Accident Analysis and Prevention 43 (2011) 1364–1370

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Indexing crash worthiness and crash aggressivity by vehicle type

Helai Huang[a,*], Chowdhury Siddiqui[b], Mohamed Abdel-Aty[c]

[a] *Urban Transport Research Center, School of Traffic & Transportation Engineering, Central South University, Changsha 410075, China*
[b] *Department of Civil, Environmental and Construction Engineering, University of Central Florida, Orlando, FL 32816, United States*
[c] *Department of Civil, Environmental and Construction Engineering, University of Central Florida, Engineering II – 211L, Orlando, FL 32816, United States*

ARTICLE INFO

Article history:
Received 21 November 2010
Received in revised form 14 January 2011
Accepted 8 February 2011

Keywords:
Crash compatibility
Crash worthiness
Crash aggressivity
Bayesian hierarchical model
Ordered logistic model

ABSTRACT

Crash aggressivity (CA), along with conventional crash worthiness (CW), has been recently studied to deal with the crash incompatibility between vehicles on roads. Clearly, injury severity depends on the attacking ability of striking vehicle as well as the protective ability of struck vehicle. This study proposes a systematic crash-based approach to index CA and CW of various vehicles. The approach deviates from existing methods in three aspects: (a) an explicit definition and specification in the model for CW and CA; (b) Bayesian hierarchical analysis to account for the crash-vehicle two-level data structure; (c) a five-level ordinal model to explicitly consider all levels of crash severity. The case study on major vehicle types illustrated the method and confirmed the consistency of results with previous studies. Both crash worthiness and crash aggressivity significantly vary by vehicle types, in which we identified the dominating effect of vehicle mass, and also highlighted the extraordinary aggressivity of Light Trucks and Vans (LTVs). While it was not surprising to identify least CA and CW of motorcycles, buses were unconventionally found to be less aggressive than other motor vehicles. The method proposed in this research is applicable to detailed crash-based vehicle inspection and evaluation.

1. Introduction

This study proposes an empirical model to systemically index crash worthiness (CW), i.e. self-protective capacity of a vehicle, and crash aggressivity (CA), i.e. hazardousness that the subject vehicle imposes on counterpart vehicle(s) involved in the same crash.

Safety characteristics of various vehicles have long been a prominent focus of both safety researchers and vehicle designers (Evans, 2004). Given that a crash occurs, of particular concern is the crash severity. The most important components affecting crash severity include CW of the struck vehicle and CA of the striking vehicle (for multi-vehicle crashes), and other external factors regarding road infrastructure, collision circumstances, driver behavior and casualty characteristics, etc.

Crash data have been extensively used to empirically investigate vehicle safety around the world (e.g. Cameron et al., 1996, 1999 in Australia; Broughton, 1994, 1996 in U.K.; Gustafsson et al., 1989; Vadeby, 2000 in Sweden; Tapio, 1995; Tapio et al., 1995; Huttula et al., 1997 in Finland; and Subramanian, 2006; Wenzel and Ross, 2005 in U.S.). One of the major criteria in large-scale evaluation is fatality rate associated with different vehicle types controlled by the number of registered vehicles (e.g. Subramanian, 2006; Wenzel and Ross, 2005), or by distance traveled (e.g. Kahane, 2003). As it controls exposure, the per-mile approach is comparatively better in reflecting fatality risk than the per-vehicle approach. But doubtless, without controlling for crash propensity (how the vehicle is driven), the per-mile approach is not able to evaluate the components affecting crash severity, i.e. CW and CA (Kahane, 2003).

Clearly, in order to examine safety performance associated with various vehicles, a crash-specific approach has to be adopted. With crash-specific approach, safety protection effect of vehicles, reflected by crash severity, could be separated from effects of crash exposure and crash propensity. Numerous crash-specific research efforts have been conducted to relate vehicle damage or occupant injury to various vehicle properties (type, make, model, etc.) by controlling for other external or instant factors (Evans and Frick, 1992, 1993; Farmer et al., 1997; Broyles et al., 2001, 2003; Ulfarsson and Mannering, 2004; Acierno et al., 2004; Huang et al., 2008; Fredette et al., 2008). Those models have usually been used to evaluate CW of different vehicle properties.

Recently, crash compatibility has been more of a concern. In the context of crash compatibility, CA of the counterpart vehicles is known as an important component affecting the severity of subject vehicle with certain level of CW. A majority of research have been focused on car-LTV compatibility due to the substantial increase of light trucks including sport utility vehicles and vans (LTV) especially in North America (Wenzel and Ross, 2005; Kahane, 2003; Acierno et al., 2004; Fredette et al., 2008; Toy and Hammitt, 2003). Various vehicle–vehicle interactions have been investigated,

* Corresponding author. Tel.: +86 731 82655326.
E-mail addresses: huanghelai@alumni.nus.edu.sg (H. Huang), kawsar_arefin@knights.ucf.edu (C. Siddiqui), mabdel@mail.ucf.edu (M. Abdel-Aty).

0001-4575/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.aap.2011.02.010

including distinct physical performances such as mass and size (Evans and Frick, 1992, 1993), structural and geometric incompatibility etc. (Wenzel and Ross, 2005; Acierno et al., 2004), and crash configuration and trends impacted by LTVs (Abdel-Aty and Abdelwahab, 2003, 2004a,b; Abdelwahab and Abdel-Aty, 2004).

Approaches have been proposed to simultaneously model CW and CA. Wenzel and Ross (2005) studied a 'combined risk' associated with each vehicle model by summing up the risk-to-drivers in all kinds of crashes and the risk-to-drivers-of-other-vehicles in two-vehicle crashes. Toy and Hammitt (2003) and Fredette et al. (2008) proposed binary logistic regression to estimate the effects of vehicle incompatibility on the risk of death and/or severe injuries in two-vehicle crashes. While most of the existing studies focused on specific vehicle types or makes, there is a need to establish a systematic approach for general vehicle safety inspection with state-of-the-art modeling techniques.

Developing from previous studies, this paper presents a systematic crash-based approach to examine CW and CA of various types of vehicles. This approach deviates from existing methods in three aspects: (a) an explicit definition and specification in the model for CW and CA; (b) Bayesian hierarchical analysis to account for the two-level data structure, or simply speaking, severity correlation of vehicles in a same crash is accommodated; (c) a five-level ordinal model to explicitly consider all levels of crash severity. Although the model is applicable to safety evaluation for any vehicle type, make, model or other properties, in this paper we only illustrate the method by an example evaluating general vehicle types.

2. Developing Crash Worthiness Index and Crash Aggressivity Index

A crash with major harmful event as "collision between two moving vehicles" is supposed to be the most similar case to laboratory vehicle-to-vehicle collision experiments. Let $i[m]$ ($m = 1, 2$) denote two vehicles involved in the crash i ($i = 1, \ldots$ I), with injury severity levels $IS_{i[m]}$. The injury severity levels are commonly defined as five ordered categories:

- Category 1 (C1): no injury/property damage only (PDO),
- Category 2 (C2): possible injury,
- Category 3 (C3): non-incapacitating injury,
- Category 4 (C4): incapacitating injury, and
- Category 5 (C5): fatality.

For this ordered outcome of severity, an ordinal model could be specified to examine the effects of various risk factors. Moreover, Huang et al. (2008) found significant severity correlations between vehicles involved in the same crashes and thus recommended a hierarchical approach to account for the crash-specific effects given the multilevel data (Huang and Abdel-Aty, 2010). Hence, a two-level specification, i.e. crash level and vehicle level, is developed for ordered logistic model (OL), called hierarchical ordered logistic model (HOL) in this study.

In an ordinal response model, a series of latent thresholds are generally formulated. Specifically, the real line is divided into five intervals by four thresholds (γ_{ik}, $k = 1, 2, 3, 4$), corresponding to the five ordered categories (C_{1-5}). It is noted that differing from OL model, the HOL model accounts for the cross-crash heterogeneities by specifying a set of variable thresholds for individual crashes. The thresholds define the boundaries between the intervals corresponding to observed severity outcomes. The latent response variable is denoted by $IS^*_{i[m]}$ and the observed categorical variable $IS_{i[m]}$ is related to $IS^*_{i[m]}$ by the "threshold" model defined as,

$$IS_{i[m]} = \begin{cases} 1 & if \quad -\infty < IS^*_{i[m]} \le \gamma_{i1} \\ k & if \quad \gamma_{i(k-1)} < IS^*_{i[m]} \le \gamma_{ik}, \quad k = 2, 3, 4 \\ 5 & if \quad \gamma_{i4} < IS^*_{i[m]} < +\infty \end{cases}$$

The ordinal models can be written as

$$IS^*_{i[m]} = \theta_{i[m]} + \varepsilon_{i[m]}$$

in which $\theta_{i[m]}$ is the linear predictor for covariates and $\varepsilon_{i[m]}$ is the disturbance term, which is assumed a logistic distribution with F as the cumulative density function. Thus, the cumulative response probabilities for the five categories of the ordinal outcome could be denoted as,

$$P_{i[m],k} = Pr(IS_{i[m]} \le k) = F(\gamma_{ik} - \theta_{i[m]}) = \frac{\exp(\gamma_{ik} - \theta_{i[m]})}{1 + \exp(\gamma_{ik} - \theta_{i[m]})}, \quad k = 1, 2, 3, 4$$

The idea of cumulative probabilities leads naturally to the cumulative logistic model

$$\mathrm{logit}(P_{i[m],k}) = \log\left[\frac{P_{i[m],k}}{1 - P_{i[m],k}}\right] = \log\left[\frac{Pr(IS_{i[m]} \le k)}{Pr(IS_{i[m]} > k)}\right] = \gamma_{ik} - \theta_{i[m]}, \quad k = 1, 2, 3, 4.$$

At the crash level, γ_{ik} could be specified as random effects,

$$\gamma_{ik} = \gamma_k + b_i, \quad k = 1, 2, 3, 4.$$

where the intercept γ_k represents a constant component for thresholds for all crashes. b_i is the random effect to accommodate for the cross-crash heterogeneities, which is normally distributed with mean of zero and variance σ^2.

In the model specification, of most interest is to define $\theta_{i[m]}$, the predictor for injury severity of the individual vehicle involved in a two-vehicle crash. Ideally, given all other factors equal, the injury severity is dependent on the difference between defensive ability of struck vehicle and attacking impact of striking vehicle. This defines the two key vehicle-safety-performance indices: Crash Worthiness Index (CWI) and Crash Aggressivity Index (CAI). Most of the previous concerns for vehicle safety in practice are only focused on CW, i.e. how a vehicle can protect its own occupants. However, very little attention has been paid to CA, i.e. how hazardous the vehicle could injure the occupants in the counterpart vehicle in the same crash. Accordingly, we define the $\theta_{i[m]}$ as,

$$\theta_{i[1]} \sim \mathrm{CAI}_{i[2]} - \mathrm{CWI}_{i[1]} + \mathrm{control} \quad \mathrm{variable}$$

$$\theta_{i[2]} \sim \mathrm{CAI}_{i[1]} - \mathrm{CWI}_{i[2]} + \mathrm{control} \quad \mathrm{variables}$$

Using this model, we will be able to establish both CWI and CAI for any vehicle with its historic crash data. This could, of course, be used to analyze results from collision experiments to test the safety performance of different vehicle designs.

The selection for control variables is very important as they are presumably able to filter external effects apart from vehicle configurations on injury severity. For example, since elderly may be more vulnerable than the youth to sustain an injury from collision of the same level, driver age should be controlled. Collision type and collision relative speed may also be controlled as different type and speed of collision may lead to different injury levels for occupants in even the same vehicle type. It should be noted that the selection of control variables could be case-specific and also depends on data availability. Following sections of this paper illustrate the method

Table 1
Description of control variables.

Variable	Description	Descriptive statistics
Driver age	<25 (=1) (reference case) Between 25 and 65 (=2) >65, (=3)	<25: 22.1% Between 25 and 65: 69% >65: 8.9%
Driver gender	Male = 0 (reference case), Female = 1	Male: 55.3% Female: 44.7%
POI	Point of impact, has 21 categories and are further grouped into 4 levels (see Fig. 2); Level 1 as reference case	Level 1–4: 61.5%, 37%, 1.43%, 0.12%
Relative speed	*Head-on collision:* sum of the estimated speeds of the colliding vehicles *Rear end collision:* absolute value of the difference between the estimated speeds of the colliding vehicles *Angle collision:* estimated speed of the hitting vehicle	Mean = 21.5 mph Std. deviation = 18.2 mph
Posted speed	Posted speed limit of the roadway facility	Mean = 39.7 mph Std. deviation = 13.9 mph
Ejected	If the driver was ejected from the vehicle at collision 1 = yes, 0 = no (reference case)	Yes: 1.79% No: 98.21%
Crash type	Head-on = 1 (reference case), rear end = 2 Angle = 3	Head-on: 5.25% Rear end: 48.59% Angle: 46.16%

by an evaluation of CWI and CAI on typical vehicle types using the Florida crash data.

3. Model specification

3.1. Data

Records for crashes occurred in 2007 were obtained from the Florida Department of Highway Safety and Motor Vehicle (DHSMV). Three criteria were used to generate the dataset for analysis. First, only two-vehicle crashes were filtered. Second, only head-on, rear-end and angle type crashes were selected. Other collision types such as side-swipe and collision with parked car were excluded as we surmise that injury severities in these three categories of crashes would to most extent be solely due to the impact among colliding vehicles. Therefore, we assume that no other major impacts, like hitting roadside objects, were imposed upon the colliding vehicles and thereby on the driver's injury severity. Third, both vehicles in a crash were made between 2000 and 2007 in indexing. It can be reasonably assumed that the vehicles which are relatively new would have similar basic safety features such as airbag installation and energy absorbing devices.

The final dataset contained 44,712 crash observations which are about 66% of the total two vehicle crashes that occurred in 2007, as shown in Fig. 1a. The distribution of five-level ordered injury severities in the final dataset is shown in Fig. 1b. It is noted that the occupant information and possible injury data in most of the crash records were missing. Hence, in this analysis, we only considered the driver injury to be the dependent variable.

3.2. Independent variables

CWI and CAI were developed for ten major vehicle categories, including Automobile, Van, Light Truck, Medium Truck (4 rear tires), Heavy Truck (2 or more rear axles), Truck Tractor (Cab-Bobtail), Motor Home (RV), Bus-I (driver + seats for 9–15), Bus-II (driver + seats for over 15), Motorcycle. Automobile is considered as the reference case. Florida DHSMV classifies 15 distinct vehicle categories among which bicycle, moped, all terrain vehicle, train and low speed vehicles were excluded in the analysis due to their low presence in the crash population and unique characteristics.

Control variables used in the analysis are enlisted in Table 1. Drivers' ages were grouped into <25, between 25–65 and >65, with young aged (<25) as reference group. The literature shows different risk to severity between male and female (Ulfarsson and Mannering, 2004). Therefore, gender was included in the model. The relative speed of the vehicles in collision was thought to be very important as driver severity is highly correlated with speed. In addition, posted speed indicating highway facility functional classification was inserted in the model. Florida crash report requires information regarding whether the driver was ejected or thrown out of the vehicle upon a collision. This variable was particularly thought important to be considered in analyzing drivers' injury level.

Florida traffic crash report also allows indicating point of impacts (POIs) in a crash in 21 different locations. These locations are shown in Fig. 2. A preliminary analysis was conducted to relate the POIs to injury severity. Specifically, an OL model was developed in which the five ordered categories of injury severity (C_{1-5}) is the dependent variable with the POIs of a vehicle in collision as independent variable. The model results are shown in Table 2. The POIs were ranked based on their estimates. As the estimated values of POIs increase, the severities of driver injury increase.

POIs were grouped into four different levels. A higher level indicates a higher risk to driver injury. The levels are illustrated in Fig. 2 with different symbol patterns. POIs with ranks 1–8 were categorized as Level 1 which constitutes least injury severity to the driver of a vehicle in a crash. As shown in Fig. 2, Level 1 comprises mainly

Table 2
Effect of point of impacts on injury severity.

Point of Impact	Level	Rank	Estimates[a]	Credible interval	
				2.5%	97.5%
1	1	7	1.669	1.4	1.938
2	1	5	1.492	1.22	1.764
3	2	10	1.843	1.562	2.123
4	3	14	2.1	1.821	2.38
5	1	6	1.602	1.312	1.892
6	1	3	1.367	1.075	1.659
7	1	2	1.301	1.017	1.584
8	2	13	1.917	1.647	2.186
9	1	1	1.296	1.014	1.577
10	1	4	1.388	1.094	1.682
11	2	9	1.816	1.528	2.105
12	3	17	2.457	2.179	2.735
13	3	15	2.14	1.861	2.419
14	1	8	1.669	1.398	1.941
15	2	12	1.913	1.451	2.376
16	4	19	2.837	2.022	3.652
17	2	11	1.868	1.277	2.46
18	3	16	2.176	1.672	2.68
19	4	20	3.912	3.518	4.306
20	3	18	2.46	1.68	3.241
21[b]	1	0	–	–	–

[a] Significant at 0.001 level.
[b] Reference case.

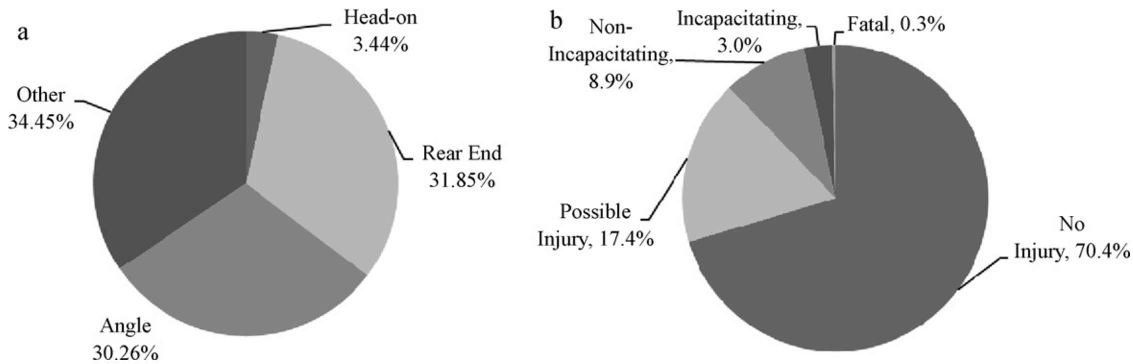

Fig. 1. Distribution of (a) two vehicle crash type in year 2007 and (b) injury severity among head-on, rear end and angle type two-vehicle crashes.

of POIs at front, rear passenger side and two rear corners of the vehicle. All of these locations are at farthest distance from the driver's seat. ranks 9–13 were grouped as Level 2. These POIs were at relatively closer distance to the driver's seat compared to Level 1 POIs and thereby increasing risk of the driver's injury severity. Level 3 POIs (ranks 14–18) were even closer to the driver seat imposing higher risk. The POIs in this level included windshield, front passenger side and front driver side of the vehicle. POIs on top of the vehicle or overturning were Leveled 4 with the highest risk to driver injury severity.

4. Results and discussion

4.1. Model estimation and comparison

The model developed above was estimated by Bayesian inference using freeware WinBUGS (Lunn et al., 2000). Non-informative priors were specified for parameters. The model converged very well using Brooks, Gelman and Rubin convergence diagnostics. The posterior parameters are presented in Table 3. It can be seen that the hierarchical model specification results in a fair variance ($\sigma^2 = 2.27$, 95% BCI(2.16,2.38)) for the crash-specific random effects. For the purpose of model comparison, an ordinary OL model was also fitted by merely removing the random effects for the HOL. The Bayesian measure for model comparison, Deviance Information Criteria (DIC) was monitored. Results showed that, to some extent, the HOL model (DIC = 138590) outperforms OL model (DIC = 147578).

4.2. CWI and CAI

CWI and CAI of different vehicle types are shown in Fig. 3. The bold line inside the box represents the mean value of each box plot. Compared to the reference case Automobile, all the other vehicles, except Motorcycle, are more crash worthy and except Bus and Motorcycle, all other vehicles have an elevated aggressivity, as reflected by the CWI and CAI. It has been extensively proven that the heavier the vehicle, the less risk to its occupants, and the lighter the vehicle, the less risk to other road users (Evans and Frick, 1992, 1993).

It is also not surprising to observe that crash worthiness consistently increases from Van to Motor Home (RV). Therefore CWI for Van (0.21) < Light Truck (0.40) < Medium Truck (1.27) < Heavy Truck (2.14) < Truck Tractor (2.26) < Motor Home (2.58). CAI, in contrary, increases from Van (0.32) until Medium Truck (0.48), and then for Heavy Truck (0.40) and Truck Tractor (0.21) it decreases. This highlights the road hazardousness associated with the Van, Light or Medium Trucks. The notorious aggressivity of LTVs have

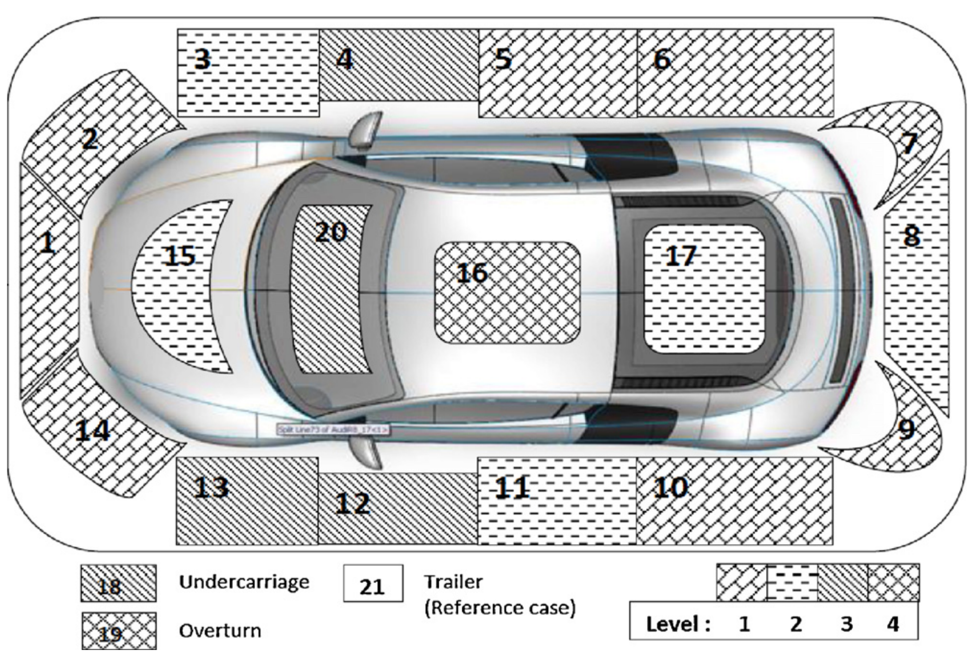

Fig. 2. Levels of different point of impacts.

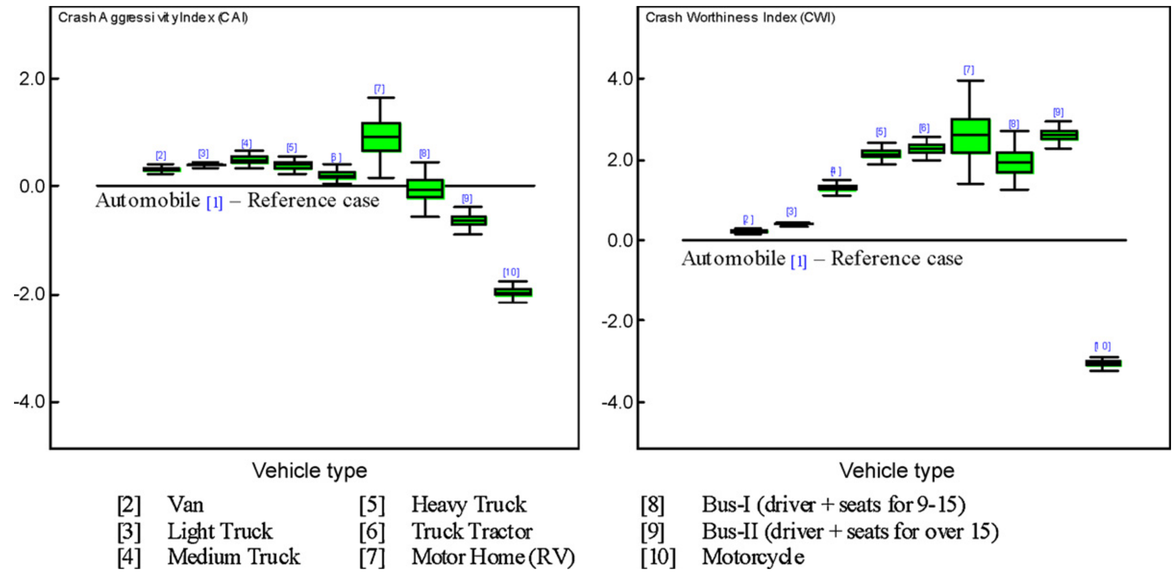

Fig. 3. Crash Worthiness Index and Crash Aggressivity Index by vehicle type.

been highlighted by numerous studies and the car-LTV incompatibility in mass, vehicle geometry and structure have been widely discussed (Wenzel and Ross, 2005; Kahane, 2003; Broyles et al., 2001, 2003; Fredette et al., 2008; Toy and Hammitt, 2003). The safety of LTVs deserves continuous effort for vehicle manufacturers as well as the traffic management authorities. Comparatively, heavy trucks and truck tractors are usually driven by commercial drivers. These drivers are expected to be more skilled in responding to surprise situations like severe conflicts. This might play an important role in reducing the CAIs of Heavy Trucks and Truck Tractors compared to that of LTVs. Motor Homes were found to have highest indices for both CWI and CAI. Typically a Motor Home has higher mass compared to a Heavy Truck and not driven by commercial drivers. These might impose a greater risk to the struck vehicle's driver injury severity. The results present evidence for traffic authorities to enhance the vehicle safety inspection and law enforcement for the use of Motor Homes.

We found interesting results for Buses. Mean value of CWI for Bus-I (1.92) was less than that of a Heavy Truck (2.14) but greater than a Medium Truck (1.27). This means crash worthiness of Bus-I lies between that of a Medium Truck and Heavy Truck. Mean CWI for Bus-II (2.60) was slightly greater than that of a Motor Home (2.58). Possibly similar structure and mass of Motor Home and Bus-II result in similar values of CWIs. Crash aggressivity for buses, in contrast, was found to be lower than all other motor-vehicles including Automobile. Apparently it seems surprising. But the presence of buses in the overall 2007 Florida crash database was only 0.96%. The distribution of buses in the dataset used for this analysis was about 1.1%. One reason of this may be due to relatively low exposure of buses compared to other modes of transport. It is worth mentioning that bus as a public transport mode in Florida is not still very popular. Most of Bus-II that travel on the streets are school buses. It is well known that school buses drive with great caution and precautions are enforced by law. All these factors might be contributing in lowering CAIs for buses in two vehicle crashes.

Motorcycles were found to have the significantly least value for both CAI (−1.98) and CWI (−3.08). Unlike other vehicles a motorcyclist does not have an external protection shield. This affects the crash worthiness of a motorcycle negatively. Additionally, Motorcycles have the least mass among the vehicles in the study. This imposes motorcycle to be at minimum risk to the struck vehicle's driver injury severity. The extraordinary vulnerability of motorcycles calls for special attention with respect to usage of airbag jacket and helmet, specific motorcycle road facilities, and speed restriction enforcement, etc.

Table 3
Estimation of hierarchical ordered logistic model.

Variable	Mean	Std. deviation	Credible interval	
			2.5%	97.5%
γ_1 (threshold $k=1$)	2.79	0.06	2.68	2.91
γ_2 (threshold $k=2$)	4.41	0.06	4.29	4.54
γ_3 (threshold $k=3$)	6.32	0.07	6.19	6.44
γ_4 (threshold $k=4$)	9.32	0.10	9.11	9.52
σ^2 (var. of random effects)	2.27	0.05	2.16	2.38
Crash Aggressivity Index (CAI)				
Van [2]	0.32	0.04	0.24	0.40
Light Truck [3]	0.39	0.03	0.34	0.45
Medium Truck [4]	0.48	0.08	0.32	0.63
Heavy Truck [5]	0.40	0.09	0.23	0.57
Truck Tractor [6]	0.21	0.09	0.03	0.40
Motor Home [7]	0.90	0.38	0.14	1.66
Bus-I [8]	−0.05	0.26	−0.56	0.47
Bus-II [9]	−0.64	0.13	−0.89	−0.39
Motorcycle [10]	−1.98	0.11	−2.19	−1.77
Crash Worthiness Index (CWI)				
Van [2]	0.21	0.04	0.13	0.28
Light Truck [3]	0.40	0.03	0.34	0.45
Medium Truck [4]	1.27	0.10	1.08	1.49
Heavy Truck [5]	2.14	0.14	1.87	2.40
Truck Tractor [6]	2.26	0.14	2.00	2.56
Motor Home (RV) [7]	2.58	0.65	1.39	3.96
Bus-I [8]	1.92	0.36	1.24	2.65
Bus-II [9]	2.60	0.18	2.26	2.96
Motorcycle [10]	−3.08	0.09	−3.25	−2.90
Control variables				
Driver – between 25 and 65	0.20	0.03	0.13	0.26
Driver – >65	0.39	0.04	0.31	0.48
Female driver	0.73	0.02	0.68	0.77
Rear end Crash	−0.84	0.06	−0.95	−0.73
Angle crash	−0.04	0.05	−0.14	0.07
POI- Level 2	0.62	0.03	0.55	0.68
POI- Level 3	0.78	0.03	0.73	0.83
POI- Level 4	1.53	0.19	1.14	1.90
Relative speed	0.01	0.00	0.01	0.01
Posted speed	0.02	0.00	0.02	0.03
Ejected (=yes)	1.57	0.09	1.39	1.75

4.3. Control variables

All of the control variables are statistically significant and their signs conform to previous findings. This confirms the *a priori* justifications in selecting control variables. Compared to young drivers (<25), we found an increase of severity in positive estimates from drivers aged between 25–65 and older drivers (>65). This implies the older age group is more inclined to higher injury severity. Many previous studies on age effect have identified a U-shape pattern of crash propensity (e.g. Huang and Chin, 2009), suggesting an elevated risk associated with both young and elderly drivers. While criticism for young are more associated with risky driving behavior, it is well accepted that the deterioration of physical condition may lead to the higher severity of injury for elderly drivers. The previous studies support, rather than refute against, our results as only crash sustainability, excluding behavior factors, is addressed in the model, and moreover, the possible vehicle-selection bias associated with different age has been controlled by the factors representing CWI and CAI.

Regarding driver gender, Ulfarsson and Mannering (2004) reported that there are significant differences between males and females with regard to how various LTVs and passenger cars affect injury severity. Our model indicates that female drivers are more prone to severe injury than male counterpart. This finding also aligns with the results found from most of the other studies (Evans, 2004; Broyles et al., 2003; Kim et al., 1995).

It is not surprising to find that injury severity greatly increases if the driver is ejected out of the vehicle. Its coefficient estimate was the highest (1.57) among the control variables in the model. Furthermore, positive estimates for both posted and relative speeds indicate a positive association between drivers' injury severity and speed. The finding is consistent with those found by Fredette et al. (2008). Their results showed speed limit as a highly significant factor in estimating drivers' risk of death. Regarding crash type, both rear end and angle crashes had negative estimates implying head-on type crashes, the reference type, to be the most dangerous for drivers' injury severity. Again this result is coherent with the findings from Fredette et al. (2008). Finally, the model also supports the preliminary results found for POIs with increasing risk from Level 1 to Level 4.

5. Conclusion

Crash worthiness has been a continuous concern for road safety and vehicle design. The recently-promoted concept of crash incompatibility generates the increasing attention to crash aggressivity. In other words, not only the capability that a vehicle can protect its occupants should be improved, the injury impact on the occupants in counterpart vehicles of a same crash may also need to be monitored to improve safety.

The current study follows up on this research question by proposing a model to explicitly index various vehicles on roads for both crash worthiness and crash aggressivity. A Bayesian hierarchical ordinal model was developed to account for all levels of injury severities, various control variables, as well as crash-specific random effects. The case study on major vehicle types illustrated the method and added to the body of knowledge. Both crash worthiness and crash aggressivity significantly vary by vehicle types, in which we identify the dominating effect of vehicle mass, and also highlight the extraordinary aggressivity of LTVs, compared to the lighter and heavier vehicles. While it was not surprising to identify least CA and CW of motorcycles, buses were unconventionally found to be less aggressive than other motor vehicles.

The method proposed in this research is applicable to detailed crash-based vehicle inspection and evaluation, which would be useful for both vehicle-design professionals and for insurance purposes. Future efforts could be made to refine the model by examining different control variables so that CW and CA could be monitored for vehicles with a variety of properties to improve crash compatibility on our roads. In addition, this study could also be expanded to include vehicle occupants, rather than drivers only in current study, to investigate the occupant protection performance at different seats.

References

Abdel-Aty, M., Abdelwahab, H., 2004a. Modeling rear-end collisions including the role of drivers visibility and light truck vehicles using a nested logit structure. Accident Analysis and Prevention 36, 447–456.
Abdel-Aty, M., Abdelwahab, H., 2004b. Analysis and prediction of traffic fatalities resulting from angle collisions including the effect of vehicles' configuration and compatibility. Accident Analysis and Prevention 36, 457–469.
Abdel-Aty, M., Abdelwahab, H., 2003. Configuration analysis of two-vehicle rear-end crashes. Journal of the Transportation Research Board 1840, 140–147.
Abdelwahab, H., Abdel-Aty, M., 2004. Investigating the effect of LTV percentages on rear-end fatal crashes (part I). ASCE Journal of Transportation Engineering 130, 419–428.
Acierno, S., Kaufman, R., Rivara, F.P., Grossman, D.C., Mock, C., 2004. Vehicle mismatch: injury patterns and severity. Accident Analysis and Prevention 36, 761–772.
Broughton, J., 1994. The theoretical basis for comparing the accident record of car models. In: Safety and Environment Resources Centre. Transport Research Laboratory, Crowthorn, Berkshire, U.K.
Broughton, J., 1996. The theoretical basis for comparing the accident record of car models. Accident Analysis and Prevention 28 (1), 89–99.
Broyles, R.W., Clarke, S.R., Narine, L., Baker, D.R., 2001. Factors associated with the amount of vehicular damage resulting from collisions between four-wheel drive vehicles and passenger cars. Accident Analysis and Prevention 33, 673–678.
Broyles, R.W., Narine, L., Clarke, S.R., Baker, D.R., 2003. Factors associated with the likelihood of injury resulting from collisions between four-wheel drive vehicles and passenger cars. Accident Analysis and Prevention 35, 677–681.
Cameron, M., Newstead, S., Le, C.M., 1999. Rating the aggressivity of Australian passenger vehicles towards other vehicle occupants and unprotected road users. Journal of Crash Prevention and Injury Control 1 (*2*), 129–141.
Cameron, M.H., Newstead, S., Skalova M., 1996. The development of vehicle crashworthiness ratings in Australia. In: 15th International Technical Conference on the Enhanced Safety of Vehicles Federal Office of Road Safety and U.S. Dept. of Transportation, NHTSA, Melbourne, Australia.
Evans, L., 2004. Traffic Safety. Bloomfield Hills. Science Serving Society, Michigan.
Evans, L., Frick, M.C., 1992. Car size or car mass: which has greater influence on fatality risk? American Journal of Public Health 82 (*8*), 1105–1112.
Evans, L., Frick, M.C., 1993. Mass ratio and relative driver fatality risk in two-vehicle crashes. Accident Analysis and Prevention 25 (*2*), 213–224.
Farmer, C.M., Braver, E.R., Mitter, E.L., 1997. Two-vehicle side impact crashes: the relationship of vehicle and crash characteristics to injury severity. Accident Analysis and Prevention 29, 399–406.
Fredette, M., Mambu, L.S., Chouinard, A., Bellavance, F., 2008. Safety impacts due to the incompatibility of suvs, minivans, and pickup trucks in two-vehicle collisions. Accident Analysis and Prevention 40, 1987–1995.
Gustafsson, H., et al., 1989. Folksam Car Model Safety Rating 1989–90. Folksam Insurance, Stockholm, Sweden.
Huang, H., Abdel-Aty, M., 2010. Multilevel data and bayesian analysis in traffic safety. Accident Analysis and Prevention 42 (6), 1556–1565.
Huang, H., Chin, H.C., Haque, M.M., 2008. Severity of driver injury and vehicle damage in traffic crashes at intersections: bayesian hierarchical analysis. Accident Analysis and Prevention 40 (1), 45–54.
Huang, H., Chin, H.C., 2009. Disaggregate propensity study of RLR accident using quasi-induced exposure method. Journal of Transportation Engineering 135 (3), 104–111, American Society of Civil Engineers.
Huttula, J., Pirtala, P., Ernvall, T., 1997. Car safety, aggressivity and accident involvement rates by car model. University of Oulu, Oulu, Finland.
Kahane, C.J., 2003. Vehicle Weight, Fatality Risk and Crash Compatibility of Model Year 1991–99 Passenger Cars and Light Trucks. Report No. DOT HS 809 662, NHTSA Technical Report, US Department of Transportation, 2003.
Kim, K., Nitz, L., Richardson, J., Li, L., 1995. Personal and behavioral predictors of automobile crash and injury severity. Accident Analysis and Prevention 27 (4), 469–481.
Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. Winbugs: a Bayesian modelling framework: concepts structure, and extensibility. Statistics and Computing 10, 325–337.
Subramanian, R., 2006. Passenger Vehicle Occupant Fatality Rates by Type and Size of Vehicle. Traffic Safety Facts, Research Note, NHTSA.
Tapio, J., Pirtala, P., Ernvall, T., 1995. The Accident Involvement and Injury Risk Rates of Car Models. University of Oulu, Oulu, Finland.
Tapio, J., Ernvall, T., 1995. Logistic Regression in Comparison of the Passive Safety of Car Models. University of Oulu, Oulu, Finland.

Toy, E.L., Hammitt, J.K., 2003. Safety impacts of suvs, minivans, and pickup trucks in two-vehicle crashes. Risk Analysis 23, 641–650.

Ulfarsson, G.F., Mannering, F.L., 2004. Differences in male and female injury severities in sport-utility vehicle, minivan, pickup, and passenger car accidents. Accident Analysis and Prevention 36, 135–147.

Vadeby, A., 2000. Including driver characteristics in a model of relative collision safety. Linkopings University, Department of Mathematics, Linkoping, Sweden.

Wenzel, T.P., Ross, M., 2005. The effects of vehicle model and driver behavior on risk. Accident Analysis and Prevention 37, 479–494.