Understanding the Relationship between Crash Severity, Change in Velocity and Driver's Reaction

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ABSTRACT

A driver's reaction may influence the risk and severity of road crashes. Even though many studies have analyzed the factors influencing drivers' injury severity, little is understood about the relationship between driver's reaction, delta–v and driver's injury severity. This study develops a modelling framework to better understand this relationship. Three models, replicating driver's reaction, change in velocity (delta-v) and the driver's injury severity, are developed to analyze the hierarchy of factors influencing these three components of a crash. The data used for this estimation consists of two-vehicle crashes extracted from the United States National Automotive Sampling System-Crashworthiness Data System (NASS-CDS) for the period between 2009 and 2014.The results show that as drivers' age increases the possibility of a reaction before the crash is increased. This possibility is also increased when there are adverse surface conditions, non-straight horizontal curves, non-level vertical curves and on local roads. Reacting before a crash reduces the delta-v of the crashes and consequently the injury severity of the driver. The modelling results confirm that a higher delta-v is associated with higher occupant injury severity. Future research should focus on a more in depth understanding of factors influencing driver inattention to reduce occupant injury severity. In addition, the results of this research suggests that improving vehicle technologies such as 'Auto Emergency Braking System', can reduce severity of road crashes.

Keywords: Injury severity, driver's reaction, delta-v, Injury Severity Score (ISS).

INTRODUCTION

Road traffic injuries cause overwhelming health and societal problems for people involved in a crash, as well as significant economic loss (*1*). Historically, reducing crash severity has been of concern for transportation authorities. They have attempted to understand the how human, vehicle, road infrastructure and environmental characteristics influencing the number and severity of traffic crashes (*2,3*). Numerous studies have investigated factors affecting injury severity. These can be looked at from three perspectives:

1) Transportation point of view which focuses on factors such as human demographics, traffic, road geometry, and environmental characteristics (*4-17*)

2) Crash analysis perspective concentrating on the relationship between crash severity and dynamic factors of the vehicles involved in the crash (*18-29*).

3) Medical point of view considering the parameters influencing the injury severity of different body regions (*30-35*).

These three perspectives improved the understanding of the factors influencing driver injury severity. This study followed a modelling framework to investigate the link between these research perspectives through explaining the relationship between driver's injury severity, change in velocity (delta-v) and driver's reaction.

The next section of this paper outlines the literature review, followed by a brief explanation of the database used in this study. Then, the data analysis method is explained. The development of the models is described after that. Finally conclusions and relevant findings are discussed.

LITERATURE REVEIW

The literature review covers three groups of studies. These groups investigate the injury severity problem from 'Transportation', 'Crash analysis' and 'Medical' perspectives. The main research models and their associated dependent and independent variables are summarized in Table 1.

Transportation perspective focused on various factors dealing to traffic characteristics and road features such as the roads profile, intersection design and speed limits. They also considered environmental factors including weather and lighting condition. In addition, some human demographics and behavioral factors such as speeding and alcohol consumption were considered. For example, studies such as, Nevarez et al. (6) ,Christoforou, Cohen and Karlaftis (10) and Yu and Abdel-Aty (16) asserted that the crash severity depends on speed, congested segments, season's conditions (or climate) and roads profile with crash types.

Researchers from crash analysis perspective use crash dynamic parameters such as delta-v, angle of impact and mass ratio as independent variables. For example, Augenstein et al. (22) , Kononen, Flannagan and Wang (26) and Bahouth et al. (27) asserted that higher delta-v is associated with higher injury severity. They further illustrated that, in two-vehicle crashes, the mass of other vehicle is directly proportional with the occupant injury severity (*18-20*).

Medical approach focuses on the injury severity of the crashes. The focus here is on human body characteristics. Detailed human body characteristics were taken into consideration to measure the level of severity for different body regions (*30-34*).

TABLE 1 Summary of Previous Studies Depends on the Point of View.

Study		Model Independent Variables					Outcome
Authors Name	**Type**	**Driver attributes**	**Reaction** [d]	**Vehicle Factors**	**Geometric and Traffic Environment**	**Crash Factors**	
Islam and Mannering *(4)*	T[a]	Wearing safety belts, driver alertness, No. of passengers, driver's license.	No D.R[e]	Vehicle age	Traffic light, surface conditions, type of road, weather.	-	Injury severity
Ma, Kockelman and Damien *(5)*	T	Age, gender, seat position, wearing safety belts.	No D.R	Curb weight, vehicle type	Roadway divided, profile, speed limit, light conditions, weather conditions	-	Injury Severity
Nevarez et al. *(6)*	T	-	No D.R	-	Land use, number of lanes, sidewalk width, roadway curves, friction factors, AADT per lane, access management level and speed limits, light conditions, weather conditions.	-	Injury Severity
Quddus, Wang and Ison *(7)*	T	-	No D.R	-	Number of lanes, radius curvature, roadway grade, speed limit, road surface, year of the accident, traffic flow, number of vehicles involved, time and day of the crash	-	Injury Severity
Rana, Sikder and Pinjari *(8)*	T	Age, gender, wearing safety belts, alcohol/drug presence	No D.R	Accident type, vehicle role, vehicle age	Alignment, profile, and road surface, traffic control sign, Speed limit, lighting condition.	-	Injury Severity
Morgan and Mannering *(9)*	T	Age, gender, alcohol/drugs presence	No D.R	Vehicle type	Alignment, profile, roadway segment.	-	Injury Severity
Christoforou, Cohen and Karlaftis *(10)*	T	-	No D.R	-	Road direction, road curvature, grade, profile, traffic volume, speed, density	-	Injury Severity
Kaplan and Prato *(11)*b	T	Age, gender, alcohol/drugs presence, fatigue	No D.R	Accident type	Alignment, profile, and number of lanes, road section type, service type, week day type, light and weather conditions	-	Injury Severity

Study		Model Independent Variables					Outcome
Authors Name	**Type**	**Driver attributes**	**Reaction** [d]	**Vehicle Factors**	**Geometric and Traffic Environment**	**Crash Factors**	
Kaplan and Prato *(12)*	T	Age, gender, wearing safety belts, alcohol/drug presence, driver alertness	D.R[f]	Vehicle type	No of lanes, traffic-way, road alignment, road profile and surface conditions, speed, light conditions field of vision, type of day	-	Injury Severity
Xie, Zhao and Huynh *(13)*	T	Age, gender, wearing safety belts, alcohol/drug presence	No D.R	Accident type, vehicle age	Roadway, shoulder, median, turn lane, road surface, travel directions Type of road, speed limit, light and weather conditions	-	Injury Severity
Kim et al. *(14)*	T	Age, gender, wearing safety belts, Alcohol/Drug presence, driver alertness, Improper turning.	No D.R	Vehicle age	Speed, light and weather conditions	-	Injury Severity
Buddhavarapu, Banerjee and Prozzi *(15)*	T	Age, gender, alcohol/drugs presence, driver's license.	No D.R	Number of airbags deployed per person	Road type, presence of grade, surface condition, shoulder width, roughness index, skid index condition, average daily traffic, average daily truck, light and weather conditions	-	Injury Severity
Yu and Abdel-Aty *(16)*	T	-	No D.R	-	Numbers of lanes, grade, speed, seasons	-	Crash Predictions
Chen et al. *(17)*	T	Age, gender, wearing safety belts, alcohol/drug presence,, driver residency	D.R	Hazard material involvement. accident type	Road type, road curvature, road grade, number of vehicles in crash, road pavement, traffic control lighting condition	-	Injury severity
Evans and Frick *(18)*	C[b]	-	No D.R	Mass Ratio	-	Delta-v	Injury risk

Study		Model Independent Variables					Outcome
Authors Name	**Type**	**Driver attributes**	**Reaction** [d]	**Vehicle Factors**	**Geometric and Traffic Environment**	**Crash Factors**	
Wood and Simms *(20)*	C	-	No D.R	Mass Ratio		-	Injury Risk
Toy and Hammitt *(21)*	C	Age, gender, wearing safety belts	No D.R	Mass Ratio, accident type, airbags deployed	-	Delta-v	Injury Severity
Augenstein et al. *(22)*	C	Occupant gender, height, weight, wearing safety belts	No D.R	Airbags deployed	-	Delta-v	Injury Severity
Tolouei *(23)*	C	Age and gender	No D.R	Mass, length, width, height and Wheelbase.	-		Injury risk
Sobhani, Young and Sarvi *(24)*	C	Age and gender	D.R	Type of crash	Surface condition, Speed , Light conditions	Kinetic energy Angle of impact	Injury Severity
Kononen, Flannagan and Wang *(26)*	C	Age, Wearing Safety Belts and Gender	No D.R	Accident type and Airbags deployed	-	Delta-v	Injury Severity
Bahouth, Digges and Schulman *(28)*	C	Age, wearing safety belts	No D.R	-	-	Delta-v, and angle of impact	Crash Prediction
Bahouth et al. *(27)*	C	wearing safety belts, seating position	No D.R	Accident type	-	Delta-v	Injury Severity
Viano and Parenteau *(29)*	C	Age, gender	No D.R	Accident type	-	Delta-v	Fatality Risk
Li et al. *(30)*	M[c]	Blood Alcohol Content	No D.R				Injury Severity
Klinich et al. *(31)*	M	Age, Seat belts use, Body occupant injury region	No D.R	Airbags Deployed		Delta-V	Injury Severity
Ammori, Eid and Abu-Zidan *(33)*	M	Age, gender, wearing safety belts, seat position,	No D.R				Injury Severity

		Body occupant injury region					
Ryb et al. (*34),*(*35*)	M	Age, gender, wearing safety belts, Body occupant injury region	No D.R	Accident type	-	Delta-v	Crash Prediction

[a] **T:** Analysis focusing transportation point of view, [b] **C:** Analysis focusing on crash analysis view, [c] **M:** Medical point of view.
[d] **Reaction**: Drivers' reactions, [e] **D.R:** Drivers have reactions, [f] **No D.R:** Drivers do not have reactions

All these studies contribute to the level of knowledge of the important factors affecting the outcome of crashes. However, alone they did not analyze all the important factors. The transportation perspective does not give a complete view of the crash severity since crash dynamic factors are not considered. The crash analysis view cannot show the effect of road, environment, and traffic characteristics on crash severity. Similarly, researchers from medical point of view ignore the effect of vehicle, road and environmental parameters. It is hypothesized that considering all these factors together improves the understanding the link between crash outcomes and different crash attributes. The relationship between these three perspectives was considered by Sobhani et al. (*24*). They developed a modeling framework to investigate the link between pre-crash, in-crash and post-crash characteristics using a sequential modelling technique. They used Australian Crash In-depth Study (ANCIS) database to develop the models. There are two main limitations in the study conducted by Sobhani et al. (*24*).

- The ANCIS database included limited number of crashes which could lead to create biased results.
- The main objective of this study was to develop a modelling framework to be implemented in a micro-simulation model to assess the risk of different road locations. Therefore, the crash attributes which could not be measured using micro-simulation were excluded from the models.

This study is conducted to address some of these shortcomings using a more comprehensive database which contains more comprehensive sets of road, environmental, human, crash and vehicle information. This study utilizes CDS[1] database, which is more comprehensive than ANCIS, to provide better understanding of the results. Differences between these databases are discussed below in the data section. Moreover, this study will include a more comprehensive combination of road, environmental, crash dynamics, driver demographic and driver behaviour characteristics in the modelling process. This study follows the same methodological framework which was developed by Sobhani et al. (*24*) to model the relationship of conflict characteristics, driver's reaction, crash kinetic energy and occupant injury severity. This study models the relationship of crash characteristics, driver's reaction, delta-v and driver's injury severity.

DATA

This paper focuses on two-vehicle crash data which are available from the national website of the United States government. The National Highway Traffic Safety Administration (NHTSA) provides sophisticated reports for motor vehicle crashes. This data includes fatality, severe injury and property damage crashes (*36*). National Automotive Sampling Systems (NASS) is a national program to collect data. This program provides NHTSA with efficient and precise crash data. NASS also includes two systems: the General Estimates System (GES) and the Crashworthiness Data System (CDS). CDS data mainly includes passenger vehicle crashes, and dynamic variables such as change in velocity. GES data is broader but it does not include crash dynamics variables.
The ANCIS database recruited crashes to be studied from occupants who were hospitalized. For this reason, the database has little crash information on crashes where no and minimal injuries occurred. On the other hand, the CDS database records a variety of crashes with all levels of injuries

[1] The Crashworthiness Data System (CDS).

obtained by individuals. In addition, the number of crash reported in CDS database is about five thousand case/year compares with few hundreds in ANCIS(37). The data used in this study includes 11065 cases (or 22130 driver) of two vehicle crashes over the period between 2009 and 2014. Only vehicle to vehicle crashes are considered in this study. Cases which are not obviously coded or are with unknown driver’s reactions, change in velocity and injury severity, are removed in order to improve the reliability of the analysis.

METHOD OF STUDY

This study investigates the factors influencing crash injury severity using the modelling framework consisting of three components. This framework is first presented by Sobhani et al. in 2013 (*24*) to find the relationship of conflict characteristics, driver’s reaction, crash kinetic energy and occupant injury severity using ANCIS data. They used binary probit model to predict the relationship between conflict characteristics and driver reaction, and used log-gamma and linear regression to model the crash kinetic energy and occupant injury severity. This study adopts the same framework as used in Sobhani et al. (*24*), on a different set of data (CDS).

Figure 1 reveals the modeling framework used in this study. The framework consists of three sequential models determining the driver’s reaction, delta-v and driver’s injury severity.

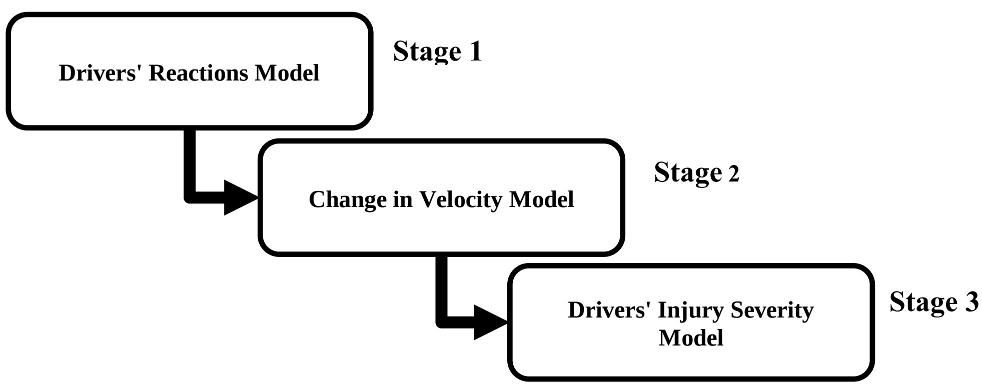


FIGURE1 Model Framework

The first stage of this framework is to understand the parameters affecting the driver’s reaction before the crash. This stage describes two possible actions taken by the driver in response to the unexpected stimulus. These actions are ‘No response’ and ‘Response’. Independent variables for the framework are ‘speed limit, age, surface conditions, road horizontal and vertical profile, traffic flow, lighting conditions’ and ‘accident type’. The output of the first model of this framework is used as input of the second model.

In the next stage the link between ‘drivers’ reactions and ‘delta-v’ is modelled. This model includes the ‘driver’s reaction’ ’accident type’, ‘mass ratio’ and ‘speed limit’ as independent variables. The dependent variable is delta-v which is a binary variable indicating whether the change in velocity exceeds 30 mile/hr, as it encouraged to use according to the results of (*26*).
The third component of the framework is to estimate the probability that the driver dies or severely injured. A binary variable indicating whether the driver seriously injured is defined as the dependent variable in this model. The output of the second model (i.e. delta-v) is used as

explanatory variable.

This study tested the goodness of fit of the binary logit and binary probit models. Binary logit was utilized as it showed better goodness of fit. Binary logistic regression model is a type of Generalized Linear Regression model in the form of Equation 1 (*38*):

$$P_i = \frac{\mathrm{EXP}(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_k X_{k,i})}{1 + \mathrm{EXP}(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_k X_{k,i})} \quad (1)$$

When the model is applied to model the driver's reaction, the logit model predicts the probability (π) of the driver taking an action at the crash scene, between 0 and 1 ($0 \leq \pi \leq 1$) for all possible independent variables in Equation 1, where, β_0 is the intercept term in the model, (β = 1, 2, . . . , n) are the regression coefficients for each independent variable. Y is the predicted probability of the event which is coded with 1 (action) rather than with 0 (no action), 1−Y is the predicted probability of no action and X is the set of independent variables. These variables include 'age', 'gender', 'speed', 'surface type', and 'crash type'. These variables can be either discrete, continuous, or a mixed trend. The parameters in the model are estimated using a maximum likelihood approach. The estimated model is evaluated by performing a likelihood ratio test to determine the significance of the covariates in the model. Equation 2 shows the log likelihood function. Because the dependent variable is modelled using a log transformation, logit (π), the interpretation of the estimated coefficient is based on the exponential transformation of the estimated coefficient, which is commonly known as the odds ratio (Equation 3).

$$\mathrm{L}(\beta)\mathrm{LL}(\beta) = \sum_{i=1}^{n} \{ y_i \ln(P_i) + (1 - y_i) \ln(1 - P_i) \} \quad (2)$$

$$Odds = \frac{P(event)}{P(no\ event)}$$

$$P(no\ event) = 1 - P(event) \quad (3)$$

RESULTS

The results will be presented for each level of model.

Drivers' Reactions Model

The first step in the modelling process is understading the factors affecting driver's reaction. A binary logit model was developed. The modelling results show a high goodness-of-fit based on Omnibus test of model coefficients and Cox and Snell R Square. Table 2 outlines the results. These will be discussed under the headings effect of driver factors, effect of crash characteristics, effect of vehicle characteristics and effect of road related factors.

Effect of driver factors:

Driver related factors include demographic information, alcohol and drug use, and speed are significantly associated with the likelihood of performing a reaction before crash.

A 20-year interval is chosen to group driver age. The four driver age groups include, ‘younger than 26 years old’, ‘26–44 years old’, ‘45–64 years old’, and ‘older than 65 years old’. Compared to the reference group (i.e. elderly drivers or 65 years or older), the likelihood of ‘reaction’ is significantly higher in other age groups. Elderly drivers, are less likely to avoid crashes than other groups do. This possibility is the highest for age group under 25 compared with other age groups (odds ratio = 2.240). Drivers aged between 25 and 64 are 80% more likely to avoid crashes than their elderly counterparts (odds ratio = 1.862).

Another factor, ‘driver drugs or illegal alcohol consumption’, is reflected in cases where there is use of illegal drugs and alcohol abuse. The blood alcohol content (BAC) of the driver indicating abuse is a measure as less /above 0.08 percent. Results revealed that ‘alcohol and drug’ use decreases the likelihood of conducting reactions. Drunk drivers are 50% less likely to avoid crashes than non-drunk drivers (odds ratio = 1.576).

In relation to ‘speed limit’, higher speed limits have a higher likelihood of the driver conducting reactions. The estimated parameters illustrates that higher speed limit locations (‘between 41 and 55 mph’) are 50% more likely to perform action than the locations with speed limit of 25 mph or less(odds ratio = 1.558).

Effect of crash characteristics:

Compared to the angle crashes (the reference group), the odds ratio shows that ‘Rear end’, ‘Head on’, and ‘Side swipe opposite direction’, are more likely to be associated with ‘reaction’. This is logical, because in these scenarios it is easier for the drivers to see each other before the crash. Results further show that the lower possibility of ‘reaction is associated with the ‘side swipe same direction’ crash type. This is also reasonable as it is difficult to observe the other driver in this type of crash (odds ratio = 0.659). Accident type and scenario details are shown in the Figure 2.

Effect of vehicle type:

As shown in Table 2, ‘vehicle type’ is also significantly associated with drivers’ reactions. Results show that large size vehicles (LSV) drivers are about 20% more likely to take actions than drivers of small cars (odds ratio = 0.849).

Effect of road related factors

Road factors such as, surface conditions, profile (grade and level), section type and traffic direction and traffic light, are significantly associated with the likelihood of engaging in reactions (see Table 2).

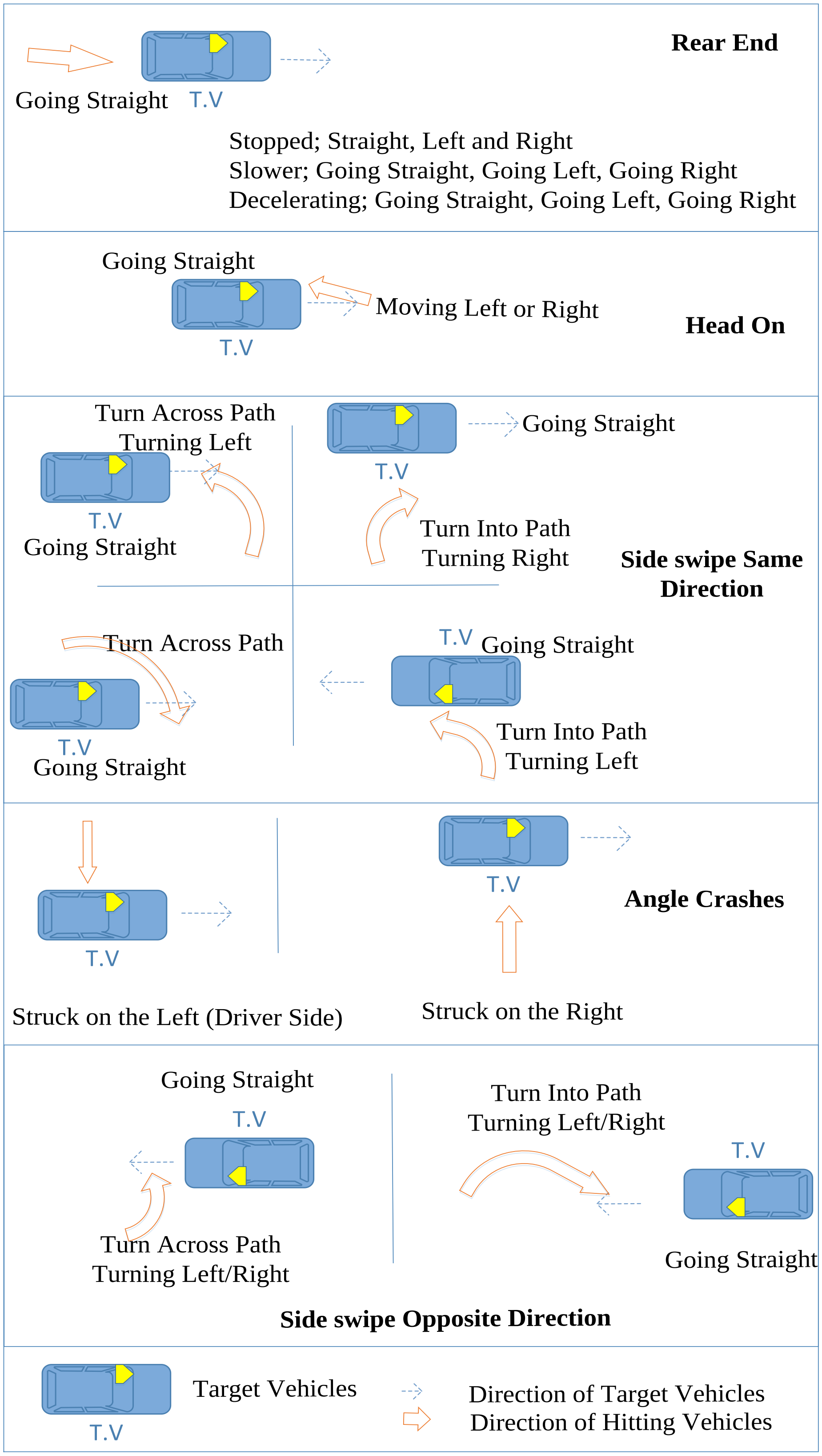
TABLE 2 Model Estimates of Drivers’ Reactions

Dependent Variable	Independent Variable	Level of the Variable	Coefficient	P-Value	Odds Ratio
	Age Groups	<26 Years old	.807	< 0.0001	2.240
		26–44 Years old	.622	< 0.0001	1.862

Drivers take a reaction		45–64 Years old	.412	< 0.0001	1.510
		>65 Years old	Ref.	-	-
	Driving Behavior Alcohol/drugs use	No	.455	.003	1.576
		Yes	Ref.	-	-
	Speed Limit in mph	25 or less	Ref.	-	-
		26 – 40	.285	.002	1.330
		41 – 55	.443	< 0.0001	1.558
		56 and Over	.287	.042	1.333
	Accident Type	Side swipe same	-.417	.009	.659
		Side swipe opposite	.776	< 0.0001	2.172
		Head on	.475	< 0.0001	1.608
		Rear end	.466	< 0.0001	1.593
		Angle	Ref.	-	-
	Vehicle Type	Small car	-.163	.005	.849
		LSV	Ref.	-	-
	Time	Day time	.227	< 0.0001	1.255
		Night time	Ref.	-	-
	Road Profile	Level	-.230	< 0.0001	.794
		Grade	Ref.	-	-
	Road Alignment	Straight	-.180	.023	.835
		Curve	Ref.	-	-
	Road Type	Local roads	.345	< 0.0001	1.412
		Arterial roads	Ref.	-	-
	Road Condition	Dry	-.222	.002	.801
		Slippery	Ref.	-	-
	The reference category is: No Reaction Number of cases = 7996 Cox & Snell R Square= 0.053	Constant	-1.894	< 0.0001	.150

Compared with driving during the day (the reference group), drivers at night time are less likely to perform any reactions. This is logical, because the drivers with low visibility most likely do not perform action at night. This results are in agreement with the results of (*39*) study.

With respect to 'Road Profile', it is found that unleveled roads or up\down grade (slope) significantly reduce the likelihood that the drivers preform positive action against crashes. The estimated value of the possibility of crashes occurring on roads with a level profile and flat roads is 21% higher on than unlevelled roads.



1
2 **FIGURE2 Accident Type and Scenario adapted from NASS-CDS Manuel (*36*)**
3 **with adding Extensive Explanations**

The effect of ‘Road Alignment’ is also significant and positive, indicating that drivers at curve alignment are more likely to perform actions than straight roads. The OR statistic tells us drivers are 20 % more likely to perform action.

The likelihood of engaging in reactions decreases with appearance of controls functioning traffic light in arterial roads. They are increasing are 40% likelihood of acting positively or to engage in maneuvers than urban roads. When traffic lights are not present on rural roads, the drivers seems to be more cautious.

Slippery pavements conditions, such as wet, snow and ice, are greatly contribute to drivers reactions. The estimated parameters suggested that the likelihood of positive reactions as a result of these wet pavements conditions is approximately 20% higher than that in dry pavement condition. Slippery pavements are more likely to associate with ‘action’ rather than ‘no action’.

Delta-v Model

The second step in the modelling process of the crash severity is modelled on ‘Delta-v’ or ‘change in velocity’ of the involved vehicles. Delta-v considers as a predictor of occupant risk due to its correlation with occupant injuries (*40*).

The value of change in velocity of the vehicles involved in crashes is obtained from NASS-CD*S (36)*. NASS-CDS uses WinSMASH computer software to estimate the change in velocity. This software uses advanced measurements from the crash scene, vehicle damage and vehicle stiffness characteristics to compute energy absorbed by the vehicle and estimate the delta-v. The WinSMASH is based on Microsoft Windows, developed and updated by NHTSA (*41*). To explain the effect of the ‘driver’s reaction’ and ‘road and vehicles dimensions’ on the delta-v, a binary logistic regression model is employed.

TABLE 3 Model Estimate of Delta-v

Dependent Variables	Independent Variables		B	Sig.	Odd Ratio
More than 30 mph*	**Mass Ratio**	Numerical	0.986	< 0.0001	2.679
	Speed limit	Numerical	0.031	< 0.0001	1.031
	Accident Type	Rear end	-2.575	< 0.0001	0.076
		Angle	-2.853	< 0.0001	0.058
		Side Swipe Same Direction	-3.416	< 0.0001	0.033
		Side swipe Opposite Direction	-0.548	0.082	0.578
		Head on	Ref	-	-
	Drivers’ reactions	Drivers Do not have Reactions	0.36	0.052	1.434
		Drivers have Reactions	Ref	-	-
*** Reference category is:** Less than 30 mph. Number of cases = 5176 Cox & Snell R Square= 0.047		Constant	-4.874	< 0.0001	0.008

As can be seen in Table 3 "Mass Ratio[2]" significantly contributed to 'delta–v higher than 30 mph' (odds ratio = 2.679). The measure of delta-v comes from WinSMASH and is depending on energy absorption of the crash. Speed limit is another contributor (odds ratio = 1.031). Looking to accident type, compared to the 'Head on' (the reference group), the odds show that vehicles in, 'Rear end', 'Angle' and 'Side swipe same direction' crashes, are less likely to associate with high delta-v, than frontal interactions. The odds show that "Head on" have much higher delta-v than 'Rear' impacts (odds ratio of 1 and 0.076 respectively). Similar trends are observed for 'Angle' and 'Side swipe same direction' crashes. This is logical, because in these crashes vehicles usually move in the same direction. That is the main reason that the odds ratio of 'sideswipe opposite direction' was higher than 'read end', 'angle' and 'sideswipe same direction' crash types (odds ratio = 0.578).

Drivers' reaction is also significant and positive contributor, indicating that drivers who do not have reactions are 40 % more likely to have higher delta-v.

ISS Model

The third step in the modelling process of the crash severity (Fig. 1) is to study the relationship between the ISS of the crash and the delta-v. The current and recommended measure of finding crash severity is through the use of the Abbreviated Injury Scale (AIS) and Injury Severity Scores (*26,42,43*). While, AIS is an anatomical scoring system describing the threat-to-life to the individuals, includes six levels from 1 to 6, one being minor and six being virtual. These levels could provide an indication to the probability of death, however, it could not provide any indication of overall injury severity.

On the other hand, Injury Severity Scores (ISS) is a numerical measure based on medical scale used to describe the overall injury severity with a range from 1 to 75. ISS is calculated by taking the sum of square of three highest AIS in body regions(*44*) as seen in Equation4.

$$ISS = AIS_1^2 + AIS_2^2 + AIS_3^2 \tag{4}$$

Sasser et al. (*45)* suggest that ISS of 15 or more is the level of being severely injured. Thus, the dependent measure for this part of study is the binary variable, 'ISS 15+', indicating whether driver of a vehicle experienced an injury of ISS 15+ or not. A binary logistic regression technique is utilized to predict the injury severity score (ISS) of the crash. Table 4 shows the dependent and independent variables of this model.

A 20 unit intervals is chosen to group delta-v. The six changes in velocity groups include '20 km/hr. or less', '20–40', '40–60', and 'over 60 km/hr.' .Compared to the over 60 (the reference group), the percentage of having severe injuries or being killed is significantly higher than that of other groups. The odds ratio (OR) tells us that the probability of having severe injuries is much higher than '20 or less' (odds ratio of 1 and 0.011 respectively). As change of velocity increases, the probability of having severe injuries increases.

[2] Mass Ratio is defined according to (*18,19*), $Mass\ Ratio = \frac{Mass\ of\ the\ other\ vehicle}{Mass\ of\ this\ vehicle}$

TABLE 4 Model Estimate of ISS

Dependent Variables	Independent Variables		B	Sig.	Odds Ratio
*Drivers have Severe Injuries or they have been killed	Change in velocity	21 km/hr. and below	-4.533	< 0.0001	.011
		21 - 40 km/hr.	-3.473	< 0.0001	.031
		41- 60 km/hr.	-1.735	< 0.0001	.176
		60 and over km/hr.	Ref.	-	-
	Wearing safety seat belts	No	1.301	< 0.0001	3.673
		Yes	Ref.	-	-
	Presences of Older Drivers	Yes	1.155	< 0.0001	3.173
		No	Ref.	-	-
	Constant		-.956	< 0.0001	.384
	Reference category is: *No injury or Minor Number of cases = 7211 Cox & Snell R Square=0.06				

Seat belts use is also significant and positive, if the drivers do not wear safety seat belts the probability of having severe injury is higher than drivers who wear safety seat belts (odds ratio of 3.673 and 1 respectively). Presences of older drivers is also significant, drivers over 55 years are more likely to have severe crashes than younger age groups (odds ratio of 3.173).

DISCUSSION AND CONCLUSION

This study focuses on the link between drivers' reactions, change in velocity and drivers' injury severity using data on two-vehicle crashes extracted from the United States NASS-CDS database for the five-year period, 2009-2014. A sequential model consisting of three steps was utilized to develop the model. Step one investigates the factors affecting driver's reactions. The second step estimates the effect of driver's reactions on change in velocity during the crash. The third step estimates the Injury Severity Score (ISS) of the drivers using the change in velocity and driver reaction models.

The results of the first model show that driver related factors are significantly associated with the reaction. The likelihood of not taking action to avoid a crash increases as the age increases, which is in agreement with the findings of previous research (*39,46,47*). Elderly drivers (65 years or older), are less likely to avoid crashes than other groups. This is because, as drivers age increases, reaction time increases. In addition, driving behaviors while under the influence of 'drunk and drugged', have a negative impact on the likelihood of performing reactions, which is in agreement with the findings of previous research (*39,46*). This is due to the fact that alcohol use may affect negatively on drivers' alertness, visibility and reaction time. These results also agree with Fell et al (*48*), who suggest that the police authorities apply effective law and regulations to address alcohol-related crashes such as, lowering blood alcohol content (BAC) limits for driving from 0.08 to 0.05 and promoting educational programs or community-specific models to address the negative consequences of drunk driver's scenarios. In comparison, 'LSVs' with cars, drivers of large size vehicles are more likely to take actions against crashes than drivers of small cars. This results may be related to drivers' behavioral, professional their confidence while driving a large vehicle. The results are in agreement with results of study Kaplan, S., and C. G. Prato (*39*). Moreover, an interesting finding is that road related factors such as adverse surface conditions, grade profile, and poor traffic light, were significantly associated with the likelihood of engaging in a reaction. These results are in agreement with the findings of other researchers (*39,46*). The results can be explained by the fact that drivers may be more likely to drive cautiously in those adverse driving surroundings.

The results of the second model, the delta-v model, show that mass ratio and speed limit at the scene of the crash have positive effects on increasing the change in velocity, which is in agreement with other research (*24*). The relationship between change in velocity and the drivers reactions is also significant and positive, indicating that at drivers who do not react are more likely to have higher delta-v.

Additionally, the third model, the injury severity model, shows that as change of velocity increases, the probability of having severe injuries increases. Drivers who wear seat belts are also safer, the two results are in agreement with other research (*21*). Similarly, drivers older the 55 years old are more likely to have severe injuries in agreement with result of Kononen et al (*26*).

Overall the relationship between dependent and independent variables are significant. This supports the approach of Sobhani et al. (*24*) and the linking of the three decisions.

With the aim of reducing the drivers' severity this study suggest that injury severity reduces if drivers have reactions. This poses a new question- what are the reasons for not taking reaction? For example, drivers do not know which reaction might be suitable under unexpected circumstances when they are shocked by being struck. In addition, very short reaction time under unexpected danger plays a larger part, more than human judgment in everyday events. So, this study suggests to include training items such as 'drivers' responses to the unexpected hazard' in driving programs. It also suggests increasing the use of 'Auto Emergency Braking' as function of the vehicle warning systems.

There are several limitations in this analysis. Firstly, The CDS data provides only a national dataset, not state-level data. Secondly, this study only explored the relationship between the probabilities of drivers' Responses/No responses and the characteristics of drivers, vehicles, and environments, but it did not distinguish between the detailed behavior and drivers' avoidance maneuvers or reactions. A further study of the association of drivers' emergency reactions such as 'braking only', 'steering', 'braking and steering', using mixed logit, is recommended.

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