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Safety Analysis Considering the Impact of Travel Time Reliability on Elderly Drivers

by Emmanuel Kidando, Ren Moses, Yassir Abdelrazig, Eren Erman Ozguven

The main goal of this research was to evaluate how travel time reliability (TTR) might be associated with crashes involving elderly drivers, defined as those age 65 and above. Several TTR metrics were used to estimate their influence on elderly crash frequency and severity of the crash on freeways and arterial highways. The results suggest that TTR is statistically significant in affecting both elderly crash frequency and the severity of a crash involving an elderly driver. In particular, the analysis of risk ratios illustrates that a one-unit increase in the probability of congestion reduces the likelihood of the elderly severe crash by 22%.

BACKGROUND

Although older drivers (defined as those age 65 and above in this paper) are less involved with speeding, alcohol use, and night driving, they are vulnerable to severe crashes (Insurance Institute for Highway Safety 2016). The major contributing factors for severe injury crashes include frailty and medical complications (AbdelRazig et al. 2016). Furthermore, researchers point out that the risk of an elderly crash to occur rises more on elderly drivers who are 70 years of age or older. For instance, research indicates that in 2008 the odds of this age group being involved in fatal crashes were nearly three times greater than the population between 35 and 54 (Cicchino and McCartt 2014). The risk of crash occurrence for this age group also rises due to hearing difficulties, a decrease in processing skills, and cognitive problems (Souders, et al. 2015).

Even though the frequency and severity of the crashes involving elderly drivers have been decreasing over the last few years (Highway Loss Data Institute 2014), studies suggest that the American population is growing older. According to population estimates and projections, by 2030 the population of elderly drivers will reach 20% of the American population (Colby and Ortman 2015). With this projected increase in senior adult population, there is a need for research to investigate ways to assist older drivers to be familiar with their changing abilities and help adapt their driving practices appropriately.

Travel time reliability (TTR) has recently been recognized as one of the traffic mobility measures (Yang and Wu 2016). However, to the authors' best knowledge, no study has evaluated the influence of this traffic mobility measure on elderly drivers' crash risk analysis. This study attempts to conduct safety analyses to provide insight on how TTR may be influencing the elderly drivers' crash frequency and severity of injuries. In the analysis, the study explores both the categorical model (binary logit) and negative binomial (NB) model to reveal significant factors affecting the probability of severe injury crash occurrence and the frequency of crashes, respectively. The study uses police-reported crash and travel speed reports from northern Florida to conduct the crash risk analysis. TTR metrics are estimated using traffic speed data, which were collected between 2010 and 2011. While four-year crash data from 2009 through 2012 were used in the analysis.

LITERATURE REVIEW

Unlike other measures of the traffic mobility, such as level of service, delays, and volume to capacity ratio, TTR estimates the consistency of a travel time beyond the average travel time (Taylor 2015). It also represents the road user experience of using a particular road over a long period of observation. In addition, TTR is easily understood by the public compared with other measures. In the literature, several metrics exist that quantify the reliability of a travel time. These metrics consider travel time variation, which measures the stability of the traffic performance (Cambridge Systematics, Inc. and Texas Transportation Institute 2005). Examples of the established indicators of this proposed TTR metric are the standard deviation, variance, the coefficient of variation, and skew statistic of the travel time. Other groups of TTR metrics are the statistical index and probabilistic methods (Kaparias et al. 2008; Chien and Liu 2012). The statistical index metrics include a buffer time, planning time, misery index, and a travel time index. The statistical index metrics are used by some state highway agencies and have also been proposed by the Federal Highway Administration (FHWA) as a measure to quantify TTR (Taylor 2015). Nevertheless, the mean-based metrics such as buffer index and travel time index obscure some of the information for heavily skewed distributions due to congestion onset and congestion offset (Pu 2010). The probabilistic group includes metrics such as congestion frequency and a percentage of on-time arrivals. In this study, measures from all three groups of TTR metrics – that is, variation, statistical index, and probabilistic – are used in evaluating the possible influence of TTR on the elderly crash risk analysis. In particular, TTR metrics selected for the analysis are the probability of congestion, the planning time index, and the standard deviation of the travel time.

Coupled with the growing elderly population, a significant effort has been undertaken to investigate the contributing factors on elderly crash frequency and severity of the crash injury. In analyzing human factors that significantly influence elderly crash severity in Florida, Alam and Spainhour (2008) indicate that older drivers have higher risk of being involved in crashes at intersections than on roadway segments. This finding is also confirmed by a later study conducted by Clarke et al. (2010). There are many factors that contribute to older drivers' involvement in intersection crashes. These studies suggest that misjudging speeds of other vehicles, cognitive failure, ignoring traffic signals, and improper left turns are examples of the major errors that lead to higher intersection crashes. The literature also indicates that injury severity of elderly drivers is significantly influenced by seatbelt use and alcohol or drug impairment. Drivers impaired by alcohol or drugs have higher risks of being injured than unimpaired drivers (Abdel-Aty and Abdelwahab 2000). The role of other factors such as gender, land use, traffic control, road geometry, weather, and traffic data have also been well established by previous studies on the injury severity analysis (Abdel-Aty and Radwan; Dissanayake and Lu 2002; Clarke et al. 2010; Ulak et al. 2017).

Previous research efforts in determining the influencing factors on the frequency of elderly crash occurrence have provided insights that help develop effective crash countermeasures. Examples of the significant factors that have been extensively investigated through statistical analysis are traffic data and segment variables, which are normally considered as exposure variables in safety analysis (Shi and Abdel-Aty 2016). Furthermore, land use, speed, road geometry (such as lane width, the number of lanes, etc.), and temporal variation have also been investigated. Nevertheless, investigations on the impact of TTR have received little attention among researchers. Among the few studies that recently explored the impact of TTR is Shi and Abdel-Aty (2016). This study conducted a safety analysis on the urban expressway and found that TTR influences multi-vehicle crashes more significantly than single vehicle crashes. It is indicated that the reason for such a finding is attributed to unexpected driver behavior, such as unsafe lane changing.

In addition, none of the existing studies have addressed the impact of TTR on roadway safety by considering different age groups. This study concentrates on determining the influence of TTR on the frequency and the severity of injury of the aging driver. In addition to TTR factor, other variables, including road geometric features, land use, and traffic data, are included in the model. It is envisaged that the findings of this study can assist transportation agencies in a deeper understanding of the impact of this new traffic mobility measure and assist in devising traffic crash risk reduction strategies.

METHODOLOGY

As mentioned earlier, two models i.e., negative binomial model and binary logit model, were used in this paper.

Negative Binomial Modeling

In modeling of the crash frequency, the literature review revealed that the negative binomial (NB) model is the foremost model used to investigate significant variables affecting crashes (Lord and Mannering 2010). This model is derived from the Poisson model to account for overdispersion of the data (Jung et al. 2014). In particular, the overdispersion takes into consideration random crash probabilities associated with differences in reaction times, driving experience, vehicle characteristics, and other influencing factors (Hermans et al. 2006). The negative binomial, which is also the Poisson with a gamma-distributed error with mean μ and variance v, is given by (Lord and Mannering 2010):

(1) $$p(y_i) = \frac{\Gamma(y_i+\alpha^{-1})}{\Gamma(\frac{1}{\alpha})\Gamma(y_i+1)}\left(\frac{1}{1+\alpha\mu_i}\right)^{\frac{1}{\alpha}}\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i}$$

(2) $$\mu_i = \exp(\beta X_i + \varepsilon_i)$$

(3) $$v_i = \mu_i + \alpha\mu_i^2$$

whereby y_i is the number of crashes of a segment, i, represents a mean rate of crash, v_i is the variance, α is the over-dispersion parameter, $\Gamma(.)$ is the gamma function, and ε_i is the error term which is gamma distributed.

Binary Logit for Injury Severity Modeling

The logit and probit are commonly used methods of modeling discrete outcomes such as crash severity. The literature review reveals that the logit model is preferred to the probit model in the crash analysis because it offers a better interpretation of variables through odd ratios (Hermans et al. 2006; Peng and Ingersoll 2002). Thus, the binary logistic model was chosen to evaluate the influence of explanatory variables on the severity of elderly crashes. Consider the random variable y_i as an elderly crash. The representation of crashes can be formulated as follows:

(4) $$y_i = \begin{cases} 1 & \textit{if the } i^{th} \textit{ crash is severe} \\ 0 & \textit{otherwise} \end{cases}$$

Understanding the relationship between the probabilities with independent variables $P(y_i = 1|X) = P_i$, the logit function with a linear relationship is used. The following mathematical form describes this relationship (Czepiel 2002):

(5) $$logit\,(P_i) = ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta X_i$$

(6) $$P_i = \frac{1}{1+\exp(-[\beta_0 + \beta X_i])}$$

where β_0 and β_i are regression coefficients, X represents a vector of explanatory variables, and P represents the probability of a crash.

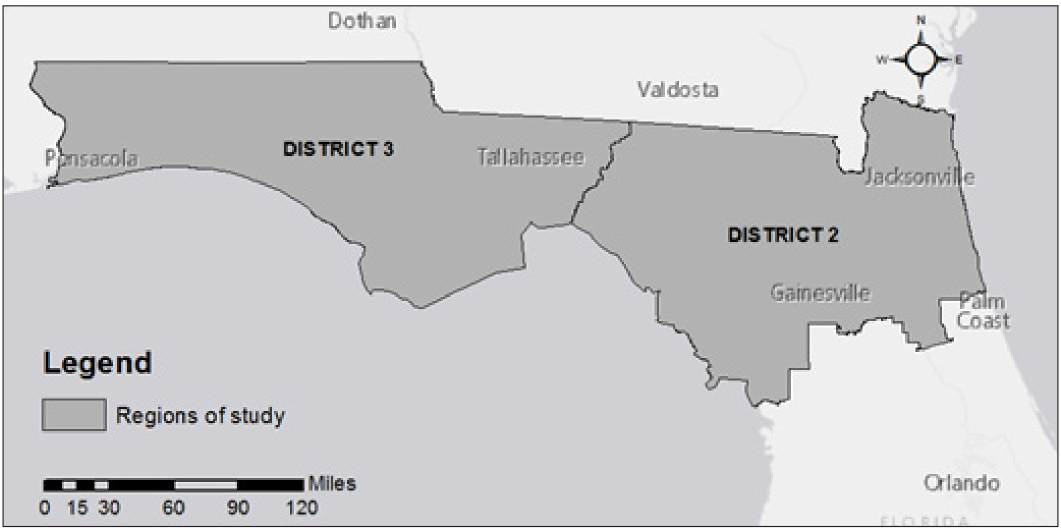
To examine the impact of the significant variables in influencing the crash severity, odds ratio (OR) values are used for comparison. The OR (in percent) of a particular variable is estimated by taking the natural exponential of the variable's parameter (OR = $\exp(\beta_i) * 100\%$). For the variables that raise the risk of severe crash occurrences, normally their OR value are greater than 100% and those which reduce the risk have OR less than 1. The effectiveness of variables that reduce the risk of severe crashes is estimated as follows (Dissanayake and Ratnayake 2008):

(7) Effectiveness of the variable = (100% – OR)

DATA DESCRIPTION AND SCREENING

Data were acquired from three sources and were then merged. The Florida Department of Transportation provided data from its crash information database and road geometry/traffic database. The third data source was INRIX, a private vendor company from which historical traffic speeds were acquired and used to compute TTR. The case study involved freeways and arterial roads located in Districts 2 and 3, which are Florida DOT administrative regions. Figure 1 shows the location of these regions in Florida. The following paragraphs summarize the characteristics of each of the attributes used in the model.

Figure 1: The Case Study Area



Traffic Speed and Reliability Metrics

As mentioned above, the study used INRIX traffic data to compute TTR. INRIX uses vehicle probes and traffic sensors to collect operating traffic speeds. The traffic speeds are summarized and reported at the Traffic Message Channel (TMC) level (INRIX Inc. 2008). The TMC is a type of road segmentation whereby traffic and weather information can be broadcast in real time. More information regarding the segment definition and its applicability to collect speed data can be found in the INRIX report (INRIX Inc. 2008). This study utilized this segmentation approach in conducting the crash analysis. The characteristics of the TMC segments, including average, minimum, and maximum length, is presented in Table 1.

The traffic speed data used to estimate TTR were aggregated on a 15-minute basis. These data were collected for one year from June 2010 to June 2011 on freeways and arterial roads. Specifically, TTR was determined by comparing traffic operating speeds to the free-flow speeds on each segment. Due to lack of other 15-minute traffic data, such as traffic volume and density, the free-flow speed was estimated by adding five miles per hour (mph) to the posted speed limit value, similar to an approach applied by McLeod et al. (2012) study. The planning time index, the standard deviation of the travel time, and the probability of congestion were used as metrics of TTR. The planning time index measures travelers' travel time in relation to free-flow travel time. An index value greater than one represents extra travel time beyond the free-flow travel time. The planning time (PT) index was computed as follows (Lomax et al. 2003):

(8) $$PT\ index = \frac{95^{th}\ Percentile\ TMC\ travel\ time}{Travel\ time\ at\ free\ flow\ speed}$$

Besides the PT index and standard deviation of the travel time, this study also evaluated the impact of the probability of congestion on highway safety. This measure was estimated following the Florida reliability method procedure. This method estimates the percentage of the trips in a given corridor that take no longer than the acceptable threshold. The percentage threshold range is between 5%, and 20% (Al-Deek and Emam 2006; Florida Department of Transporation 2000). In this study, the probability of congestion was computed by determining the percentage of trips that were less than the free-flow speed by 10 mph. This speed drop indicating congestion occurrences is consistent with a study by Al-Deek and Emam (2006).

(9) $$Probability\ of\ congestion = \frac{Number\ of\ observed\ speed\ less\ than\ 10\ mph\ of\ a\ free\ flow\ speed}{Total\ number\ of\ observed\ speed\ samples\ at\ each\ TMC}$$

Descriptive Statistics of the Variables Affecting Crash Frequency

The crash data for analysis were provided by the Florida Department of Transportation in a GIS shape file. In the file, each crash record is reported with associated feature including traffic data, driver characteristics, and road geometry. The variables considered in modeling the crash frequency analysis are traffic volume, road geometry, and TTR metrics. These variables were aggregated at the TMC segment level using the average value of each variable. The summary of the attributes is presented in Table 1. Review of descriptive statistics in this table reveals that many elderly crashes occur when the PT index is 1 or 2 with few crashes occurring above index 2.

Prior to modeling, the association among independent variables was analyzed. The Pearson correlation (PC) method is commonly used to check whether a correlation exists between variables. However, PC only tests the linear relationship between the variables (Kobelo et al. 2008; Dissanayake and Roy 2014). To address the weakness of the PC method, the study also used the maximal information coefficient (MIC) to capture the nonlinear relationships between variables. The MIC uses mutual information theory to detect the association between two variables. The mathematical expression of MIC can be found in the studies by Reshef et al. (2013) and Zhao et al. (2013).

The PC coefficients displayed in Table 2 show an association among the variables considered in the analysis. These findings are also confirmed by the MIC values displayed in Table 2 as well. Although the PC coefficient of AADT and the surface width indicated a moderate linear relationship (PC = 0.58 or MIC = 0.57), both variables were included in the final model because their association is not strong. On the other hand, TTR metrics such as the PT_index and the standard deviation of the travel time had the highest correlation (PC = 0.9 or MIC = 0.58) followed by the PT_index and the probability of congestion (PC = 0.58 or MIC = 0.84). In modeling the crash severity analysis, each TTR metric is separated and evaluated with other variables as independent models.

Table 1: Descriptive Statistics of Data Used in a Crash Frequency Analysis

Metrics	AADT	Med. width	Surf. Width	Shoul. width	TMC distance (miles)	PT Index (TTR metric)	Standard deviation of the travel time (TTR metric)	Pro. of congestion (TTR metric)	Crash frequency
Mean	23203.7	20.88	24.33	4.42	1.77	1.49	0.15	43.59	6.75
Standard deviation of data	21621.3	19.74	6.76	2.61	2	0.59	0.2	40.57	7.94
Minimum	1170.83	4	10	1.5	0.02	0.65	0	0.01	0
25%	9243.01	13	21.61	2	0.55	1.16	0.06	2.73	2
50%	17107.2	14.44	24	4	1.04	1.33	0.1	32.02	4
75%	29041.1	20.85	24.33	5	2.12	1.61	0.17	89.91	9
Maximum	143444	458.28	48	17	20.22	8.57	2.94	100	76

Table 2: Correlation Analysis of Variables Used in a Crash Frequency Analysis

Variables	AADT	Med. width	Surf. Width	Shoul. width	TMC length	Pro. of congestion (TTR metric)	Standard deviation of the travel time (TTR metric)	PT index (TTR metric)	Crash frequency
AADT	-								
Median width (ft.)	0.22	-							
Surface width (ft.)	0.58	0.19	-						
Shoulder width	0.42	0.43	0.21	-					
TMC length (miles)	-0.19	0.26	-0.04	0.25	-				
Probability of congestion **(TTR metric)**	-0.10	-0.16	0.01	-0.27	-0.17	-			
Standard deviation **(TTR metric)**	0.02	-0.09	-0.01	-0.13	-0.33	0.34	-		
Planning time index **(TTR metric)**	-0.03	-0.12	-0.004	-0.20	-0.30	0.58	0.90	-	
Elderly crash frequency	0.13	-0.04	0.14	-0.14	0.04	0.10	-0.06	0.02	-
Maximal Information Coefficient (MIC)									
AADT	-								
Median width (ft.)	0.42	-							
Surface width (ft.)	0.57	0.46	-						
Shoulder width (ft.)	0.37	0.33	0.34	-					
TMC length (miles)	0.37	0.26	0.29	0.29	-				
Probability of congestion **(TTR metric)**	0.32	0.24	0.23	0.27	0.25	-			
Standard deviation of the travel time **(TTR metric)**	0.35	0.28	0.25	0.32	0.49	0.42	-		
Planning time index **(TTR metric)**	0.37	0.26	0.24	0.32	0.36	0.84	0.58	-	
Elderly crash frequency	0.35	0.24	0.23	0.27	0.27	0.27	0.26	0.26	-

Descriptive Statistics of the Variables Influencing Injury Severity

A total of 6,757 crashes and 1,546 TMC links were identified for modeling. In the developed binary model, incapacitating injury and fatal injury crashes were grouped as severe crashes while non-injury, possible injury, and non-incapacitating injury were grouped as non-severe crashes. The descriptive statistics indicated that severe crashes accounted for about 7.3% of the total crashes in the dataset (Figure 2). Meanwhile, 92.7% of crashes were of the "no injury" category. Tables 3 and 4 show the definition of categorical variables and the descriptive statistics of each continuous variable used in the model, respectively.

Figure 2: Descriptive Statistics of Elderly Crash Severity

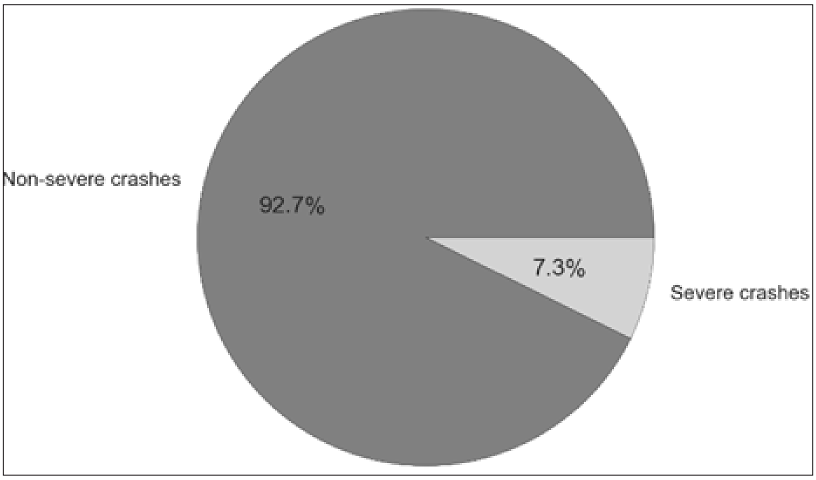


Table 3: Description of Categorical Data Used in Crash Severity Analysis

Categorical Data Definitions		
Variables	**Description**	**Code for modeling**
Alcohol	0= none, 1 = alcohol involved, 2 = drugs involved, 3 = alcohol and drugs involved, 4 = undetermined	1, 2 and 3 =1 else 0
Land use characteristics	Urban and rural	Rural = 1 else 0
Road characteristics	1 – divided, 2 – undivided	Divided 1 else 0
Safety belt usage	categorical	Usage = 0 else 1
Speed	Posted speed limit (categorical)	Less than 45 mph = 0 else 1
Age	Categorical	Between 65 and 75 = 0, greater than 75 = 1
Skid number	Continuous variable	Less than 28 = 0 else 1
Visibility	Smoke, fog, inclement weather conditions, load on vehicles, parked vehicles and vision not obscured	Not obscured = 0 else 1
Median width	Continuous variable	Less than 25 ft. = 1 else 0
Time	Peak hours and off-peak hours	Peak hours 6 a.m. to 9 a.m. and 4 p.m. to 7 p.m. = 0 else off-peak hours = 1
Day of a week	Weekend days and week days	Weekend days and week days

Table 4: Descriptive Statistics of Continuous Data Used in Crash Severity Analysis

Metrics	AADT	% of truck volume	Med. Width (ft.)	Surf. Width (ft.)	Shoul. Width (ft.)	TMC distance (miles)	PT Index (TTR metric)	Probability of congestion (TTR metric)	Standard deviation of the travel time (TTR metric)
Mean	29513.3	6.27	21.23	24.98	4.06	1.76	1.5	46.54	0.15
Standard deviation of data	19666	6.12	27.83	7.62	3.02	2.12	0.44	39.39	0.15
Minimum	2600	0.71	3	10	1.5	0.01	0.65	0.01	4.9E-3
25%	16600	2.2	13	24	1.5	0.6	1.21	3.85	0.07
50%	26500	4.07	13	24	2	1.07	1.43	43.42	0.12
75%	35000	7.85	20	26	5	1.78	1.69	89.6	0.17
Maximum	172000	35.84	999	48	15	20.22	8.57	100	2.94

RESULTS AND DISCUSSION

Negative Binomial Model Results

A total of 8,745 elderly crashes were identified in 1,290 TMC segments for crash frequency analysis. The results of the three developed models (i.e., with the planning time index, the standard deviation of the travel time, and the probability of congestion) are presented in Table 5. To compare the goodness of fit of these models, the Akaike information criterion (AIC) is used. The AIC balances between the model complexity and model prediction accuracy (AIC = -2**log-likelihood* + 2* *number of free parameters*) to reduce the over-fitting problem (Hilbe 2011). Over-fitting is a problem in statistics. It occurs when a model fits well the data used to estimate parameters but fails to generalize on a new dataset. The model with the smallest AIC score value usually is selected over other models (Hilbe 2011). The results in Table 5 suggest that model 1 and model 2 have no statistical difference in goodness of fit. On the other hand, model 3 indicates a strong difference with rest of the model, by having a difference of nearly 13 scores. A score difference greater than 10 is usually considered a strong difference between the models (Hilbe 2011). Thus, these results suggest that model 3 is more appropriate for fitting the dataset than model 1 or 2.

The results of model 3 show that the standard deviation of the travel time is significant at 99% confidence level. This finding suggests that higher standard deviation in travel time reduces the likelihood of a crash. Particularly, a unit increase of the standard deviation of travel time indicates a reduction in the crash frequency. Although all age groups were considered in the analysis, finding by Shi and Abdel-Aty, 2016, contrast with our results, which suggest that the increase in standard deviation of the travel time increases the crash frequency occurrence.

The probability of congestion was found significant in influencing the crash frequency occurrence. Higher likelihood of congestion on the road segment is associated with high traffic density and characterized by shorter headways. Vehicle interactions are increased when headways are shorter, thus increasing the likelihood of crash occurrence. This result is consistent with the findings in the literature (Kononov et al. 2008; Rothenberg et al. 2007; Shi and Abdel-Aty 2016). The planning time index (in model 2), on the other hand, was found insignificant in our study.

Table 5: Model Results of Elderly Drivers' Crash Frequency

Models	Model 1	Model 2	Model 3
Variables	**Model coefficient**	**Model coefficient**	**Model coefficient**
Intercept	-2.92 *(0.000)*	-2.95 *(0.000)*	-2.95 *(0.000)*
TMC length (miles)	0.20 *(0.000)*	0.19 *(0.000)*	0.18 *(0.000)*
log(AADT)	0.71 *(0.000)*	0.70 *(0.000)*	0.70 *(0.000)*
log (Median width [ft.])	-0.46 *(0.000)*	-0.50 *(0.000)*	-0.45 *(0.000)*
log (Surface width [ft.])	-0.23 *(0.026)*	-0.22 *(0.035)*	-0.23 *(0.021)*
log (Shoulder width [ft.])	-0.39 *(0.000)*	-0.41 *(0.000)*	-0.40 *(0.000)*
Posted speed limit (mph) (less than 45 = 0 else 1)	-0.24 *(0.000)*	-0.28 *(0.000)*	-0.30 *(0.000)*
log (Probability of congestion)	0.029 *(0.040)*	-	-
Planning time index	-	-0.063 *(0.671)*	-
Standard deviation of the travel time	-	-	-0.61 *(0.000)*
Log-likelihood at convergence	-3725.5	-3725.7	-3719.5
Akaike information criterion (AIC)	7468.93	7467.46	7455.03

Note: Log(variable name) represents a logarithmic transformation of variables and value in a parenthesis is p-values

Moreover, in models 1 and 3, road geometry, including the median width, the surface width, and the shoulder width, is statistically significant suggesting that increases in the values of these variables reduce the likelihood of elderly crash frequency. Shi and Abdel-Aty (2016) suggest that increasing the values of these variables increases the freedom of drivers in avoiding a traffic conflict. Similar to other crash modeling studies, traffic volume (AADT) and segment length revealed a positive relationship with elderly crash frequency (Kononov et al. 2008; Shi and Abdel-Aty 2016; Quddus et al. 2010). The findings suggest that longer travel length and higher traffic volume contribute to the rise in the likelihood of crash occurrence.

Binary Logit Model Results

The results of the binary logit model are reported in Table 6. In the table, four model results are presented. The model with the probability of congestion as a TTR metric (model 4) provides the most variables, which significantly influence the severity of the crash with at least a 90% confidence level**.** Overall, the model fitted data fairly well with 66% as the area under the curve (AUC) of the receiving operating characteristic curve (ROC). The area under ROC measures the performance trade-off between the true positive and false positive error rate by changing the threshold value in classifying response groups (Fawcett 2006). Understanding the model performance, the AUC above 54% is normally accepted that the model can fit the dataset with reasonable accuracy; on the other end, the perfect model is the one with AUC score equal to 100% (Fawcett 2006). Although model 4 revealed the best fit, there is no significant difference among model 1, 2, 3, and 4 based on their AUC and AIC values (see Table 6).

Travel Time Reliability and Traffic Density

The results of the analysis of TTR metrics revealed that only the probability of congestion is significant (at 90% confidence level) in influencing the severity of a crash. Higher probability of congestion is found to be associated with the lower elderly severe crash. The risk of a severe crash is reduced by 22% with a one-unit increase of this variable. This value was estimated by taking the difference between 100% and the odds ratio (see equation 7). Moreover, the probability plot of categorical variables in Figure 3 shows that the probability of congestion has a negative linear relationship with the odds of severe crashes. This finding is consistent with the literature, which shows that congested highways have relatively low speeds, thus reducing the probability of a severe crash to occur (Duncan et al. 1998; Chang 2003). Nonetheless, this result contradicts the results of a study conducted by Quddus et al. (2010) on the M25 orbital motorway in London. This study suggests that congestion has no significant influence on the likelihood of a severe crash. Our results further show that the planning time index and the standard deviation of the travel time were not significant in influencing the severity of the crash.

In the modeling results, the impact of traffic density was found to be significant, suggesting that as the traffic density increases, the risk of injury decreases. The likelihood of severe crash occurrence decreases by 9% (see equation 7 and result of the odds ratio in Table 6) when the traffic density increases by a unit. Figure 3 indicates a non-linear relationship with a sharp decrease in the odds of a severe crash up to nearly 100 vehicles per mile, thereafter there is a gradual decrease. This could be attributed to the fact that when density is high, headways are reduced, which yield slower speeds, thus reducing the possibility of a crash being severe. These findings mirror the results found by other researchers (Duncan et al. 1998; Chang 2003).

Driver Characteristics and Time of a Day

Analysis shows that impaired elderly drivers are associated with higher risks of severe crashes than unimpaired drivers. The risk ratio is 2.18, suggesting that the probability of a severe crash on impaired drivers is 2.18 higher compared with unimpaired drivers. This result is consistent with the results of previous studies (Dissanayake and Roy 2014; Quddus et al. 2010). The result of proper seatbelt use was found to reduce the severity of a crash by 45% as compared with unbelted drivers. The finding of seatbelt effectiveness is consistent with the study conducted by Ratnayake (2006), which also found that seatbelt usage reduces the severity of a crash by 56%. Furthermore, the result shows that the likelihood of a crash for a driver 75+ years of age is higher than those aged 65 to 74 by 27%. This is a very important result, which may be related to diminished or reduced cognitive and physical capabilities with age.

The visibility factor is reported in the crash database to reflect vision obstruction. The factors that impair visibility listed in a database include smoke, fog, inclement weather conditions, parked vehicles, and others. The model's findings revealed that poor visibility reduces the severity of a crash by 37% as compared with clear conditions. Similar findings were documented by Pisano et al. (2008) who argued that in inclement weather conditions, drivers adjust their behavior sufficiently (e.g., by reducing speed and driving more cautiously), thus reducing the probability of a severe crash.

Table 6: Model Results of the Crash Severity Analysis

	All variables			Significant variables		
Variables	**Model 1 Coef.**	**Model 2 Coef.**	**Model 3 Coef.**	**Model 4 Coef.**	**Odd ratio**	**Marginal effect (dy/dx)**
Traffic data						
Log (Traffic density)	-0.097*	-0.09	-0.12	-0.10 (*0.095*)	0.91	-0.006
Percentage of truck volume	0.34	0.42	1.23	-	-	-
Road Characteristics						
Shoulder width	-0.06*	-0.05***	-0.05***	-0.06 *(0.019)*	0.94	-0.004
Median width	-0.18	-0.17**	-0.37**	-0.22 *(0.093)*	0.80	0.015
Surface width	-0.01	-0.01	-0.0057	-	-	-
Road characteristics	-0.32**	-0.33**	-0.32**	-0.30 *(0.013)*	0.74	-0.019
Speed	0.53**	0.54***	0.55***	0.54 *(0.002)*	1.71	0.035
Skid number	-0.72**	-0.74***	-0.74***	-0.72 *(0.028)*	0.49	-0.047
Location of the highway						
Land use characteristics	0.81***	0.81***	0.81***	0.85 *(0.000)*	2.24	0.055
Driver characteristics						
Safety belt use	-0.59***	-0.60***	-0.60***	-0.60 (*0.000*)	0.55	-0.039
Age	0.23**	0.23**	0.24**	0.24 *(0.016)*	1.27	0.015
Alcohol	0.79***	0.80***	0.80***	0.78 *(0.001)*	2.18	0.051
Visibility	-0.45*	-0.45**	-0.44**	-0.46 *(0.030)*	0.63	-0.030
Temporal factors						
Time	0.22*	0.22*	0.22*	0.22 *(0.023)*	1.25	0.015
Day of a week	-0.11	-0.10	-0.11	-	-	-
Travel time reliability						
Probability of congestion	-0.22	-	-	-0.24 *(0.083)*	0.78	-0.016
Planning time index	_	-0.02	-	-	-	-
Standard deviation	_	-	0.19	-	-	-
Intercept	-0.42	-0.48	-0.52	-0.63	-	-
Number of observation	6757	6757	6757	6757		
ROC	0.66	0.66	0.65	0.66		
Akaike information criterion (AIC)	3375.9	3378.12	3378.0	3372.4		
Restricted log-likelihood				-1765.1		
Log-likelihood at convergence				-1672.2		

(Table 6 continued)

Variables	All variables			Significant variables		
	Model 1 Coef.	Model 2 Coef.	Model 3 Coef.	Model 4 Coef.	Odd ratio	Marginal effect (dy/dx)
p-value				1.073e-32		

Note: Traffic density = AADT/segment length, *** represents $p < 0.01$, ** is $p < 0.05$ and * is $p < 0.1$ and value in a parenthesis is the *p*-value.

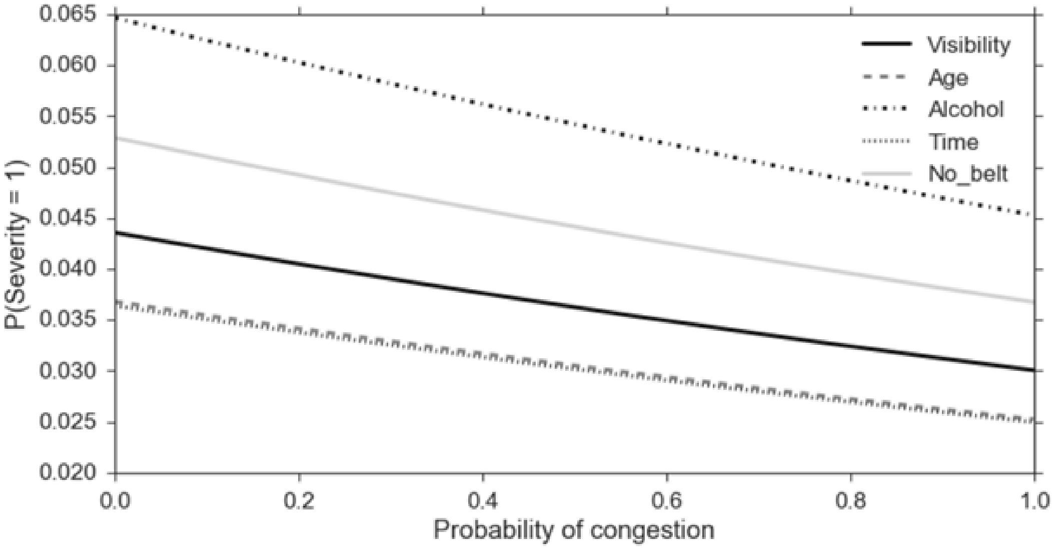
Road Characteristics and Location of the Highway

Analysis of rural versus urban characteristics of a road shows that the odds of a severe crash rise in rural areas by 2.24. There might be many possible explanations for this phenomenon. One explanation perhaps could be that urban roadways are more congested with slower speeds than rural roadways, resulting in less severe crashes. The results further show that divided highways reduce crash severity by 26% compared with undivided highways. The median provides an area for the driver to avoid collisions with other vehicles, which in turn reduces crash severity. Moreover, the analysis of posted speed limit (PSL) indicates that the probability of a severe crash increases by 1.71 for highways with PSL higher than 45 miles per hour (mph) compared with lower speeds. Similar results were found by other researchers (Dong et al. 2015; Duncan, et al. 1998).

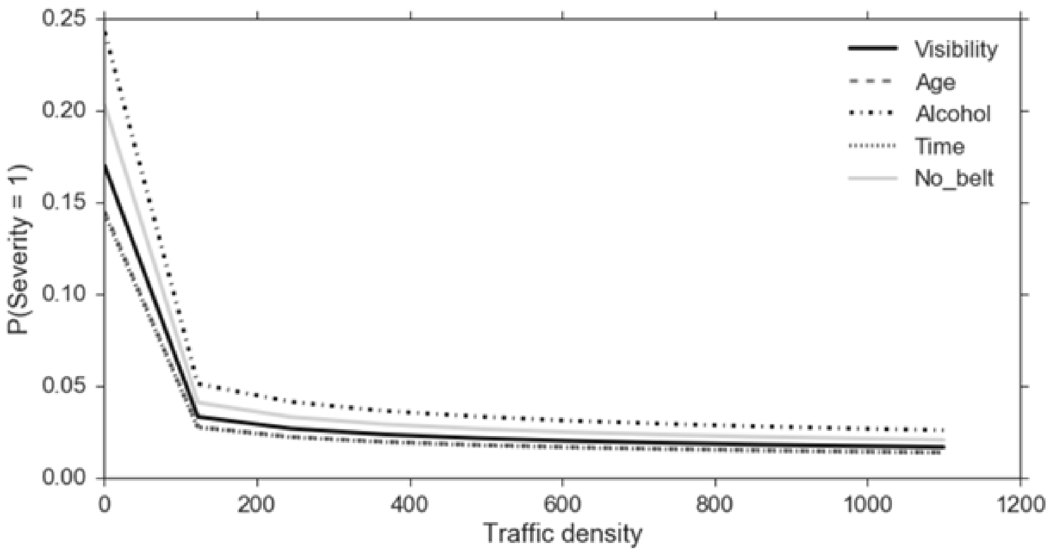
Analysis of road geometry shows that median widths wider than 15 feet reduce the odds of a severe crash by 20% compared with those less than 15-feet wide. A similar pattern was observed on shoulder width, indicating that one unit change of this variable reduces the severity of a crash by nearly 6%.

A skid number less than 28 (friction number from locked wheel testing at 40 mph using a ribbed tire) is considered insufficient and could contribute to crashes (Federal Highway Administration 2014). In our study, the results show that highway crashes with a skid number higher than 28 reduces the severity of a crash by 51%. Moreover, Figure 3 illustrates that, of all road geometry factors, the skid number has the highest impact on crash severity. On the other hand, road characteristics (divided or undivided) revealed the least impact compared with the rest of the variables. The results further show that surface widths, the day of the week, and the percentage of trucks, the planning time index, and the standard deviation of the travel time have minimal influence on crash severity.

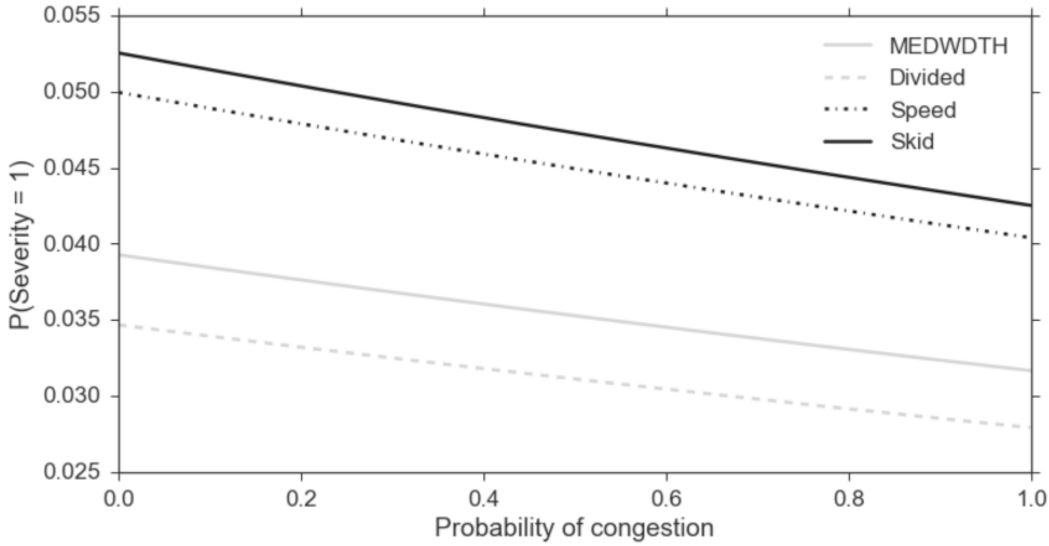
Figure 3: The Influence of Variables on Elderly Crash Severity



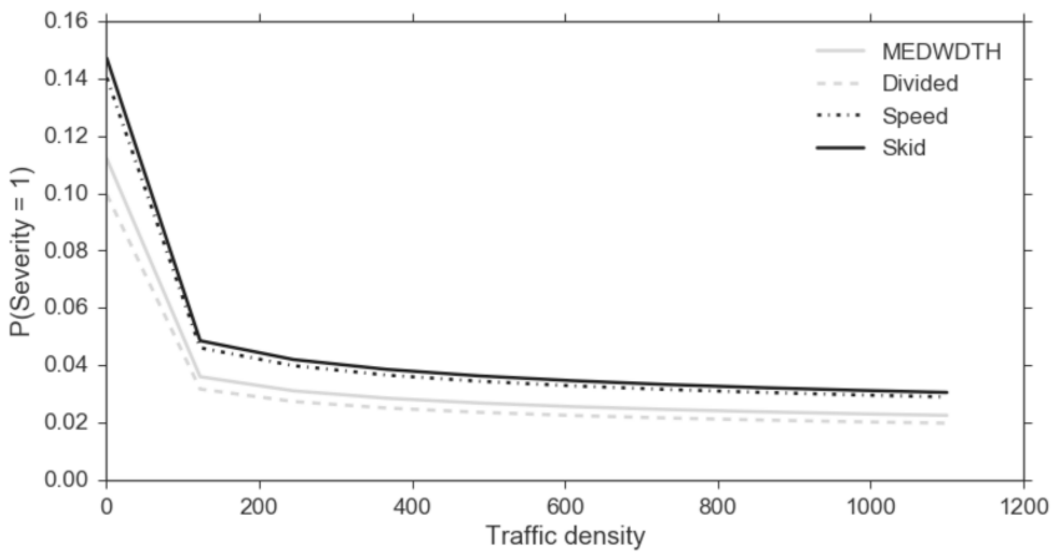
(a) Driver characteristics against probability of congestion



(b) Driver characteristics against traffic density



(c) Road characteristics against probability of congestion



(d) Road characteristics against traffic density

The analysis of hours of travel showed the significance of off-peak hours on severe crashes. The odds of a crash being severe during off-peak hours were 25% more compared with peak hours. Further, a review of graphs of the driver characteristics shows that the impaired driving with alcohol or drugs in both traffic density and probability of congestion is associated with the highest probability of injury (Figure 3).

CONCLUSIONS AND RECOMMENDATIONS

As the proportion of the elderly driving population continues to grow, coupled with increased congestion on U.S. highways, the safety of the driving public will continue to be a major focus of transportation research. Given that congestion affects the travel time reliability (TTR), the main goal of this research was to evaluate how TTR might be associated with crashes involving elderly drivers. TTR metrics used in the modeling were the planning time index, the standard deviation of the travel time, and the probability of congestion. Speed data for calculating TTR metrics were acquired from the INRIX database comprising 1,290 traffic-messaging channels (TMCs). Four-year crash data were acquired from the Florida Department of Transportation. A total of 8,745 crashes involving elderly drivers were identified as occurring in the study area. In addition to TTR metrics, important geometric and traffic variables were also included in the modeling process as the predictors of crashes.

The negative binomial model was used to evaluate variables that could be influencing elderly crash frequency, while the binary logit model was used to evaluate variables that could be influencing elderly crash severity. The results of the negative binomial modeling showed that the probability of congestion and the standard deviation of travel time were statistically significant in affecting the number of crash occurrences. A unit increase of the probability of congestion was associated with the increase of crash frequency, while a unit increase in the standard deviation of the travel time reduced the crash frequency. The binary logit model revealed that only one TTR metric, i.e., the probability of congestion, was significantly associated with crash severity. As the probability of congestion increases in a segment, lower levels of crash severity involving elderly drivers were experienced as the odds of severe crashes dropped by 22% with each unit increase in the probability of congestion.

This study is not without limitations. Crashes involving elderly drivers were isolated and modeled separately; thus, it is not clear if similar results would apply if crashes involving drivers of all age groups were included in the modeling process. In future studies, exploring the impact of the TTR for other age groups is needed to answer the aforementioned question. It is also worth noting that the study area comprised freeway links whose high-speed operating characteristics pose high cognitive, sensory, motor, and physical demands on elderly drivers compared with surface streets. Additional qualifications are in order. The crash data used were from 2009 to 2012 while the travel time data used were from one year, mid-June 2011 to mid-June 2012. Although care was taken to exclude data from weekends, holidays, and days in which incidents occurred in order to smoothen the TTR, it would have been better to use TTR data encompassing the four years from which crash data were extracted. Unfortunately, such data were not available and future studies may strive to correct this shortcoming by using other regression models.

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