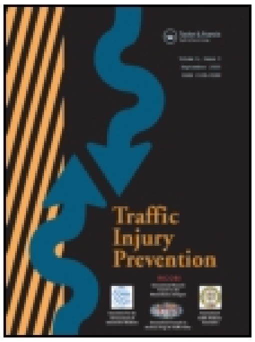

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Two-Vehicle Injury Severity Models Based on Integration of Pavement Management and Traffic Engineering Factors

XIMIAO JIANG[1], BAOSHAN HUANG[1], XUEDONG YAN[2], RUSSELL L. ZARETZKI[3], and STEPHEN RICHARDS[1]

[1]*Department of Civil and Environmental Engineering, The University of Tennessee, Knoxville, Tennessee*
[2]*MOE Key Laboratory for Transportation Complex Systems Theory and Technology, School of Traffic and Transportation, Beijing Jiaotong University, Beijing, P.R. China*
[3]*Department of Statistics, Operations and Management Science, The University of Tennessee, Knoxville, Tennessee*

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Objective: The severity of traffic-related injuries has been studied by many researchers in recent decades. However, the evaluation of many factors is still in dispute and, until this point, few studies have taken into account pavement management factors as points of interest. The objective of this article is to evaluate the combined influences of pavement management factors and traditional traffic engineering factors on the injury severity of 2-vehicle crashes.

Methods: This study examines 2-vehicle rear-end, sideswipe, and angle collisions that occurred on Tennessee state routes from 2004 to 2008. Both the traditional ordered probit (OP) model and Bayesian ordered probit (BOP) model with weak informative prior were fitted for each collision type. The performances of these models were evaluated based on the parameter estimates and deviances.

Results: The results indicated that pavement management factors played identical roles in all 3 collision types. Pavement serviceability produces significant positive effects on the severity of injuries. The pavement distress index (PDI), rutting depth (RD), and rutting depth difference between right and left wheels (RD_df) were not significant in any of these 3 collision types. The effects of traffic engineering factors varied across collision types, except that a few were consistently significant in all 3 collision types, such as annual average daily traffic (AADT), rural–urban location, speed limit, peaking hour, and light condition.

Conclusions: The findings of this study indicated that improved pavement quality does not necessarily lessen the severity of injuries when a 2-vehicle crash occurs. The effects of traffic engineering factors are not universal but vary by the type of crash. The study also found that the BOP model with a weak informative prior can be used as an alternative but was not superior to the traditional OP model in terms of overall performance.

Keywords: traffic injury severity, pavement management factor, Bayesian ordered probit (BOP) model, pavement distress index (PDI), pavement serviceability index (PSI), rutting depth (RD)

Introduction

As the number of automobiles in use worldwide increases, traffic safety issues have become more critical than ever. Numerous traffic crash studies have attempted to determine the influences of traffic engineering factors on both the occurrence and outcome of crashes. Among these studies, some have concentrated on variables that affect the severity of traffic-related injuries. However, few studies have taken into account pavement management factors such as pavement cracking, rutting, and roughness as possible causes of traffic-related crashes or as influences on the severity of corresponding injuries.

According to previous studies in the Long-Term Pavement Performance Program, many pavements experience rapid wear-off that leads to structurally deficient and functionally obsolete pavements (Özbay and Laub 2001). A high level of pavement distress may either lead drivers to lose control of their vehicles or cause vehicles to change trajectories and consequently increase the possibility of triggering crashes (Quinn and Hildebrand 1973; Wambold et al. 2009). In addition, observable defects such as potholes and severe rutting may distract drivers and cause them to avoid the defects, which may result in vehicles colliding or running off the road (Tighe et al. 2000). Treat et al. (1979) conducted a 3-level study (baseline data collection, on-site investigation, multidisciplinary in-depth analysis) on the causes of traffic crashes. They indicated that road environmental factors of all kinds, including slick roads, were causes for at least 12.4 percent of crashes and were probable causes for about 33.8 to 34.9 percent of crashes investigated.

Despite the significant effect of pavement quality on driver behavior and vehicle trajectory, statistical studies of pavement's impact on traffic safety are rare. Jacobs (1976) and

Address correspondence to Baoshan Huang, Department of Civil and Environmental Engineering, The University of Tennessee, Knoxville, TN 37996. E-mail: bhuang@utk.edu

Kamel and Garshore (1982) reported that the increase in road roughness would increase crashes on rural roads. Recent research conducted by Anastasopoulos et al. (2008, 2012), and Anastasopoulos and Mannering (2009) found similar effects of roughness on urban interstate highways. To the contrary, Cleveland (1987) reported that the occurrence of crashes increased slightly but significantly with a smoother pavement surface on 2-lane rural roads having an annual average daily traffic (AADT) range from 1000 to 8000 vehicles per day. Moreover, Al-Masaeid (1997) found that rougher roads would decrease the single-vehicle crash rate but increase the multiple-vehicle crash rate, which is consistent with the research conducted by Tighe et al. (2000).

Strat et al. (2004) conducted a study to quantify the effects of pavement rutting on crash rates. The results indicated that the defined rut-related crash rate begins to increase at a significantly greater rate as rutting depth (RD) exceeds 7.6 mm (0.3 in.). This study also reported that rutting is more hazardous in wet weather when water accumulates in the rut path and leads to hydroplaning. Similarly, Anastasopoulos et al. (2008) employed the tobit model to identify how factors affect highway crash rates using 5-year data from urban interstates in Indiana. They also found that lower rutting depth was associated with lower crash rates. Their successive research utilizing a random-parameter model (Anastasopoulos and Mannering 2009; Anastasopoulos et al. 2012) consolidated this finding. Moreover, Chan et al. (2010) suggested that a high level of rutting depth and roughness produces significantly adverse effects on the occurrence of crashes on interstate highways at night and under rainy weather conditions.

Even fewer studies have been conducted on pavement management factors as related to injury severity. Anastasopoulos and Mannering (2011) performed an empirical evaluation of fixed and random-parameter logit models utilizing crash data from 231 freeway segments in Indiana. Their study considered pavement quality indexed by RD, friction number, International Roughness Index (IRI), and pavement condition rating (PCR) as possible factors on injury severity. The results indicated that the increase in RD is likely to decrease the probability of injury. However, evaluating the influence of pavement condition on traffic safety issues on freeways has its limitation because the pavement quality measured in one direction is unlikely to represent that in the other direction. More recently, Buddhavarapu et al. (2012) specifically evaluated the influence of pavement condition on traffic crash–related injury severity. A data set consisting of 22,860 2-lane curve crashes during 2006–2009 was used in the study. Pavement quality measurements were averaged over a span of 1-mile radius on both sides of a crash location. The results indicate that distressed pavements are likely to have a higher probability of severe crashes. In addition, IRI was found to be negatively correlated with crash severity; that is, roadways with lower IRI values are associated with more severe injuries. However, the employment of average pavement quality in a long spatial distance and over a long time period may lose some important information. Moreover, none of these studies has specifically investigated the influence of pavement management factors on various types of 2-vehicle crashes.

Previous studies have focused primarily on the influences of traffic engineering factors on traffic-related injury severity. These traffic engineering factors generally include roadway features (number of lanes; lane, median, and shoulder width; horizontal and vertical alignment; etc.), environmental factors (weather and light conditions, traffic condition, etc.), driver conditions (age, gender, alcohol, etc.), vehicle attributes (passenger car, single-unit truck, multi-unit truck, etc.), as well as collision manners (rollover, sideswipe, angle, etc.).

A large number of crash injury studies have attempted to identify driver factors that have contributed to the traffic injury severity, such as drunk driving (S. P. Baker et al. 2002; C. Lee and Abdel-Aty 2005; Smink et al. 2005), seat belt use (Abdel-Aty 2003; Bedard et al. 2002; Valent et al. 2002), as well as age and gender (Boufous et al. 2008; Lyman et al. 2002; Zhang et al. 2000). Zajac and Ivan (2003) and Keall et al. (2004) reported that drunk driving can significantly increase the risk of fatal crashes. Khattak et al. (1998) found that older drivers have a greater likelihood of severe injury compared to younger drivers, and male drivers are likely to be more severely injured than females. Similarly, Finison and Dubrow (2002) revealed that the risk of hospitalization and death for older drivers increases by 3.5 percent for every year's increase in age. However, a few other scholars (Bauer et al. 2003; Chipman et al. 1992; Kockelman and Kweon 2001) indicated that older drivers generally display safe driving behaviors, including lower speed, wearing seat belts, not driving under the influence, and so forth, which may lead to less severe crashes.

Many researchers considered environmental conditions as potential factors that may affect traffic-related injury severity (Awadzia et al. 2008; T. K. Baker et al. 2003; Brodsky and Hakkert 1998; Finison and Dubrow 2002). Adams (1985) concluded that practical speeds decrease in adverse weather conditions, which leads to less severe crashes. Similarly, Khattak et al. (1998) performed a study to explore the role of adverse weather in key crash types on limited-access roadways. They concluded that adverse weather significantly decreases crash severity. In contrast, the National Transportation Safety Board (1980) reported that the risk of a fatal crashes in the United States as a whole was 3.9 to 4.5 times greater on wet than on dry pavements. On the other hand, Krull et al. (2000) analyzed driver injury severity in single-vehicle crashes. The results indicated that driver injury severity increased in daylight conditions relative to nighttime. Conversely, Abdel-Aty (2003) concluded that dark lighting conditions contribute to a higher probability of injury on roadway sections.

Quite a few other factors have been proven to have a significant impact on the severity of traffic-related injuries. For example, Shankar et al. (1996) investigated the influence of different variables on the severity of crash injuries. They indicated that increases in the number and grade of horizontal curves are more likely to result in higher level injuries. Noland and Oh (2004) conducted a study on the effect of infrastructure changes on traffic fatalities and crashes based on Illinois county-level data. The results showed that increased number of lanes, lane widths, and outside shoulder widths were associated with higher traffic-related fatalities. In addition, vehicle type (Chang and Mannering 1999; Kockelman and Kweon 2001), collision manner (J. Lee and Mannering 2002; Rifaat and Chin 2007; Rifaat and Tay 2009), driver and vehicle action (Chang and Wang 2006), traffic volume (Chang and Wang 2006; Khattak et al. 1998), speed limit (Kockelman and Bottom 2006; Malyshkina and Mannering 2008), roadway location (J. Lee and Mannering 2002; Rifaat and Tay 2009), and cause of accidents (Al-Ghamdi 2001; Hutchinson 1986) were also found to be critical in determining the severity of injuries due to traffic crashes.

Methodologically, a large variety of statistical models has been used to evaluate the factors that contribute to the severity of traffic-related injuries (Savolainen et al. 2011). Among them, ordered logit and probit models have been frequently employed (O'Donnell and Connor 1996; Shimamura and Fujita 2005). Traditional ordered logit and probit models are based on maximum likelihood (ML) estimation, which is a classic method for model fitting. However, ML estimation is very sensitive to the quality of data. If the data cannot fully represent the characteristics of each population, the result is likely to be biased. In response, Bayesian inference was introduced into the analysis for the severity of traffic-related injuries. For example, Xie et al. (2009) performed a series of studies on the prediction of severity of crash injuries utilizing both the ordered probit (OP) model and the Bayesian ordered probit (BOP) model with various priors. The result showed that the BOP model outperformed the OP model in both the parameter estimates and the predictive capabilities, especially for small data samples.

As summarized above, numerous traffic engineering factors related to traffic injury severity have been investigated and the results generated so far have made considerable contributions to the improvement of roadway safety. However, few studies have specifically focused on 2-vehicle collisions, and even fewer have identified the effects of factors separately by different types of collisions, such as rear-end, sideswipe, and angle collisions. Moreover, previous studies have not reached a consensus on the influence of some factors and, thus far, few studies have taken into account pavement management factors as points of interest to predict the severity of traffic-related injuries. Hence, an evaluation of traditional traffic engineering factors under different 2-vehicle collision types incorporating pavement management factors is desirable.

The objective of this article is to explore the effects of pavement management and traffic engineering factors on the outcome of 2-vehicle crashes. The data used in this study were based on crashes on Tennessee state route highways from 2004 to 2008. Three types of 2-vehicle collisions were studied, including rear-end collisions, sideswipe collisions, and angle collisions. Both the OP models and the BOP models were established and evaluated based on their parameter estimates and deviances.

Methodology

Data Preparation

The primary source of traffic crash data was the Tennessee Roadway Information Management System (TRIMS). The data were obtained in computer-ready form, which included coded information on reported crashes that occurred on state highways in Tennessee. The coded information for each crash contains important attributes describing the conditions that contributed to the collision and the outcome. The information regarding pavement management status was obtained from the Pavement Management System maintained by the Tennessee Department of Transportation (TDOT). The crashes occurred on state route roadways from 2004 to 2008 and corresponding traffic engineering data were linked to the pavement management factors through the common variable id_number, which is a combination of county, county sequence, route type, and route number.

Pavement management factors considered in this article include Present Serviceability Index (PSI), Pavement Distress Index (PDI), RD, as well as rutting depth difference (RD_df). RD_df represents the difference between the RD on the right and left sides of vehicles when measured. PSI is a measure of the roughness of roadways on a scale of 0 to 5, representing worst to perfect. PDI is specified as a scale from 0 to 5 representing worst to perfect for the overall pavement quality. Distresses that are evaluated in PDI include fatigue, rutting, longitudinal cracks, patching, block cracking, raveling, and transverse cracks. RD is the original measurement of rutting depth in inches.

In the State of Tennessee, roughness, rutting, cracks, and other pavement defects are measured once every 2 years on state route highways. Measurements are recorded for each 0.1-mile (0.16-km) pavement section. The pavement management data from 2004 to 2009 were collected, screened, and treated according to the following criteria:

- Records with PSI and PDI less than 1 were excluded because they may be subject to missing values or located in a short section where there may be a railroad crossing, intersection, or other discontinuity.
- Records with RD in either left or right wheel greater than 1.0″ (25.4 mm) were removed because they are abnormal in terms of the overall pavement quality for the state routes in Tennessee.
- PDI, PSI, RD, and RD_df records in each year were substituted for by the combination of the original records in the current year and the records of the following year because the pavement quality indices were measured every 2 years. For example, the pavement quality information for 2004 was a combination of those measured in 2004 and 2005, the pavement quality information for 2005 was a combination of those measured in 2005 and 2006, and so on.

The pretreated pavement management observations from 2004 to 2008 were linked to traffic accidents by both road segment and the year; that is, crashes were linked to the pavement quality condition records measured in the corresponding 0.1-mile (0.16-km) road segment in the specific year. Table 1 shows the overall statistics for the pavement management factors for Tennessee state routes after preliminarily processing.

Traffic engineering factors considered in the present study include types of terrain, rural or urban, lane width, median width, AADT, speed limit, grade of horizontal alignment, peak hour, light condition, weather condition, vehicle type, driver's age, and driver's gender. Thousands of AADT

Table 1. Distribution of overall pavement management factors

Variables	Min	Max	Median	Mean	SD
PDI	1.00	5.00	5.00	4.62	0.58
PSI	1.00	4.50	3.34	3.25	0.57
RUT	0.00	0.94	0.07	0.09	0.08
RUT_df	0.00	0.99	0.03	0.05	0.06

(thAADT) was employed in the regression modeling as an exposure variable, which was calculated by dividing AADT by 1000, because the change in injury severity with an increment of one vehicle would be too trivial. Some of these factors were categorized into subclasses from the original records as shown in Table 2.

The combined data set of pavement management information, traffic engineering data, and collision records was pretreated according to the following criteria:

- Rear-end, sideswipe, and angle crashes were selected for this study because they are the most common types of 2-vehicle crashes.
- All of the intersection-related collisions were removed because the crash patterns were different from those that occurred on continuous roadways.
- The observations with missing values either in the dependent variable or in each of the predictors were excluded for the purpose of completeness.
- Speed limits of 30 mph (48 km/h), 35 mph (56 km/h), 40 mph (64 km/h), 45 mph (72 km/h), 50 mph (80 km/h), and 55 mph (88 km/h) were selected for this study because they are quite common for Tennessee state route highways.
- Road sections with 1, 2, 3, or 4 lanes in each direction were investigated in detail because they are typical for state routes.
- Pedestrian, motorcycle, and nontraditional types of vehicles involved in accidents were screened out because they have different injury mechanisms.

The treated data set applied in this article included 50,908 2-vehicle crashes that occurred on state routes within the 5 years from 2004 to 2008. In this study, the severity level of each crash was determined by the injury level of the worst-injured occupant in all of the vehicles involved. Table 3 provides the

Table 2. Variables' classification criteria

Variables	Description	Categories	Classification criteria
PDI	Pavement Distress Index	No_dfct	PDI = 5
		Minor_dfct	PDI ≥ 4 and PDI < 5
		Severe_dfct	PDI < 4
PSI	Present Serviceability Index	Good	PSI > 3
		Fair/Bad	PSI ≤ 3
RD	Rut depth	Shallow	Rut depth ≤ 0.2″
		Med/Deep	Rut depth > 0.2″
RD_df	Rut depth difference	Small	Rut depth difference ≤ 0.2″
		Large	Rut depth difference > 0.2″
tyterrain	Type of terrain	Flat	Flat region
		Rolling	Rolling region
		Mountain	Mountain region
rururb	Rural or urban	Rural	Rural area
		Urban	Urban area
light	Light condition	Daylight	Daylight
		Nighttime	Dark lighted and unlighted, dawn and dusk
weather	Weather condition	Clear	Clear
		Inclement	Rainy, foggy, snowy, etc.
phour	Peak hour	No	10:00 a.m.–4:00 p.m. and 7:00 p.m.–6:00 a.m.
		Yes	6:00 a.m.–10:00 a.m. and 4:00 p.m.–7:00 p.m.
vehtype	Vehicle type	Pass_Pass	Passenger car[a] to passenger car
		Ltrk_Pass	Light truck[b] to passenger car
		Ltrk_Ltrk	Light truck to light truck
		Htrk_inv	Heavy truck[c] involved
drvage	Driver's age	Yng_Yng	Youngers[d] to youngers
		Midage_Yng	Middle-aged[e] to youngers
		Midage_Midage	Middle-aged to middle aged
		Old_inv	Older drivers[f] involved
drvsex	Driver's gender	M_M	Male to male
		M_F	Male to female
		F_F	Female to female
spd_lmt	Speed limit	30, 35, 40, 45, 50, 55 mph	

[a]Convertible, hatchback, sedan hardtop, etc.
[b]Pickup, SUV, minivan, light truck, etc.
[c]Large van, bus, heavy truck, etc.
[d]Driver's age between 16 and 24.
[e]Driver's age between 25 and 64.
[f]Driver's age ≥ 65.

Table 3. Injury severity distribution on key variables and description of continuous variables

Distribution of injury severity by categorical variables

Variables	Categories	Injury severity: 1 (No injury)	2 (Minor injury)	3 (Incapacitating)	4 (Fatal)
PDI	No_dfct	77.77	20.57	1.35	0.31
	Minor_dfct	78.71	19.79	1.28	0.22
	Severe_dfct	79.71	19.16	1.05	0.09
PSI	Good	75.66	22.27	1.67	0.40
	Fair/Bad	80.98	18.03	0.90	0.09
RD	Shallow	78.25	20.18	1.31	0.26
	Med/Deep	79.66	19.18	1.04	0.12
RD_df	Small	78.38	20.11	1.27	0.24
	Large	81.34	17.57	1.03	0.06
Light	Daylight	79.17	19.50	1.15	0.18
	Nighttime	75.04	22.61	1.84	0.50
weather	Clear	78.33	20.16	1.29	0.22
	Inclement	79.45	19.13	1.12	0.31
phour	No	77.57	20.75	1.40	0.28
	Yes	79.67	19.07	1.08	0.18
tyterrain	Flat	80.41	18.26	1.14	0.19
	Rolling	78.42	20.09	1.26	0.24
	Mountain	73.19	23.43	2.90	0.48
rururb	Rural	70.37	26.05	2.63	0.95
	Urban	79.68	19.13	1.06	0.13
spd_lmt	30 mph	82.19	16.89	0.90	0.02
	35 mph	81.01	17.84	1.10	0.05
	40 mph	80.24	18.90	0.79	0.07
	45 mph	78.05	20.37	1.37	0.21
	50 mph	78.40	19.80	1.22	0.58
	55 mph	70.44	26.17	2.54	0.85
vehtype	Pass_Pass	76.75	21.97	1.14	0.14
	Ltrk_Pass	78.91	19.57	1.27	0.26
	Ltrk_Ltrk	80.34	18.13	1.27	0.26
	Htrk_inv	78.26	19.51	1.77	0.46
drvage	Yng_Yng	82.56	16.19	1.05	0.20
	Midage_Yng	78.45	20.34	1.07	0.14
	Midage_Midage	77.90	20.52	1.35	0.23
	Old_inv	78.38	19.74	1.45	0.42
drvsex	M_M	79.92	18.35	1.37	0.36
	M_F	77.89	20.64	1.26	0.21
	F_F	77.75	21.02	1.12	0.12

Statistical description of continuous variables

Variables	Label	Min	Max	Mean	Median	SD
thAADT	Thousands of AADT	0.08	131.14	23.32	22.15	14.43
lanewid	Lane width (ft)	8.00	17.00	11.66	12.00	0.76
medwid	Median width (ft)	0.00	60.00	5.42	0.00	11.27
pct_grde	Percent grade of vertical alignment	0.00	10.00	1.17	0.30	1.56

distribution of injury severity for some key factors, as well as summarized statistics for continuous variables considered in this study. The overall crashes were further grouped into 3 classes according to the collision types in each crash: rear-end collisions, sideswipe collisions, and angle collisions. The number of observations selected for 2-vehicle rear-end collisions, sideswipe collisions, and angle collisions was 27,456, 8911, and 14,541, respectively.

The OP and BOP Models

The OP model is commonly used to analyze data sets when the response variable is inherently ordered categorical data. A typical example is a survey where the respondents are asked to rate the quality of service on a scale of 1 to 5. The central idea for the OP model is that there is a latent continuous metric underlying the ordinal responses. Let $x_i = \{x_{i1}, x_{ij}, \cdots, x_{im}\}^T$ represent variables that may affect the injury severity, where i indicates the ith crash, j indicates the jth variable, and m indicates the total number of explanatory variables. The latent variable z_i is assumed to be expressed as:

$$z_i = x_i^T \beta + \varepsilon_i; \quad i = 1, n, \tag{1}$$

where $\beta = \{\beta_1, \{er\beta_j, \cdots, \beta_m\}$ is a vector of parameters to be estimated and ε_i is a random error term (assumed to follow an independent and identically distributed standard normal distribution); n is the total number of crashes.

Let y_i be a categorical random variable with C categories that represents the injury severity. In the current work, the response has 4 categories: no injury, minor injury, incapacitating injury, and fatality. The observed variable $Y = \{y_1, \cdots y_i \cdots y_n\}$ can be connected to the latent variable $Z = \{z_1, \cdots z_i \cdots z_n\}$ through a function $g(Z)$:

$$y_i = g(z_i) = \begin{cases} 1 & \text{if} \quad -\infty = \gamma_0 < z_i \le \gamma_1 \\ 2 & \text{if} \quad \gamma_1 < z_i \le \gamma_2 \\ \vdots & \\ c & \text{if} \quad \gamma_{c-1} < z_i \le \gamma_c = +- > \end{cases}, \tag{2}$$

where $\gamma = \{\gamma_0, \gamma_1, \{er\gamma_{c-1}, \gamma_c\}$ is the threshold value for all categories, wherein $\gamma_0 = -\infty$, $\gamma_c = +\infty$, and the remaining threshold values are subjected to the constraint $\gamma_1 \le r_2 \le \cdots \le \gamma_{c-1}$. The function $g(Z)$ is taken to be nondecreasing, so that small and large values of z_i can be interpreted as corresponding to small and large values of y_i. This also means that the sign of a regression coefficient β_j indicates whether Y is increasing or decreasing with x_j.

Given the value of x_i, the probability that the injury severity of individual i belongs to each category is

$$\begin{aligned} P(y_i = 1) &= \Phi\big(\gamma_1 - x_i^T\beta\big) \\ P(y_i = 2) &= \Phi\left(\gamma_2 - x_i^T\beta\right) - \Phi\left(\gamma_1 - x_i^T\beta\right) \\ P(y_i = c) &= 1 - \Phi\big(\gamma_{c-1} - x_i^T\beta\big), \end{aligned} \tag{3}$$

where $\Phi(\cdot)$ stands for the cumulative probability function of the standard normal distribution.

To calculate β and γ, one restriction is applied to the threshold values to make $\gamma_1 = 0$ (Mckelvey and Zavoina 1975). In the classical OP model, the values of β and $\gamma^* = \{\gamma_2, \{\gamma_{c-1}\}$ can be determined by the ML estimation method. Based on the knowledge in the above text, the likelihood function can be presented as Eq. (4).

$$L(\beta, \gamma^*|y) = \prod_{i=1}^{n}\prod_{k=1}^{c}\left[\Phi\left(\gamma_k - x_i^T\beta\right) - \Phi\left(\gamma_{k-1} - x_i^T\beta\right)\right]^{I(y_i=k)}, \tag{4}$$

where $k = (1, 2, c)$ and $I(y_i = k)$ is an indicator function: if $y_i = k$, then $I(y_i = k)$ is 1; otherwise 0. The parameters β and γ can be determined by maximizing $L(\beta, \gamma^*|\mathrm{y})$.

There are several limitations with the traditional method. The most critical issue is that the parameter estimation results depend completely on the data, which may bring about bias in the estimated parameters when the data cannot represent the population. In addition, the maximization process is a nonlinear optimization problem, which does not guarantee a convergence to a global optimal solution (Mckelvey and Zavoina 1975).

Due to the limitations of ML estimation method, Bayesian inference was introduced to estimate the coefficients, denoted as the BOP model. If a normal prior distribution was applied to β and γ, the joint posterior distribution of $\{\beta, \gamma_1, \ldots, \gamma_{c-1}, z_1, \ldots, z_n\}$ given $\mathrm{Y} = (y_1, y_2, \ldots, y_n)$ can be approximated using Gibbs sampler. The algorithm employed was discussed in depth by Cowles (1996).

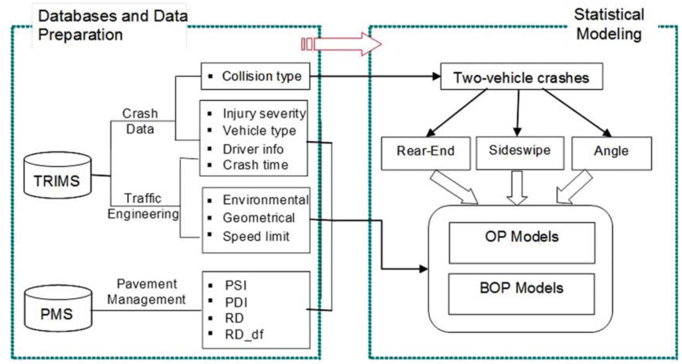

Fig. 1. Flowchart of methodology (color figure available online).

In this article, both the OP and BOP models were constructed using the Zelig package (Goodrich and Lu 2007) in R software (R Development Core Team 2011), which calls the function MCMCoprobit from the MCMCpack package (Andrew et al. 2011). The normal prior with both the mean and precision parameter for each coefficient equal to zero was employed in the BOP model, which is known as a weak informative prior. The corresponding posterior distribution of $\{\beta, z, \gamma\}$ was approximated with a Gibbs sampler consisting of 17,000 scans. The first 2000 iterations were removed to meet stationary status of simulation. The samples were saved every 15th scan and resulted in 1000 values for each parameter with which to approximate the posterior distribution.

The performance of the BOP models was evaluated compared to the corresponding OP models based on the parameter estimates and the deviances (−2*log-likelihood). The smaller the deviance, the better the model fits. Figure 1 illustrates the overall structure of the methodology.

Results

First, the performance of the OP models and BOP models was evaluated. It turns out that the parameter estimates and deviances from the OP model and the BOP model for each of these 3 types of 2-vehicle crashes were very close. This similarity of the OP model and the BOP model was expected for 2 reasons: (1) the weak informative prior was employed in the BOP model, which did not bring too much information to the posterior estimates, and (2) the sample size employed in these models was very large. When the sample size is large enough, the Bayesian and the ML estimation methods will generally produce similar results (Xie et al. 2009).

Because of the similarity of the parameter estimates from the OP and BOP models, only the results of the BOP models are presented in this article. For each collision type, the means and corresponding 2.5 percent and 97.5 percent quantiles of posterior estimates computed from Markov chain Monte Carlo simulation are presented in Table 4. The 2.5 percent

Table 4. Parameter estimates of BOP models

Variable	Classes	Rear-end collisions			Sideswipe collisions			Angle collisions		
		Mean	95% PI		Mean	95% PI		Mean	95% PI	
PSI	Good									
	Fair/bad	−0.089	−0.126	−0.053	−0.116	−0.192	−0.042	−0.192	−0.238	−0.145
PDI	No_dfct									
	Minor_dfct	0.017	−0.020	0.056	0.016	−0.060	0.090	−0.007	−0.054	0.043
	Severe_dfct	0.009	−0.040	0.055	−0.021	−0.118	0.074	−0.016	−0.079	0.041
RD	Shallow									
	Med/deep	0.029	−0.019	0.075	0.046	−0.053	0.143	0.014	−0.049	0.078
RD_df	Small									
	Large	−0.067	−0.164	0.031	−0.140	−0.360	0.080	−0.030	−0.160	0.106
thAADT	NA	−0.004	−0.006	−0.003	−0.004	−0.007	−0.001	−0.004	−0.006	−0.003
lanewid	NA	0.005	−0.020	0.029	−0.016	−0.061	0.027	0.006	−0.022	0.034
medwid	NA	−0.003	−0.004	−0.001	−0.006	−0.009	−0.003	−0.001	−0.004	0.001
pct_grde	NA	0.008	−0.002	0.019	0.011	−0.009	0.031	0.001	−0.014	0.014
rururb	Urban									
	Rural	0.108	0.054	0.168	0.225	0.119	0.327	0.209	0.127	0.284
spdlmt	30 mph									
	35 mph	0.046	−0.038	0.121	0.091	−0.072	0.264	0.163	0.066	0.257
	40 mph	0.032	−0.038	0.102	0.067	−0.090	0.226	0.238	0.155	0.322
	45 mph	0.072	0.004	0.140	0.181	0.031	0.333	0.319	0.234	0.407
	50 mph	−0.010	−0.103	0.079	0.334	0.154	0.521	0.433	0.314	0.557
	55 mph	0.269	0.189	0.348	0.524	0.358	0.692	0.537	0.427	0.649
tyterrain	Flat									
	Rolling	0.044	−0.029	0.121	0.025	−0.121	0.188	0.045	−0.053	0.143
	Mountain	−0.062	−0.280	0.151	0.166	−0.131	0.452	0.207	−0.044	0.461
weather	Clear									
	Inclement	−0.080	−0.127	−0.032	−0.020	−0.122	0.095	−0.030	−0.096	0.034
light	Daylight									
	Nighttime	0.191	0.144	0.236	0.108	0.029	0.194	0.145	0.090	0.199
phour	Yes									
	No	0.090	0.056	0.124	0.115	0.042	0.189	0.093	0.045	0.135
drvsex	M_M									
	M_F	0.065	0.026	0.106	−0.001	−0.074	0.075	0.108	0.060	0.158
	F_F	0.092	0.046	0.140	−0.056	−0.156	0.044	0.099	0.038	0.159
drvage	Yng_Yng									
	Mage_Yng	0.240	0.174	0.311	0.110	−0.038	0.280	0.025	−0.075	0.120
	Mage_Mage	0.311	0.241	0.378	0.146	−0.010	0.314	0.046	−0.050	0.146
	Old_inv	0.298	0.226	0.375	−0.024	−0.191	0.158	0.078	−0.020	0.175
vehtype	Pass_Pass									
	Ltrk_Pass	−0.074	−0.113	−0.036	−0.067	−0.159	0.021	−0.035	−0.087	0.016
	Ltrk_Ltrk	−0.124	−0.174	−0.075	−0.105	−0.224	0.005	−0.132	−0.203	−0.057
	Htrk_inv	0.062	−0.009	0.133	−0.043	−0.170	0.079	−0.033	−0.128	0.065

NA = not applicable.

and 97.5 percent quantiles construct the 95 percent posterior interval (PI), indicating where the posterior estimate for each parameter is located: If it does not contain 0—that is, both the 2.5 percent quantile and 97.5 percent quantile are negative or positive—it can be deemed that this attribute has a significant effect on the injury severity compared to the reference attribute; if it does contain 0, then it can be concluded that this attribute does not produce a significant effect on injury severity.

Of interest, the results show the significant effects of PSI on the severity of injures for all 3 types of 2-vehicle crashes. The "fair/bad" indicator of the PSI is associated with less severe injuries than a "good" PSI. In other words, 2-vehicle rear-end, sideswipe, and angle crashes occurring on rougher roads are less likely to result in severe injuries. This might contradict commonsense because driving on rough roads is less comfortable than driving on smooth roads. However, rough roads may lead drivers to operate at relatively lower speed and pay more attention to their driving. In addition, roughness has been proved to reduce braking distance (Reul and Winner 2009), which may also ameliorate the severity of injuries when crashes occur. The other possible reason is that a fair/bad PSI is associated with roadways with relatively low speed limits, which was true for the employed data set: More than 60 percent of fair/bad PSIs were on roadways with speed limits between 30 and 40 mph, which was much higher than that of the good PSI (around 30%).

The results also revealed that the PDI, RD, and difference between RDs on the right and left wheels were not significant in any of these 2-vehicle collisions. This is understandable. In contrast to the PSI, the indices PDI, RD, and RD_df are measures of pavement distress, especially observable defects such as rutting, cracking, and pot holes. On one hand, drivers may slow down and pay more attention to their driving when they notice road distress. On the other hand, the severe distress may cause vehicles to perform poorly when braking or turning or lead drivers to avoid them and thus hit other vehicles or fixed objects, run out of the lane, or even roll over. The insignificance of these variables implies that the existence of both the advantages and disadvantages cancel each other out for these 2-vehicle crashes. The other possible reason is that the sampled road sections on average have very high PDI (indicating no defect) and low RD and RD_df, which may not be sufficient to reflect their influence on the severity of injuries.

With regard to traffic engineering factors, AADT, lanewid, pct_grde, rururb, tyterrain, light, and phour were significant and played identical roles in all 3 types of 2-vehicle collisions. The increase in AADT resulted in less severe injuries. This is reasonable because high traffic volume restricts driving speeds, thus decreasing the possibility of severe injuries. Nonpeak hours were found to have a higher probability of severe injuries compared to peak hours in all 3 collision types. This finding matches many previous studies. For example, Duncan et al. (1998) claimed that a high level of congestion is likely to reduce injury severity. Rural locations are more likely to have severe injuries compared to urban areas, which is consistent with the results from several published studies (Abdel-Aty 2003; Krull et al. 2000). A possible reason is that more than 50 percent of rural roadways have speed limits of 50 and 55 mph, whereas only around 10 percent of urban roadways do. Nighttime condition increases the likelihood of severe injuries compared to daytime, which supports the finding of Abdel-Aty (2003). There are 2 possible reasons. First, this may be attributed to drivers having poor sight to discern unexpected vehicles and other objects at night. Secondly, nighttime is associated with low traffic volume, which may encourage drivers to maintain higher speeds, thus leading to increased chances of severe injury. Lane width, vertical grade, and type of terrain were not significant in any of these collision types.

The influence of speed limit was similar in all 3 types of collisions: The increase in speed limits from 30 mph (48 km/h) to 40 mph (64 km/h) or higher was likely to increase the injury severity. It is interesting that the severity of injuries in angle collisions was more sensitive to speed limit change than that in rear-end and sideswipe collisions. This makes sense because the outcome of angle collisions relies on the absolute speeds of colliding vehicles, whereas in rear-end and sideswipe crashes the outcome is mostly determined by the relative speeds of the 2 vehicles and their resulting trajectories.

Other factors act diversely among different types of collisions. For example, the coefficients for weather and drvage were significant in rear-end crashes but not in the other 2 types. In rear-end crashes, inclement weather is more likely to be associated with less severe injury compared to clear weather. This result supports the findings of Khattak et al. (1998) and Krull et al. (2000) and can be explained by the drop in practical speeds in bad weather conditions (Adams 1985). In addition, people driving in bad weather, particularly rain, tend to avoid the spray and splash caused by vehicles ahead of them. Therefore, they are likely to maintain longer gaps for safety and comfort. The influence of age was also significant only in rear-end crashes: Crashes involving middle-aged and older drivers were more likely to have severe injuries compared to crashes with only younger drivers. This may be caused by the relatively weaker physical status and longer reaction time of middle-aged and older drivers. Collisions involving female drivers were more likely to produce severe injuries in rear-end and angle collisions but not in sideswipe collisions.

Additionally, the increase in median width appeared to decrease the severity of injuries in both rear-end collisions and sideswipe collisions but not in angle collisions. The positive effect of median width was expected. With wider medians, drivers have more space to take action, possibly preventing serious injuries. For example, when one vehicle is about to hit another, the driver can turn the wheel toward the median to prevent full contact, which may reduce the possibility of severe injuries.

The influence of vehicle type was complicated across different collision types. Collisions involving heavy vehicles did not show a significant difference in injury severity compared to passenger car collisions in any of these collision types. Collisions between light trucks tended to produce less severe injuries compared to passenger car collisions in both rear-end and angle crashes but not in sideswipe crashes. Light truck to passenger car collisions had less severe injuries compared to passenger car collisions in rear-end crashes but not in the other 2 types of collisions. The relative safety of collisions involving light trucks was to some extent consistent with the results reported by Krull et al. (2000), who indicated that injury severity increased with passenger cars as opposed to pickup trucks. The lower injury propensity of crashes involving light trucks might be attributed to the relatively higher rigidity of a light truck compared to a passenger car.

Conclusions

With the growing rate of pavement deterioration in the United States, pavement management has become a major concern for pavement and traffic engineers. The research presented in this article investigated the effects of pavement management factors and traditional traffic engineering factors on the injury severity of 3 types of 2-vehicle crashes.

Based on crashes that occurred on Tennessee state route highways from 2004 to 2008, both the OP and BOP models were fitted for 2-vehicle rear-end, sideswipe, and angle collisions separately. The results indicate that PSI, as a measure of pavement roughness, produced significant effects in all 3 crash types studied in this article: Rougher roads were associated with less severe injuries compared to smoother roads. PDI, rutting depth, and rutting depth difference between left and right wheels were not significant in affecting the severity of injuries in any of these crash types. These findings indicate that improved pavement quality does not necessarily contribute to the reduction of injury severity in 2-vehicle rear-end, sideswipe, or angle collisions.

Traffic engineering factors that consistently exhibited a considerable influence on the injury severity of these 3 types of crashes include AADT, rural–urban location, speed limit, light condition, and peak hour traffic. A few other traffic engineering factors act diversely for different types of crashes, including median width, weather condition, driver's gender and age, and vehicle type.

By comparing parameter estimates and deviances, the authors found that the BOP model with a weak informative prior and the traditional OP model based on the ML estimation method performed equally well. To employ Bayesian inference with noninformative or weak informative priors provides an alternative to the traditional OP model but does not necessarily improve the fitness of models, especially when a large amount of sample data is available.

This article is subject to its limitations. A few variables were not accounted for in this research due to information missing in the database, such as driver's consumption of alcohol, use of seat belts, horizontal alignment, type of shoulder, and shoulder width. The pavement management information considered here is basically a general reflection of the real roughness and distress, and specific recording of pavement distress such as cracking, potholes, and friction was lacking. Further study of the influence that each specific distress has on injury severity is desirable.

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