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Incorporating Travel Time Reliability in Predicting the Likelihood of Severe Crashes on Arterial Highways Using Non-Parametric Random-Effect Regression

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Original Research Paper

Incorporating travel time reliability in predicting the likelihood of severe crashes on arterial highways using non-parametric random-effect regression

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HIGHLIGHTS

- Analysis of the impact of the travel time reliability on the severe injury crash occurrence was conducted.
- The analysis was done using a non-parametric random-effect regression.
- The non-parametric random-effect regression was compared to traditional random-effect regression in the analysis.
- Tighter credible intervals were estimated in the non-parametric random-effect than in traditional random-effect regression.
- The TTR was found to significantly influence the severity of a crash at 95 percent credible intervals.

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ABSTRACT

Travel time reliability (TTR) modeling has gain attention among researchers' due to its ability to represent road user satisfaction as well as providing a predictability of a trip travel time. Despite this significant effort, its impact on the severity of a crash is not well explored. This study analyzes the effect of TTR and other variables on the probability of the crash severity occurring on arterial roads. To address the unobserved heterogeneity problem, two random-effect regressions were applied; the Dirichlet random-effect (DRE) and the traditional random-effect (TRE) logistic regression. The difference between the two models is that the random-effect in the DRE is non-parametrically specified while in the TRE model is parametrically specified. The Markov Chain Monte Carlo simulations were adopted to infer the parameters' posterior distributions of the two developed models. Using four-year police-reported crash data and travel speeds from Northeast Florida, the analysis of goodness-of-fit found the DRE model to best fit the data. Hence, it was used in studying the influence of TTR and other variables on crash severity. The DRE model findings suggest that TTR is statistically significant, at 95 percent credible intervals, influencing the severity level of a crash. A unit increases in TTR reduces the likelihood of a severe crash occurrence by 25 percent. Moreover, among the significant

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variables, alcohol/drug impairment was found to have the highest impact in influencing the occurrence of severe crashes. Other significant factors included traffic volume, weekends, speed, work-zone, land use, visibility, seatbelt usage, segment length, undivided/divided highway, and age.

1. Introduction

Due to recent technological advances in traffic data collection method, the estimation of travel time reliability (TTR) has been made possible and it has become a popular approach for assessing traffic operation in the highway system (Kidando et al., 2018). TTR measures travel time variability (i.e., predictability) of a journey (Yang and Wu, 2016). This is one of the advantages of TTR approach over other conventional performance measures, such as level of service, delay, queue length, and volume to capacity ratio. Furthermore, TTR is reported to be more appropriate than conventional performance measures in managing traffic of the existing system while most of the conventional measures are relevant in design to meet desired capacity (Lyman, 2007). Improved TTR offers efficient transportation services through providing information regarding hourly, daily, and weekly traffic variations. By so doing, it enables travelers to predict travel times between origins and destinations hence making travel decisions effectively.

Although several studies have been conducted to develop metrics that quantify TTR as well as modeling the distribution characteristic of TTR, there is limited research regarding TTR impact on the crash severity (Kidando et al., 2017). As such, this paper seeks to conduct a safety analysis to provide insight on how TTR may be influencing crash severity. Two random-effect models were applied to accommodate for unobserved heterogeneity associated with each crash observation. The first model assumed the random-effect to be non-parametrically distributed. This assumption is achieved by using the Dirichlet process (DP) prior on the weight of mixture component, implemented through the stick-breaking process. This model has been reported to have improved data fit in social science research (Kyung et al., 2011; Ohlssen et al., 2007; Traunmüller et al., 2015) while it is not commonly used in highway safety studies (Kitali et al., 2018a, b; Yu et al., 2016). The second model used in this study assumes the random-effect distribution is normally distributed (Gaussian distribution), a common assumption applied in highway safety studies (Mannering et al., 2016; Xie et al., 2017). The two models mentioned above were used in the analysis of all crashes that occurred on Northeast Florida arterial roads from 2009 to 2011. Travel speeds from five counties from June 2010 to June 2011 in Northeast Florida were used in the analysis to estimate TTR. The missing TTR in the years that travel speeds were not available to researchers were approximated using the 2010–2011 data.

2. Literature review

Travel time variability perhaps is one of the earliest measures that quantify the reliability of a journey travel time. The standard deviation, variance, the coefficient of variation, and skew statistic of the travel time are examples of the established indicators in a variability category. Although these metrics are simple to compute, recent empirical studies have criticized their appropriateness to quantify TTR. The travel time distribution is asymmetrical, skewed to the upper tail (Taylor, 2013). Due to these characteristics, using the variation method could under-represent the actual traffic condition. Also, the variability of the travel time during rush and free-flow hours might both be small, which might reveal contradicting interpretations. In fact, other than transportation analysts, the variability metrics do not provide a straightforward description of the traffic condition to road users.

Recent empirical studies proposed new indicators of TTR, which can be categorized as either probabilistic or statistical indices (Chien and Liu, 2012; Kaparias et al., 2008). The probabilistic TTR indicators include metrics such as congestion frequency and the percentage of on-time arrivals. On the other hand, the statistical index metrics comprise of a buffer time, planning time, misery index, and a travel time index. The unique characteristic of the statistical index metrics is that they use percentile values to derive measures (Taylor, 2013). The Federal Highway Administration (FHWA) proposed some of the statistical index metrics as indicators of TTR and they are even used by some state highway agencies to assess traffic mobility (Taylor, 2015). Therefore, the present study used a measure from the statistical index group of TTR metrics to evaluate the possible influence of TTR on crash severity.

Statistical approach is widely used in transportation safety as one of the decision-making tools for developing crash risk reduction strategies and reducing crash severity. The basic logistic regression model (i.e., without random-effect parameter) perhaps is the most popular model applied in safety studies, in particular, for analysis of crash severity. However, this model neglects observation dependencies and random variation across crash observations. The variations might be due to factors that are not captured during crash data recordings, such as some of the human-related, traffic-related, road features, vehicles, and environmental factors (Islam and Hernandez, 2013; Mannering et al., 2016). Mannering et al. (2016) point out that when variation across observations is overlooked in the analysis, the resulting model estimates may be biased, which could lead to invalid statistical conclusions being made.

In efforts to address the problem, several approaches have been proposed including the use of mixture and random-effect models. The mixture model has been applied in traffic safety analyses and revealed promising results (Behnood et al., 2014; Behnood and Mannering, 2016; Mohamed et al., 2013). However, this model requires specifying the number of mixture components that must be pre-specified before the analysis (Heydari et al., 2016; Mannering et al., 2016). The information criteria are the most widely used statistics to select the mixture model with an optimal number of mixture component. Nevertheless, this procedure could lead to model over- or under-fitting problem depending on the amount of data used to build the model (Heydari et al., 2016; Mannering et al., 2016).

Another approach to accommodate crash observation dependencies is to use the extension of the basic regression models by including the random-effect. This is accomplished by adding the unobserved heterogeneity term(s) in the basic regression model (Mannering et al., 2016). At present, the unobserved heterogeneity term in the analysis of crash severity is assumed to follow a parametric distribution specified by the analyst (Park and Lee, 2017; Ukkusuri et al., 2011). The Gaussian distribution is the most commonly applied distribution in random-effect injury severity models (Traunmüller et al., 2015). However, studies point out that the Gaussian distribution does not fit well multimodal and skewed data, including outliers such that it might not detect the true unobserved heterogeneity (Gelman et al., 2014; Lee and Thompson, 2008). To account for this problem, some studies propose the use of robust distributions, such as the gamma, Student-T, and Cauchy distribution, to mention a few (Gelman et al., 2014; Lee and Thompson, 2008; Müller and Quintana, 2004; Traunmüller et al., 2015).

Although the TRE model improves the fitness of the model, it restricts the distribution of the random-effect factor. As a result, the model fails to recognize the existence of a cluster of observations with a similar structure of parameters. Further, constraining to a particular parametric form may limit the scope and type of inference that can be drawn from such a model (Lee and Thompson, 2008; Müller and Quintana, 2004). Another robust approach introduced recently assumes the random-effect term follows a non-parametric distribution. This method uses the DP mixture to account for the existence of groups of observations with the same random-effects structure (Heinzl and Tutz, 2013; Kitali et al., 2018a, b; Ohlssen et al., 2007; Traunmüller et al., 2015). The DP mixture provides great flexibility than does the parametric analysis. In this study, the non-parametric random-effect regression model will also be referred to as the Dirichlet random-effect (DRE) logistic regression model. The DRE model can offer improved fits compared to the basic logistic and the TRE model (Kitali et al., 2018a, b). Therefore, the study also adopts the DRE model to examine and quantify the effect of TTR on the severity of crashes occurring on arterial roads. This study adds to the body of the existing literature of injury severity analysis by integrating TTR and applying a more robust regression model in estimating significantly associated variables.

3. Data preparation

In this study, five counties located in Northeast Florida were selected for analysis; Clay, St. Johns, Putnam, Duval, and Nassau Counties (Fig. 1). From the Florida Department of Transportation (FDOT) crash database, vehicle crashes that occurred on arterials between 2009 and 2012 were extracted and used in the analysis. In addition to traffic volume, road geometry, and crash-specific attributes, this data consists of geographical coordinates, which were used to match the crash locations with those of TTR data.

The FDOT crash database reports injury severity in seven levels, 0) “not coded”, 1) no injury, 2) possible injury, 3) non-incapacitating injury, 4) incapacitating injury, 5) fatality, and 6) non-traffic fatalities. The distribution of crashes observed during the analysis period is as follows: 13,630 were no injury crashes (51.39 percent), 6835 possible injuries (25.77 percent), 4627 were non-incapacitating injury (17.45 percent), 1219 were incapacitating injury (4.6 percent), 195 were fatal crashes (0.73 percent), and 16 were non-traffic fatalities and “not coded”

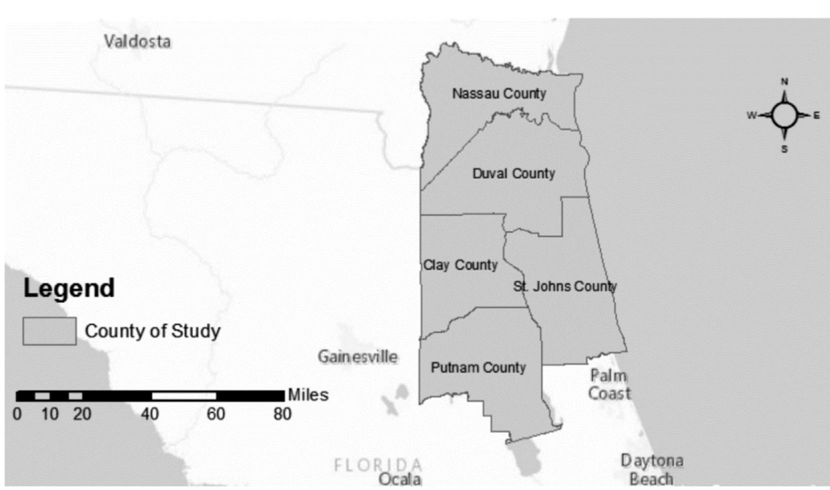

Fig. 1 – Case study area.

(0.06 percent). Since the “not coded” and non-traffic fatal crashes did not have clear information about their level of severity caused by a vehicle accident, they were omitted in the analysis. While fatal and incapacitating crashes were combined forming a “severe crash” category, no injury, possible injury, and non-incapacitating injuries created a “non-severe crash” category.

In addition to the crash data, data for TTR estimations were obtained from the INRIX Company (INRIX Inc., 2008). These data are the historical traffic speed collected daily for one year from June 2010 to June 2011 recorded at a 15 min interval for vehicles traveling on segments. TTR of each segment was estimated by using the segment length and the traffic speed. In particular, a buffer time index (BTI) was selected to represent TTR of a segment. The BTI is one of the measures that provide appealing results and consistent analytical conclusion (Lomax et al., 2003; Mahmassani et al., 2014). The BTI measures the additional time that drivers will have to spend on their journey to reach a destination on time (Lomax et al., 2003). It is usually computed as a ratio of the 95th percentile travel time and the average travel time difference to the average travel time. Due to the asymmetrical characteristics of the travel time distribution, an approach proposed by Pu (2011) was chosen. This approach suggests that the 95th percentile and the median travel time difference (Eq. (1)) is more appropriate than mean-based for the BTI. Applying the mean-based buffer index could obscure some of the information for skewed distributions due to congestion onset and offset (Pu, 2011). After obtaining the BTI, the crash and TTR data were merged using geographical coordinates to obtain attributes for analysis. The descriptive statistics of the segments, the BTI, and traffic data including description of categorical variables are presented in Tables 1 and 2. The correlation analysis between these variables was checked before fitting the regression models. The highest estimated correlation coefficient was 44% (buffer index and segment length variables). Due to a reason that the coefficients were less than 50%, all the variables in Tables 1 and 2 were used to develop the regression models.

$$\text{Buffer time index} = \frac{\text{95th percentile travel time} - \text{Median travel time}}{\text{Median travel time}} \tag{1}$$

4. Methodology

As it was aforementioned, this study applied two binary logistic regressions to evaluate the influence of TTR and other variables on the occurrence of severe crashes (Tables 1 and 2). The first model was the traditional random-effect (TRE) logistic regression model with the Gaussian distributed random-effect. This approach is commonly applied in the crash analysis to define the error term to account for variations within the observed crash data (Ukkusuri et al., 2011; Xie et al., 2017). The Gaussian distribution was applied in Eq. (2) to define the random-effect distribution, $F \sim N(0, \sigma_{1i})$. Table 3 shows the definition of variable and parameter symbols used in the study.

Table 1 – Basic information for continuous predictors.

Variable	Mean	Standard deviation	Minimum	Maximum
AADT (vehicles per day)	29,064	17,413	2600	172,000
Truck volume (%)	0.040	0.036	0.007	0.320
Segment length (miles)	1.198	1.075	0.004	10.190
Buffer time index (BTI)	0.336	0.365	0.005	4.000

Note: AADT is the annual average daily traffic.

$$\begin{cases} y_i \sim \text{Bernoulli}(P_i) \\ \text{logit}(P_i) = \ln\left(\dfrac{P_i}{1-P_i}\right) = \beta_0 + \beta_j X_i + \epsilon_i \\ \epsilon_i \sim F \end{cases} \tag{2}$$

The Dirichlet random-effect logistic regression was the second model employed in this study. This approach relaxes the parametric assumption by assuming that the random-effect comprises of infinite distributions (i.e., non-parametric distribution). The non-parametric distribution of the random-effect was built on the basis of the multi-state distribution property. As such, the developed model can recognize clusters of observations with similar random-effect structures (Heinzl and Tutz, 2013). Furthermore, unnecessary variations in the parameter estimates can be removed, which can yield a better fit of data compared to the TRE regression model. To account for the clusters in the random-effect distribution, the DP prior was used to build the random-effect term in the model. In order to reduce the computational burden, the infinite distributions for the random-effect were approximated using the truncated DP (TDP) prior in the model. The truncation process follows the following definitions (Ohlssen et al., 2007):

$$\begin{cases} F|G \sim G \\ G|\alpha, H \sim \text{DP}(\alpha, H) \\ G = \sum\limits_{k=1}^{\infty} \pi_k \delta_{\theta_k} \approx \sum\limits_{k=1}^{N} \pi_k \delta_{\theta_k} \sim \text{TDP}(\alpha, H, N) \\ \sum\limits_{k=1}^{N} \pi_k = 1 \end{cases} \tag{3}$$

Constructing the truncation process presented in the Eq. (3) above, a stick-breaking process was used to assign the mixing proportion/weights π_k. This process splits a unit length stick repetitively until N pieces are obtained. The initial piece w_1 corresponding to the first weight π_1 is split randomly from

Table 2 – Road characteristics, crash attributes and temporal predictors.

Variable	Description	Code for modeling	Count	%
Road characteristics and location of the highway				
Segment	Undivided segments	1	15,459	58.29
	Divided segments	0	11,062	41.71
Posted speed limit (mph)	Less than 45	0	23,441	88.39
	Greater than or equal to 45	1	3080	11.61
Intersection	No	0	10,526	39.69
	Yes	1	15,995	60.31
Work-zone	No	0	25,620	96.60
	Yes	1	901	3.40
Land use characteristics	Urban	0	25,190	94.98
	Rural	1	1331	5.02
Crash characteristics				
Safety belt usage	Yes	0	23,280	87.78
	No	1	3241	12.22
Age	<65 years old	0	24,840	93.66
	≥65 years old	1	1681	6.34
Alcohol/drug involvement	No	0	25,074	94.54
	Yes	1	1447	5.46
Visibility	Obscured (smoke, fog, inclement weather conditions, load on vehicles, parked vehicles)	1	1521	5.74
	Vision not obscured	0	25,000	94.26
Temporal characteristics				
Time	Day hours	0	13,797	63.00
	Night hours	1	12,724	37.00
Day of a week	Weekday	0	20,647	77.85
	Weekend	1	5874	22.15

Table 3 – Variable/parameter definitions.

Variable/parameter	Description	Equation number
y_i	Crash severity level – either 1 or 0	Eq. (2)
P_i	Probability of severe injury occurrence	Eq. (2)
β_0	Intercept parameter of the model	Eq. (2)
β_j	Vector of predictor parameters for j variables	Eq. (2)
X_i	Vector of the explanatory variables for an accident i	Eq. (2)
ϵ_i	Vector of random-effects associated with each crash observation i	Eq. (2)
F	Random-effect distribution	Eqs. (2) and (3)
G	Random distribution drawn from the DP(α, H)	Eq. (3)
α	Positive precision parameter	Eq. (3)
DP(α, H)	DP with parameters α and H	Eq. (3)
TDP (α, H, N)	Truncated DP with parameters α, H, and N	Eq. (3)
δ_{θ_k}	Represents a Dirac delta function concentrated at θ	Eq. (3)
N	Total mixture components in the TDP	Eq. (3)
H	Represents the base distribution, which is normally distributed	Eqs. (3) and (4)
π_k	Mixing proportion/weight of the mixture component	Eqs. (3) and (4)
w_k	Proportion of weight being broken off	Eq. (4)
k	Represents the number of mixture components	Eqs. (3) and (4)
σ_{2i}	Variance in the base distribution H	
σ_{1i}	Variance parameter in the random-effect term for the TRE model	

the unit stick (Fig. 2). The second piece to be broken w_2 $(w_1 - 1)$ represents the second weight π_2. This piece is obtained by breaking the left-out stick from the first break. Continuously breaking the remaining stick to N pieces (N total mixture components) in Fig. 2 yields Eq. (4) (Fan and Bouguila, 2013).

$$\begin{cases} \pi_k = w_k \prod_{i=1}^{k-1} 1 - w_i \\ w_k \sim \text{Beta}(1, \alpha) \\ \theta_k | H \sim H \end{cases} \tag{4}$$

The prior distributions were taken as non-informative for both the DRE and TRE model. In these models, normal (mean = 0, std. = 100) for intercept β_0 and predictor parameters β_j prior was used. The hyperprior for the standard deviation in the TRE's random-effect term was assigned to follow the half-Cauchy distribution, that is, $\sigma_{1i} \sim$ half-Cauchy (0, 5). The base distribution H in the DRE regression was assigned to be normally distributed, H~normal (mean = 0, std. = σ_{2i}). The hyperprior for σ_{2i} was the half-Cauchy distribution,

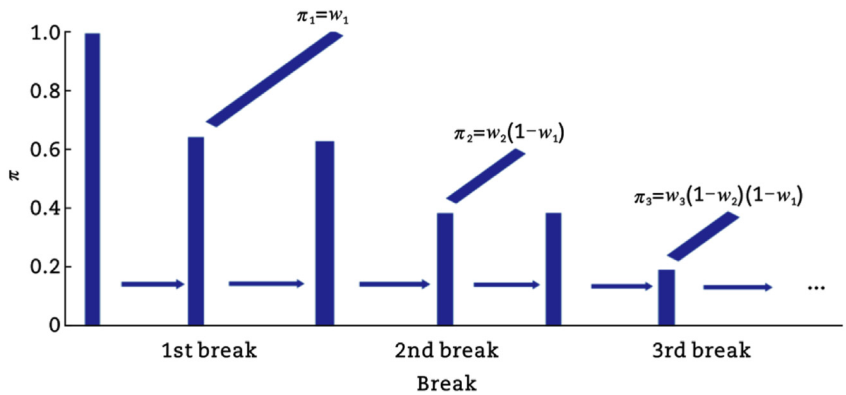

Fig. 2 – Illustration of the stick-breaking construction.

$\sigma_{2i} \sim$ half-Cauchy(0, 5). The prior distribution for the concentration parameter α was assigned to follow the uniform distribution, $\alpha \sim$ uniform(0.3, 10). The number of mixture components set in the TDP depends on the α prior used in the analysis. Researchers indicate that using 10 upper boundaries in the uniform distribution prior for α, the infinite DP can be approximated by 52 mixture components (N) in the stick-breaking process (Heydari et al., 2016; Kitali et al., 2018a, b; Ohlssen et al., 2007). Thus, this study used $N = 52$ in the DRE model. A detailed explanation and derivation of this truncation is reported by Ohlssen et al. (2007).

The parameters' posterior distributions for the TRE and DRE regressions were both inferred using the Markov Chain Monte Carlo simulations. The models were implemented in PyMC3, an open source Python package (Salvatier et al., 2016). The No-U-turn sampler (NUTS) was used to estimate the regression parameters β_0, β_j, and variances (σ^2_{1i} and σ^2_{2i}). For the precision parameter α, the proportion of weight w_k being broken off, and mixture components π_k, the Metropolis-Hasting Sampler was used instead of NUTS to accommodate for the discrete variables.

5. Model comparison

The deviance information criterion (DIC) is the mostly used goodness-of-fit statistic in the Bayesian crash analysis to select the best model out of many fitted models (Spiegelhalter et al., 2002). However, some literature criticizes the reliability of the DIC when used to compare hierarchical and multimodal posterior models (Geedipally et al., 2014; Heydari et al., 2016; Millar, 2009). Due to this criticism, this study uses an approximate Bayesian cross-validation method to compare the two developed models. More specifically, the Bayesian leave-one-out cross-validation (LOO-CV) estimated using the Pareto smoothed importance sampling (PSIS) is employed. This approach is proposed by Vehtari et al. (2016) and has successfully been applied in Bayesian model selection including the hierarchical and multimodal posterior models. The study by Vehtari et al. (2016) discusses the LOO-CV method in detailed.

Another goodness-of-fit statistic employed in this study was the widely available information criterion (WAIC) proposed by Watanabe (2010). The WAIC is somewhat similar to the DIC as both criteria not only measure the prediction accuracy but also penalizes models with excessive complexity (i.e., the excessive effective number of parameters) to account for the overfitting problem. On the other hand, the WAIC is a fully Bayesian approach, can evaluate the hierarchical models, and it is estimated using the log pointwise posterior predictive density, instead of point estimate used by the DIC (Vehtari et al., 2016). The pointwise approach tends to incorporate uncertainty in the estimated values. The WAIC expression is defined as

$$\mathrm{WAIC} = -2{*}\mathrm{lppd} + 2{*}\mathrm{p}_{\mathrm{waic}} \tag{5}$$

where $\mathrm{p}_{\mathrm{waic}}$ is the effective number parameters, lppd is the log pointwise posterior predictive density.

6. Model results and discussion

The convergence of the iterations of the two developed models was analyzed based on the trace plots, and it was found that 10,000 iterations out of the 20,000 were sufficient to draw the inference of the parameters' posterior distribution. In selecting the best-fitted model, a model with the lowest WAIC and LOO-CV is usually selected over other fitted models. Table 4 summarizes model results including, the posterior mean, posterior standard deviation, and credible intervals. The LOO-CV estimate for the DRE regression model was 10,467 compared to 10,846 for the TRE regression model. This suggests that the DRE regression outperforms the TRE regression in fitting the data at hand. The results for the WIC goodness-of-fit statistic were consistent with those of the LOO-CV statistic. Findings suggest that the DRE model performs better (WAIC = 10,461) compared to the TRE regression model (WAIC = 10,882).

Looking at the magnitude of the model coefficients, sign (negative or positive coefficients), and the credible intervals, all variables indicated a similar sign and a slight difference in magnitude between the DRE and TRE parameter's posterior mean. For instance, the TRE and DRE had respective values of −0.351 and −0.300 for AADT parameter and −1.955 and −1.605 for the percentage of truck volume. The overall pattern can be inferred that the DRE regression model has

Table 4 – Model results of the crash injury severity analysis.

Variable	TRE model				DRE model			
	Posterior mean	Posterior Std.	95% credible intervals		Posterior mean	Posterior Std.	95% credible intervals	
			2.5%	97.5%			2.5%	97.5%
Intercept	−0.731	0.596	−1.722	0.615	−0.722	0.631	−1.942	0.374
Traffic data								
Log (AADT)	−0.351*	0.061	−0.484	−0.237	−0.300*	0.047	−0.396	−0.223
Truck volume (%)	−1.955*	0.802	−3.744	−0.556	−1.605*	0.775	−3.100	−0.057
Road characteristics and location of the highway								
Segment length (miles)	0.112*	0.026	0.060	0.159	0.088*	0.023	0.042	0.132
Road characteristics (Undivided road)	0.340*	0.067	0.209	0.470	0.304*	0.060	0.187	0.421
Posted speed limit (mph) (≥45 mph)	0.669*	0.086	0.507	0.843	0.608*	0.076	0.468	0.766
Intersection (Yes)	0.095	0.060	−0.015	0.218	0.099	0.060	−0.018	0.221
Work-zone (Yes)	0.797*	0.132	0.549	1.060	0.657*	0.115	0.410	0.861
Land use characteristics (rural areas)	0.572*	0.130	0.307	0.810	0.516*	0.111	0.300	0.729
Crash characteristics								
Safety belt use (No)	0.731*	0.083	0.563	0.886	0.616*	0.070	0.485	0.758
Age (greater and equal to 65 years old)	0.699*	0.120	0.461	0.934	0.590*	0.100	0.384	0.764
Alcohol/drug involvement (Yes)	1.172*	0.130	0.922	1.421	0.950*	0.088	0.773	1.112
Visibility (obscured)	0.286*	0.115	0.051	0.500	0.233*	0.111	0.023	0.452
Temporal factors								
Time (night hours)	0.053	0.063	−0.062	0.179	0.042	0.057	−0.072	0.150
Day of a week (weekend)	0.471*	0.065	0.350	0.597	0.438*	0.065	0.318	0.554
Travel time reliability								
Buffer time index (BTI)	−0.349*	0.102	−0.545	−0.151	−0.297*	0.095	−0.477	−0.101
LOO-CV	10,846				10,467			
WAIC	10,882				10,461			
Number of crash observations	26,521				26,521			

Note: * represents a variable that is significant at 95% credible intervals. Std. is standard deviation.

slightly tighter credible intervals than those of the TRE regression model. Fig. 3 shows the summary of the variables' 95 percent credible intervals difference for both the TRE and the DRE regression models. The tighter 95 percent credible intervals signify that the standard deviation of the posterior distribution is small, for which the lower the value, the better the reduction of parameters' uncertainty. It further suggests that the DRE regression fits the data appropriately than the TRE regression model. These findings are similar to those found by the previous studies suggesting that shorter credible intervals in the DRE model are attributed to the fact that the model can remove unnecessary variability, the issue that the TRE model does not address (Kyung et al., 2009, 2011; Traunmüller et al., 2015). The DRE model eliminates unnecessary variability by identifying clusters of random unobserved heterogeneity. Based on these outcomes, the DRE regression was selected to explain the pertinent factors that impact the injury severity of the crashes.

Out of 15 variables evaluated, 13 variables were found to be significant at 95 percent credible intervals. The odds ratio (odds ratio $= \exp(\beta) \times$ 100%) was applied in assessing and comparing the effect of the variables on the crash injury severity occurrence. In general, the variable with the positive sign coefficient has the odds ratio greater than 100 percent and that with the negative sign estimate has the odds ratio less than 100 percent. The effectiveness of variables that reduce the risk of severe crashes was determined by taking the difference between 100 percent and the odds ratio value (i.e., 100 percent − odds ratio).

6.1. *Travel time reliability*

This study found that the BTI is significantly influencing the likelihood of having the severe crash at 95 percent credible intervals. The impact suggests that a one BTI increase the probability of the severe crash reduces by 26 percent. This finding agrees with intuition because the BTI measures the extra time beyond a median travel time a road user is expected to use to reach a destination on time. A longer duration beyond the median travel time required to complete a journey is associated with congestion on the roadway (that is, lower travel speed). Crashes occurring under low-speed condition have a low likelihood of being severe due to low associated kinetic energy (Kidando et al., 2017).

6.2. *Crash characteristics*

Impaired occupants with either alcohol or drug have the highest impact on the likelihood of the severe crash occurrences (Fig. 4). The direction of the effect shows that impaired occupants are associated with higher risks of severe crashes than unimpaired occupants. The odds ratio is 1.59 greater than unimpaired drivers. A similar finding is reported by the existing studies (Dissanayake and Roy, 2014; Quddus et al., 2010). Work-zone area was also found to be significant at 95 percent credible intervals associated with severe crash occurrences. It was found that the odds ratio of a severe crash occurrences in these areas rises by 93 percent compared to non-work-zone areas. Seat belt restrained usage was another significant factor deemed in this study. The odds ratio of a severe crash to occur is higher by 85 percent when unbuckled vehicle occupants are involved than when all occupants involved in a crash are buckled. These results mirror those reported by the previous studies (Dissanayake and Roy, 2014; Ratnayake, 2006).

Compared to drivers who are younger than 65 years old, aging drivers (aged 65 years and above) were found at a higher risk of being involved in severe crashes than drivers who are less than 65 years old. Analysis depicted that the odds ratio of severe crash occurrences for aging drivers is 80 percent higher than drivers who are less than 65 years old. This result can be related to the age-frailty and reduced physical capabilities (bone strength and fracture tolerance) of aging drivers (Zeeger et al., 1994). This finding agrees with those obtained by (Augenstein, 2001), who suggests that just a minimal impact could cause severe injuries to aging drivers.

Visibility was divided into two categories, i.e., adequate and inadequate visibility. Inadequate visibility reflects vision obstruction during driving. Causes of poor visibility on the road include but not limited to smoke, fog, inclement weather conditions, parked vehicles and others. Model results suggest that the likelihood of severe crash to occur was higher for impaired visibility than adequate visibility. Poor visibility increases the odds ratio of a severe crash to occur by 26 percent compared to adequate visibility.

Furthermore, the day of the week was also found significant at 95 percent credible intervals affecting severity level of the crashes. Surprisingly, the results indicate that there is a higher risk to be involved in a severe crash on weekends than weekdays. The odds ratio of a severe crash to occur is 58 percent greater during weekends than on weekdays. One can speculate that the weekends perhaps are associated to lower traffic volume (less congestion) such that traffic speeds are higher than weekdays.

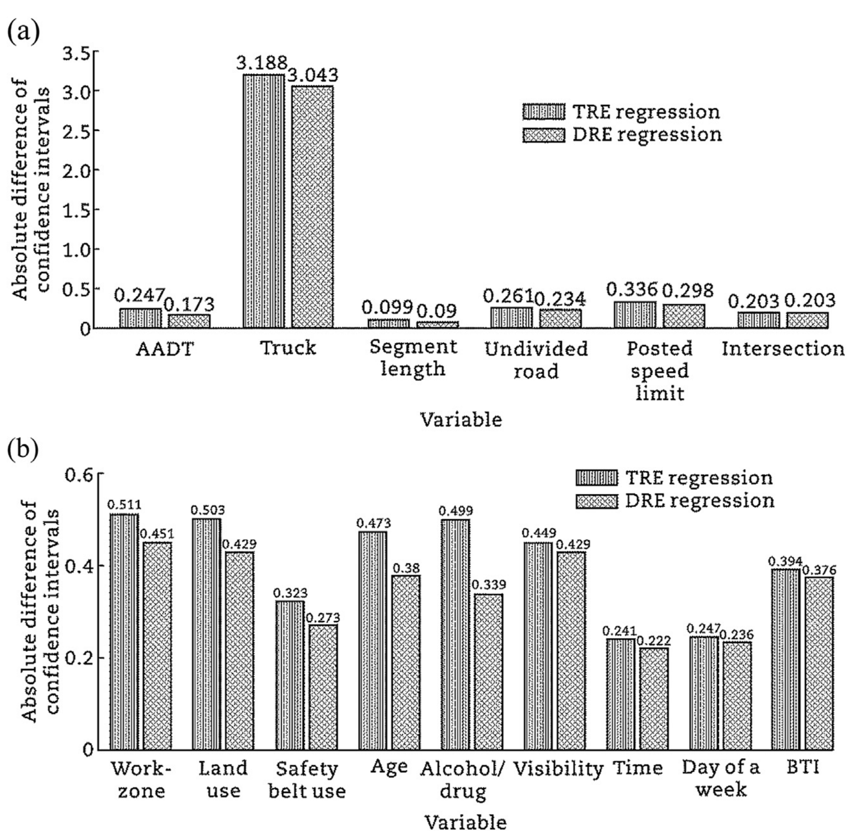

Fig. 3 – Comparison of the credible intervals between the TRE and DRE regression models (difference = |2.5%–97.5%|).

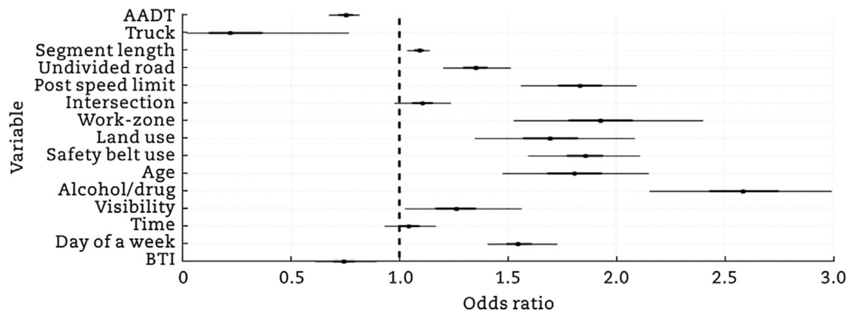

Fig. 4 – Comparison of the variables' odds ratio – DRE model.

6.3. *Traffic volume*

Traffic volume (AADT) was found significant at the 95 percent credible intervals. The finding suggests that as one log of AADT increases, the odds ratio of a severe crash occurrence reduces by 26 percent. Usually, when the number of traffic is high on a particular roadway, gaps are smaller with reduced travel speeds; as a result, the likelihood of the severe crash to occur is reduced. This finding aligns with those reported in the literature (Chang, 2003; Duncan et al., 1998). Furthermore, the percentage of truck volume revealed a similar pattern. The analysis indicates that 1 percent rise in the truck volume percentage reduces the odds ratio of a severe crash occurrence by nearly 80 percent.

6.4. *Road characteristics and location of the highway*

In evaluating the influence of land use setting, the study assigned two categories – rural and urban areas. The land use is statistically significant at 95 percent credible intervals and indicates that rural areas are associated with more severe crashes than urban areas. The odds ratio analysis illustrations that the likelihood of a crash occurred being severe is higher by nearly 67 percent in rural areas than in urban areas. It is reasonable to think that perhaps rural areas are associated with high speeds and lower traffic volumes than urban areas. Due to vehicle interaction with pedestrians and numerous access points along the highways, urban areas have lower posted speed limit than rural areas.

Another significant variable found influencing crash severity is the posted speed limit. The analysis indicates that the odds ratio of severe crash occurrence increases by 84 percent for highways with the posted speed limit higher than 45 mph compared to lower speeds. This finding is consistent with intuition, usually posted speed limit influence the traffic operating speed in a way that higher posted speed limit is associated with higher vehicle operating speed. Crashes occurring on high-speed highways are usually severe due to the impact of high kinetic energy. Similar observations were found by other researchers (Dong et al., 2015; Duncan et al., 1998).

Moreover, the posterior mean of the segment length is positive and statistically significant, indicating that longer segments have a higher risk than shorter ones. A unit increase in the segment length increases the odds ratio of severe crash occurrence by 9 percent. Generally, segment length in the highway safety analysis is referred to as exposure variable. That is to say, a driver is exposed for a longer time and distance when driving on the segment that is longer as compared to when it is shorter.

In addition, the study found that undivided highways have a higher odds ratio than divided highways. The estimate of odds ratio was found to be higher by 36 percent for undivided than divided highways. One of the contributing reasons for this finding is due to the passing maneuver that can possibly lead to head-on collisions. Based on the geometric characteristics, this type of the collision is more likely to occur on undivided highways compared to divided highways. The head-on collision is severe due to momentum impact. Thus, the chances of a severe crash occurrence are higher on the undivided highway than on the divided highway.

7. Conclusions and recommendations

Travel time reliability (TTR) is one of the best approaches that are used to define traffic mobility for both transportation agencies and road users. At present, extensive studies have attempted to develop TTR metrics and modeling TTR distribution. However, the impact of TTR in highway safety is not fully explored. This study aimed at investigating the influence of TTR, using the buffer time index (BTI), on the severity of crashes that occurred on arterial roads. Four years (2009–2012) of crash data were obtained from five counties in Northeast Florida and used in the analysis. These data were acquired from Florida Department of Transportation (FDOT) crash database. The historical traffic speed aggregate on a 15-min basis obtained from the INRIX database was used to estimate TTR. To accomplish the study objective, two random-effect models were applied to accommodate for the unobserved heterogeneity problem, which might be caused by correlation of the crashes and some of the important variables not being taken into consideration. Specifically, the study applied the logistic regression with the Dirichlet random-effect (DRE) and the traditional random-effect (TRE), a model with the Gaussian random-effect distribution. The Bayesian leave-one-out cross-validation (LOO-CV) and the widely available information criterion (WAIC) were applied to evaluate the goodness-of-fit of the two developed models.

Comparing the two competing models, the results of the analysis indicated that the DRE model outperformed the TRE model by having the lowest LOO-CV and WAIC estimates.

Furthermore, this study found that majority of the analyzed factors in the DRE model had slightly shorter 95 percent credible intervals than those of the TRE regression model. These findings demonstrate that the DRE regression model can remove unnecessary variability that in turn can improve the model fit. Consequently, this model was further used in modeling the influence of TTR and other variables on the crash injury severity.

The impact of TTR on the probability of the severe crash occurrences was found statistically significant at 95 percent credible intervals. A unit increase of the BTI reduces the likelihood of a severe crash by 26 percent. Moreover, of the significant variables analyzed, the influence of alcohol/drug impairment showed the highest impact (based on odds ratio) in influencing the severity of a crash. It was found that the odds ratio of encountering severe crash by impaired occupants is 1.59 higher than sober drivers. The presence of a work-zone was the second pertinent factor that highly associates with a severe crash. The odds ratio of the severe accident occurring in work-zone areas is 93 percent greater than crashes occurring on non-work-zone areas. Seat belt use was found to be the third most influential factor in the analysis. The odds ratio that a crash will be severe is higher by 85 percent when occupants involved in a crash were not restrained than when they were restrained. Other significant factors analyzed in this study are traffic data, weekends, speed, land use, visibility, segment length, undivided highway, and age factor.

As indicated in the results section, TTR significantly influence the severity of crashes. Thus, incorporating this variable in crash prediction model will improve the reliability of the developed models. Adding the TTR into crash prediction models will also allow the models to have a mobility element and hence assist transportation agencies make a better decision while developing countermeasures for improving safety of particular locations.

Despite the demonstrated promising findings from the research using the DRE regression model, there are some limitations. The crash data used were from 2009 to 2012, while the speed data used to estimate TTR were from June 2010 to June 2011. Although there is an overlapping time of the crash and speed data, using recent data that cover the crash data years will make the prediction more reliable with the current situation. Unfortunately, such data were not available to the authors. Future studies may strive to correct this shortcoming. Moreover, the study will be extended by using the DRE model in assessing the disaggregated injury outcomes as well as evaluating the ordinal scale of the injury severity levels (i.e., the use of multinomial logit/probit regression). Additionally, local streets and freeways were not included in the analysis. The reason for local roads not being analyzed is TTR data was not available to researcher while freeways pose different operating characteristics compared to arterial highways. Future studies can extend the analysis to include these type of the facilities in crash injury severity analysis.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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Glossary of Terms

TTR	Travel time reliability
DRE	Dirichlet random-effect
TRE	Traditional random-effect
FHWA	Federal Highway Administration
DP	Dirichlet process
FDOT	Florida Department of Transportation
BTI	Buffer time index
AADT	Annual average daily traffic
Mph	Miles per hour
TDP	Truncated Dirichlet process
DIC	Deviance information criterion
LOO-CV	Leave-one-out cross-validation
PSIS	Pareto smoothed importance sampling
NUTS	No-U-turn sampler
WAIC	Widely available information criterion

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