This variable was found insignificant for fatal injury and serious injury from table 2 but was found to have a decreasing effect for minor injury outcomes for 4 of the models. This variable was also found as random for minor injury outcomes for the 9 am to 2 pm model in table 3.

Age group 3 variable represents drivers who are more than 50 years old. Table 2 shows that being an older driver increases the probability of serious injury for the combined model and 9 am to 2 pm model and fatal injury for the 9 am to 2 pm model. From table 3, this group of drivers is found to decrease the probability of minor and possible injuries in 4 of the models, but in all these cases the variable is found as random. The positive influence of this variable is supported by the findings of [12], [11], and [13] where it is shown that drivers aged 65 and over experienced much severe injury outcome than other age groups. This variable is found as insignificant for minor injury and possible injury outcomes.

5.5 Gender of Driver:

This category has two variables: male and female. From table 2, results from all the models show that crashes involving female drivers produced a decreased probability of fatal injury and in three of these instances this variable was found as random (12 am to 5 am, 5 am to 9 am and 9 am to 2 pm models). This finding indirectly supports the finding of [17] and [12] which stated that being a female driver increased the probability of more no injury outcome than male drivers but contradicts the findings of [18] which says female drivers experience more severe injuries in low-risk segments. From table 3, results show that female drivers increase the possibility of either minor injury or possible injury or both outcomes for all the models.

Table 2 shows that being a male driver increases the probability of serious injury outcome for the 9 am to 2 pm period and for the 2 pm to 7 pm period but decrease the probability of serious injury for the whole day model and the 7 pm to 12 am model but in these two instances the variables were random. The positive influence is supported by [11] which showed that being male drivers increases the probability of fatal injury crashes than female drivers [11]. However, this finding is the opposite of the findings of [3] which showed that male drivers were found to mostly experience no injury outcome. In table 3, this variable was found significant only for minor injury outcomes for the 12 am to 5 am model.

5.6 Human Characteristics of Drivers:

Table 2 shows that oversteering by drivers increase the probability for serious injury for four models except for two models where this variable was found to decrease the possibility of serious injury (combined model and 7 pm to 12 am model), although in these two cases the variable was found as random variables. Oversteering may lead to losing control of the vehicle, which can cause severe crashes and cause serious injury. From table 3, results show that this variable increases the probability of minor injury for the combined model, 5 am to 9 am model and for 7 pm to 12 am model but found as random variables with decreasing impact for minor injury for 9 am to 2 pm model and 2 pm to 7 pm model.

From table 2, results show that losing control of the vehicle always increases the probability of fatal or severe injury for all the models except for fatal injury for the 12 am to 5 am model, where it is found to decrease the fatal injury possibility. However, in this case, the variable is found as random with a mean value of -6.1 and a standard deviation of 5.52. This variable is also found to be random for fatal injury for the 2 pm to 7 pm model and for serious injury for the 7 pm to 12 pm model. In both these cases, the variable showed a positive influence on the respective injury outcomes.

Driving under influence of alcohol or drugs always increased the possibility of both fatal and serious injury but was found insignificant for the 2 pm to 7 pm model for both the injury outcomes, and was found as a random variable for the 12 am to 5 am model for fatal injury with a mean of 0.64 and standard deviation of 1.75. This result is strongly supported by previous studies which stated that Alcohol or illicit drugs are found to increase fatality/ severe injury outcome [19][20] [3] [6] [8][10]. However, Alcohol-impaired driving caused less severe injuries for male drivers less than 31 years old but caused severe injury for the female of the same age group and had no significant effect on drivers over 31 years old [16]. This finding does not match our findings.

Driving too fast or speeding increases fatal injury possibility for the 12 am to 5 am model in table 2. Previous studies support this finding. Speeding is found to increase fatal crash injury across all ages and genders [12] [15] [10], also increased the probability of large trucks being involved in severe crashes [21]. From table 3, this variable is found to decrease the minor injury possibility for the 12 am to 5 am model.

Driver falling asleep while driving increases serious injury possibility for 12 am to 5 am model. This finding is supported by the previous studies which state that fatigue, the effect of medication, falling asleep/fainted are found to produce severe injury outcomes [21] [11] [3] [10].

A variable that represents no specific characteristics of the driver was not recorded found insignificant for fatal injury and serious injury for all the models shown in table 2. But from table 3, results show that this variable decreases the possibility of minor injury and possible injury for all the models.

Table 5: Elasticity values of parameters for fatal and serious injury for the models

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
Roadway Characteristics and Conditions												
Curve & hill (1 if roadway characteristics is curve & hill; 0 otherwise)	3.43		8.07		13.38		-11.13					
Straight & grade (1 if roadway characteristics is straight & grade; 0 otherwise)	5.68				16.19							
Dry (1 if roadway condition is dry; 0 otherwise)	52.84	38.52		27.53	37.88		93.03	29.42	37.85	72.48	23.32	
Ice (1 if roadway has ice; 0 otherwise)	14.6	10.16					47.8	14.11		23.63		
Weather Condition												
Cloudy (1 if the weather condition is cloudy; 0 otherwise)		3.32				32.12		4.46				3.43
Lighting Condition												

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
Day (1 if daylight; 0 otherwise)	23.55						-1.13		70.37		7.35	
Lighton (1 if highway is lighted and light is on; 0 otherwise)	12.34	-10.14	45.99						-12.35		28.49	-18.46
No light (1 if the highway has no light; 0 otherwise)		-3.39							-2.69			-5.63
Driver Age												
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)	34.31	-8.88		-9.71				26.22	-29.31	-17.23	29.65	
Age group 3 (1 if the driver age is over 50 years; 0 otherwise)	45.89	2.66			30.54		32.71	10.33	49.04		36.79	
Gender												
Male (1 if the driver is male; 0 otherwise)		26.88						9.63		12.51	46.8	
Female (1 if the driver is female; 0 otherwise)	2.53		30.52		76.85		7.71		60.11		-28.51	
Human Characteristics												
Oversteering (1 if the driver has done		11.63		4.8				5.93		3.71		9.49

Explanatory Variables	*Whole day model*		*12 am-5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm-12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Fatal	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*	*Fatal*	*Serious*
oversteering; 0 otherwise)												
Control (1 if vehicle is not under proper control; 0 otherwise)	26.32	18.10	31.1		23.07	11.71	24.11	18.64	48.35	20.03	25.2	29.79
Inattention (1 if driver demonstrated inattention; 0 otherwise)												
Alcohol (1 if driver was found driving drunk; 0 otherwise)	6.34	5.47	25.78	17.56	2.28	1.2	1.6	0.93			10.35	10.62
Too Fast (1 if the vehicle was moving too fast; 0 otherwise)			4.7									
Asleep (1 if the driver fell asleep; 0 otherwise)				5.6								

Table 6: Elasticity values of parameters for minor and possible injury for the models

Explanatory Variables	*Whole day model*		*12 am -5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm -12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Roadway Characteristics and Conditions												
Curve & hill (1 if roadway characteristics is curve & hill; 0 otherwise)		6.86		-3.15				-2.12				
Ice (1 if the roadway has ice; 0 otherwise)		4.9				2.66		9.72		5.9		5.03
Weather Condition												
Cloudy (1 if the weather condition is cloudy; 0 otherwise)		1.68		2.93								2.11
Lighting Condition												
Day (1 if daylight; 0 otherwise)		10.66				8.76				18.62		2.34
Lighton (1 if the highway is lighted and light is on; 0 otherwise)	-3.72						-1.22		-8.71		-7.85	-3.79
Nolight (1 if highway has no light; 0 otherwise)	-1.39	-1.84		6.36		-1.01			-2.47	-0.69		-4.02

Explanatory Variables	*Whole day model*		*12 am -5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm -12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
Driver Age												
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)	-4.96				13.18		-7.47		-5.83			
Age group 2 (1 if the driver's age was in the range of 26-50; 0 otherwise)	-6.72				-14.53		-0.12		-6.42			
Gender												
Male (1 if the driver is male; 0 otherwise)			-7.18									
Female (1 if driver is female; 0 otherwise)	4.8	10.49		7.15	12.32	12.97	5.83	23.92		9.48		7.31
Human Characteristics												
Oversteering (1 if the driver has done oversteering; 0 otherwise)	2.2				1.8		6.08		5.39		1.1	
Control (1 if vehicle is not under proper control; 0 otherwise)	4.40	-1.49		-4.75		-3.26	5.07		7.95		3.41	
Inattention (1 if driver demonstrated	-2.91	-2.91	-8.39	-5.63			-1.91			-2.09	-4.59	-3.91

Explanatory Variables	*Whole day model*		*12 am -5 am*		*5 am-9 am*		*9 am-2 pm*		*2 pm-7 pm*		*7 pm -12 am*	
	Elasticity (%)		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*		*Elasticity (%)*	
	Minor	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*	*Minor*	*Possible*
inattention; 0 otherwise)												
Too Fast (1 if the vehicle was moving too fast; 0 otherwise)			-2.62									
None (1 if no specific driver characteristic was identified; 0 otherwise)	-44.39	-41.28	-62.85	-52.1	-52.02	-43.18	-26.11	-19.78	-24.81	-33.02	-75.39	-62.9

Tables 5, 6, and Appendix 3 show the elasticity values in percentages for different variables of the models for different injury outcomes. These elasticity values are for the indicator variables used in the models and are 100% normalized. One advantage of using pseudo elasticity values is that it can help in prioritize variables based on their elasticity values [28]. For example, being a driver of 50 years old and older increases the probability of fatal and serious injuries (large positive numbers as elasticity values) in all the models whereas drivers within the age group of 26 to 50 years old found to be insignificant for fatal and serious injury outcome in all the models. This means that older drivers on the road are more vulnerable requiring more priority and policies should be implemented focusing on the reduction of fatal and serious injury for this driver group.

From table 5, crashes involving female drivers produce more fatal injury outcome (increases fatality by 76.85%) in the 5 am to 9 am period and in the 2 pm to 7 pm period (fatality increases by 60%) but are found to decrease the probability of fatal injury by 28.51% in the 7 pm to 12 am period. It shows that crashes involving female drivers are more prone to produce fatal/serious injury during the daytime than the nighttime. Also, the female driver variable overall increases all types of injury outcomes in all the models.

Alcohol variable is found to positively influence the probability of fatal and serious injuries for all the models. For example, alcohol has a pseudo elasticity value of 25.78 for fatal injury in the 12 am-5 am model and 10.35 for fatal injury in the 7 pm-12 am model. This shows that this variable is a strong influencer for fatal injury, and it is more dangerous during the nighttime. So, authority can think about checking for drunk driving more from 7 pm to 5 am.

Drivers no more than 25 years old produce a mixed effect during different times of the day. From table 5, this variable is found to increase the probability of serious injury and fatality in 3 of the models, but in these 3 occasions, this variable was a random parameter. This explains the variation in the effect of this variable.

One interesting fact can be seen from table 6." None" variable is found to significantly decrease the probability of both minor and possible injuries in all the models. Elasticity values for this variable are found to be relatively high in all cases. This might be due to the large number of absent human characteristics reported by police. As the dataset that we used was police reporting crash data, we found many datapoints to have this variable, which might have created some bias in the analysis. The authority might take measures to be more diligent and efficient in reporting necessary driver characteristics. The same bias might be in work for the dry road surface variable as well, which is found to significantly increase the probability of fatal and serious injuries across all the models.

When streetlights are on, it increases the probability of fatality for the whole day model, 12 am-5 am model, and 7 pm-12 am model but is found to decrease the probability of serious injuries in those models. It shows that during nighttime if streetlights are installed and they are on, crashes might lead to fatality more than severe injury.

CHAPTER 6. CONCLUSION

Using five years of police crash report data from Kentucky, this research examined the effect of time of day on resulting injury severities on single-vehicle crashes. A total of five injury types were considered for the analysis and four of them were shown here (fatal injury, serious injury, possible injury, and minor injury). In total six models were produced using the random parameters logit modeling technique, five of the models representing models for different times of a day, and the other model representing the whole dataset for all times of a day. A broad range of possible factors was considered to have a significant impact on the resulting injury outcome. These factors were classified into several categories namely roadway characteristics, roadway condition, weather condition, lighting condition, driver age, driver gender, and human characteristics of drivers. Likelihood ratio test results justified the necessity of building separate models for different times of a day rather than building just one model including all times of a day. However, some variables were found to produce a varying effect with different times of a day and also some of them produced contradicting findings with respect to previous studies (e.g. roads with curves and hills, age group 3, dark roads with streetlights on, dark roads with no light, female drivers and age group 1). For example, crashes during daylight increases fatal injury probability in the 12 am to 5 am period but decreases fatal injury probability in the 9 am to 2 pm period. Also, age group 1 is found to decrease fatal and severe injury probability in almost all the models, which contradicts the findings of some previous studies that being younger drivers increase the probability of fatal/serious injury. Losing control of a vehicle found to consistently increase the probability of fatal/serious injury, but also found to increase the probability of minor injury and decrease the probability of possible injury. Some variables such as alcohol, female drivers, no human characteristics of drivers are found to produce a temporally stable effect over all the models. The pseudo elasticity values for different variables showed in table 6, table 7, and Appendix 2 provides us a good idea of which variables have more influence over different injury outcomes. Our findings indicate that older drivers and female drivers on the roads of Kentucky are more prone to be involved in fatal and serious injuries. So, state authority can think about taking measures such as social awareness, public programs, and training for older and female drivers to reduce the fatality and severity of these two consumer classes.

Some caution should be exercised while interpreting these results. One thing to note here is we analyzed for urban and rural roads data combinedly, we did not split the data for urban and rural roads. As crash data entries for rural roads were much higher than urban crash entries, our analysis might be prone to some bias from rural roads data. On top of that, road type was not considered as a variable for the models. We labeled all types of urban roadways as urban roads and rural roadways as rural roads. In the future, we can add different roadways as a variable and split the data for urban and rural roads to generate models for five times of a day to get a more precise idea about the influence of the variables. Moreover, the mixed logit approach required to have data entries for all the variables. For this reason, any data entry containing any null value/void cell was dropped, which left us with approximately 39% of the raw dataset. Future research can look in to this matter and find an efficient way to allow more data points for this type of modeling approach. Also, we can generate models for different roadways for different times of a day, which will show how the variables behave at different times of a day on different roadways. On top of that, the influence of different vehicles on injury types (large trucks, passenger cars, motorcycles, etc.) was found as insignificant for all the models. But we have found studies which modeled time-of-day effect on injury-severity outcome for specific vehicles. So, for future research, this same approach can be followed for different vehicle types as well. Moreover, we did not split the data for each year. The variables can be tested for different year's models as well. This will show the effect of longer time durations on the variables.

On top of that, the findings of this research can be used in the improvement of current state-specific Safety Performance Functions (SPF) and Crash Modification Factors (CMF). For example, we have found female drivers, dry roads, icy roads, drivers aged more than 50 years, drunk driving, losing control of vehicles to have a significant positive correlation with fatality and serious injury in all the models. Also, the degree of effect of these variables changes with different times of the day. Incorporating these influential variables into the SPFs and updating the CMFs for different times of a day respectively will increase the precision for the prediction of crash frequency even more.

This study can be used as a reference for studying the temporal effects of different factors of injury severity and how and which factors vary with different times of a day. In addition, this study can be used as a starting point for evaluating the effects of time of day for different vehicles, different road types, different road geometry design, different states and regions, which can be helpful for traffic engineers, crash researchers and for different DOTs.

APPENDIX 1

Table A- 1: Before and after the cleaning of the functional class variable

Category	Before cleaning	After Cleaning	% reduction
Rural	109521	75980.00	30.63
Urban	26275	19154.00	27.10

Table A- 2: Before and after cleaning of Roadway Characteristics variable

Before Cleaning		**After Cleaning**		
RDWYCHRC	**Count**	**RDWYCHRC**	**count**	**% reduction**
Curve & Grade	39388	Curve & Grade	17141.00	56.48
Curve & Hillcrest	9302	Curve & Hillcrest	3956.00	57.47
Curve & Level	41100	Curve & Level	17579.00	57.23
Straight & Grade	38222	Straight & Grade	15082.00	60.54
Straight & Hillcrest	10044	Straight & Hillcrest	3933.00	60.84
Straight & Level	105526	Straight & Level	37443.00	64.52

Table A- 3: Before and after the cleaning of Roadway condition variable

Before Cleaning		**After Cleaning**		
RDWYCOND	**Count**	**RDWYCOND**	**count**	**% reduction**
Dry	158060	Dry	59808	62.16
Ice	9392	Ice	4126	56.07
Other	404	Other	133	67.08
Sand, Mud, Dirt, Oil, Gravel	648	Sand, Mud, Dirt, Oil, Gravel	128	80.25
Snow/Slush	8980	Snow/Slush	3823	57.43
Wet	63013	Wet	27116	56.97

Table A- 4: Before and after the cleaning of weather condition variable

Before Cleaning		**After Cleaning**		
WEATHER	**Count**	**WEATHER**	**count**	**% reduction**
Blowing Sand, Soil, Dirt, Snow	2021	Blowing Sand, Soil, Dirt, Snow	873	56.80
Clear	136412	Clear	51329	62.37
Cloudy	50120	Cloudy	19945	60.21

Fog with Rain	1121	Fog with Rain	490	56.29
Fog/Smog/Smoke	2402	Fog/Smog/Smoke	1140	52.54
Other	340	Other	123	63.82
Raining	41486	Raining	16882	59.31
Severe Crosswinds	284	Severe Crosswinds	128	54.93
Sleet/Hail	1896	Sleet/Hail	929	51.00
Snowing	7572	Snowing	3295	56.48

Table A- 5: Before and after the cleaning of driver gender variable:

Before cleaning		**After cleaning**		
DRVRGNDR	**count**	**DRVRGNDR**	**count**	**% reduction**
F	67423	F	36841	45.36
M	110613	M	58293	47.30

Table A- 6: Before and after the cleaning of the age group variable

Before Cleaning		**After Cleaning**		
DRVRAGE	**count**	**DRVRAGE**	**count**	**% reduction**
AgeGrp1	54048	AgeGrp1	29369	45.66
AgeGrp2	81075	AgeGrp2	43281	46.62
AgeGrp3	43055	AgeGrp3	22484	47.78

Table A- 7: Before and after the cleaning of the person type variable

Before Cleaning		**After Cleaning**		
PRSNTYPE	**Count**	**PRSNTYPE**	**count**	**% reduction**
Bicyclist	8	Bicyclist	0.00	100.00
Driver	178495	Driver	95134.00	46.70
Passenger	65175	Passenger	0.00	100.00
Pedestrian	8	Pedestrian	0.00	100.00

Table A- 8: Before and after the cleaning of the unit type variable

Before Cleaning		**After Cleaning**		
UNITTYPE	**count**	**UNITTYPE**	**count**	**% reduction**
Bus	1399	Bus	104	92.57
Emergency Vehicle—In Response	673	Emergency Vehicle—In Response	196	70.88
Emergency Vehicle—Non-Response	2146	Emergency Vehicle—Non Response	586	72.69

Farm Tractor and/or Farm Equipment	135	Farm Tractor and/or Farm Equipment	52	61.48
Go-Cart	30	Go-Cart	7	76.67
Hit & Run/Unknown	299	Hit & Run/Unknown	29	90.30
Lt. Truck	85987	Lt. Truck	33265	61.31
Military Vehicle	87	Military Vehicle	33	62.07
Motor Home/Recreational Vehicle	459	Motor Home/Recreational Vehicle	120	73.86
Motor Scooter or Motor Bicycle	506	Motor Scooter or Motor Bicycle	119	76.48
Motorcycle	4338	Motorcycle	2097	51.66
Other	601	Other	119	80.20
Other Public Owned Vehicle	330	Other Public Owned Vehicle	71	78.48
Passenger Car	128283	Passenger Car	51552	59.81
Passenger Car & Trailer	665	Passenger Car & Trailer	268	59.70
School Bus	1928	School Bus	88	95.44
Taxicab	70	Taxicab	21	70.00
Truck & Tractor	3799	Truck & Tractor	1412	62.83
Truck Tractor & Semi-Trailer	7503	Truck Tractor & Semi-Trailer	3422	54.39
Truck-Other Combination	615	Truck-Other Combination	211	65.69
Truck—Single Unit	3815	Truck—Single Unit	1362	64.30
Bicycle	8	Bicycle	0.00	100.00
Pedestrian	7	Pedestrian	0.00	100.00

Table A- 9: Before and after cleaning of human characteristics variable

Human Characteristics	**Before cleaning**	**After Cleaning**	**% reduction**
Alcohol Involvement	13625	4854	64.37
Cell Phone	1578	612	61.22
Disregard Traffic Control	914	269	70.57
Distraction	8670	2757	68.20
Drug Involvement	5616	2063	63.27
Emotional	1380	363	73.70
Exceeded Stated Speed Limit	4946	1472	70.24
Failed to Yield Right of Way	203	67	67.00
Fatigue	2537	1219	51.95
Fell Asleep	5701	2950	48.25
Following Too Close	528	209	60.42
Improper Backing	1087	102	90.62
Improper Passing	379	150	60.42
Inattention	36710	11994	67.33
Lost Consciousness/Fainted	3052	1132	62.91
Medication	663	230	65.31
Misjudge Clearance	12839	2327	81.88
Not Under Proper Control	55191	21797	60.51
Overcorrecting/Oversteering	18628	8399	54.91
Physical Disability	657	210	68.04
Sick	1180	470	60.17
Too Fast for Conditions	19688	7640	61.19
Turning Improperly	949	160	83.14
Weaving in Traffic	214	74	65.42
Other	11860	4069	65.69
None Detected	95234	41043	56.90

APPENDIX 2

Table : Availability of variables in the dataset

Variables Previously Used	**Availability in our dataset**
Age of driver	Yes
Gender of driver	Yes
Alcohol Involvement	Yes
Safety Belt Use	No
Roadway Type	Yes
Distracted Driving	Yes
Vehicle Occupancy	Yes
Airbag Deployment	No
Distraction due to electronic device (e.g. Cellphone)	Yes
Road surface condition	Yes
Weather condition	Yes
Lighting Condition	Yes
Number of lanes	No
Point of impact on vehicle	No
Time of crash	Yes
Vehicle’s age	No
Functionality of traffic control device	No
Crash occurring on/off pavement	No
Speed limit	No
Vehicle Type	Yes
Ran off the roadway	No
Improper lane change	No
Skidding/lost control	Yes
Improper passing	Yes
Exceeding speed limit	Yes
Too fast for conditions	Yes
Pavement surface condition	No
Pavement Friction	No
Pavement roughness	No
Hit fixed object	No
Shoulder width	No
Traffic volume	No
Presence of Work zone	No
Functional Class of roadway	Yes
Time took to arrive help	No
Vehicle caught on fire	No
Specific Accident Location	Yes

Fatigue	Yes
Medical condition (e.g. Sick)	Yes
Physical Handicap	No
Insufficient Driving Indicator	No
Wide Median	No
Effect of Drug	Yes
Daylight	Yes
Driver fall asleep	Yes
Embankment	No
Ditch	No
Poll/Tree	No
Vehicle Weight	No
Concrete Median Barrier	No
Obstruction in visibility	No
Race of Driver	No
Improper Backing	Yes
Crash on a weekend	No

APPENDIX 3

Table: Elasticity values for Property Damage Only (PDO) Crashes

Explanatory Variables	*Whole day model*	*12am-5am*	*5am-9am*	*9am to 2pm*	*2pm to 7pm*	*7pm-12am*
	Elasticity (%)	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*
Roadway Characteristics and Conditions						
Curve & grade (1 if roadway characteristics is curve & grade; 0 otherwise)	1.04	1.3		0.94	1.33	1.46
Curve & hill (1 if roadway characteristics is curve & hill; 0 otherwise)	-1.28	-1.12	-0.95	-2.07	-1.64	-0.77
Straight & grade (1 if roadway characteristics is straight & grade; 0 otherwise)	-1.5	-1.7	-1.01	-2.05	-1.56	-1.29
Dry (1 if roadway characteristics is dry; 0 otherwise)	-3.4			-7.56	-6.02	-3.54
Weather Condition						
Cloudy (1 if weather condition is cloudy; 0 otherwise)						

Explanatory Variables	*Whole day model*	*12am-5am*	*5am-9am*	*9am to 2pm*	*2pm to 7pm*	*7pm-12am*
	Elasticity (%)	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*	*Elasticity (%)*
Blowing (1 if weather condition is blowing/sand/slit ; 0 otherwise)	-2.12	-1.49	-1.74	-1.27	-2.44	-1.24
Human Characteristics						
Inattention (1 if driver demonstrated inattention; 0 otherwise)	-0.46	-1.57				-0.83

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