Investigating the Effect of Roadside features on Single-Vehicle Roadway Departure Crashes on Rural Two-Lane Roads

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Abstract

One of the most important tasks in traffic safety is to investigate the relationship between motor vehicle crashes and the geometric characteristics of roadways. There is a large amount of previous work that has provided meaningful results in knowing the impacts of geometric design on crash frequency. However, little attention has been paid in finding the relationship between road departure crashes and relevant roadside features such as lateral clearance, side slope condition and driveway density. The lack of roadside data for estimating rigorous statistical models has been a major obstacle of roadside safety research for many years. The objective of this paper is to investigate the relationship between single-vehicle roadway departure crashes and roadside features. Two types of models were developed: Crash frequency models using a negative binomial model and crash severity model using a multinomial logit model. The objective was accomplished by using field data collected in four districts in Texas. The results of this study show that shoulder width, lateral clearance and side slope condition has a significant effect on the roadway departure crashes. The crash frequency and severity will increase when there is a decrease in lateral clearance or shoulder width and when the side slope condition becomes worse. Driveway density is not found to be significant in influencing the crash frequency or their severity.

Key words: lateral clearance, side slope rating, driveway density, negative binomial model, multinomial logit model, single vehicle roadway departure crashes
1. Introduction

One of the most important tasks in traffic safety is to investigate the relationship between motor vehicle crashes and the geometric characteristics of roadways. There is a large amount of previous work that has provided meaningful results in knowing the impacts of geometric design on crash frequency (1-7). However, studies of some factors related to roadside features that influence roadway departure (aka run-off-the-road) (ROR) crashes (number and severity) have been less successful. ROR crashes have been identified as an important leading cause of traffic fatalities on highways and have consequently been identified as a significant problem in traffic safety. In 1999, using data from the Fatality Analysis Reporting System (FARS), Neuman et al. (8) reported that nearly 39 percent of all fatal crashes (all road types) were classified as single-vehicle (SV) ROR crashes. Torbic et al. (9) reported a slightly lower value in their study of safety effects of rumble strips. According to the FHWA (10), over 25,000 people in 2005 were killed because drivers left their lane and crashed either with an on-coming vehicle, rolled over, or hit an object located along the highway. These crashes account for about 60 percent of all fatalities. Of all these crashes, it is estimated that about 17,000 were categorized as SVROR crashes. Examining these characteristics more closely, about 80 percent of ROR fatalities occurred on rural roadways, with about 90 percent of these occurring on two-lane highways alone. Moreover, recent statistics show that the percentage of fatal ROR crashes has been steadily increasing (11). It is estimated that the societal costs associated with ROR crashes are 2.53 times more compared to other accidents (12). The social costs amount to more than 1 trillion dollars per year.

Crashes involving a vehicle leaving the traveled-way have also been grabbing the headline outside the U.S. According to the World Health Organization (WHO) statistics, about 1.2 million people died annually worldwide due to all kinds of road accidents, and the number is expected to rise by 67 percent by the year 2020 (13). According to Transport Research Laboratory (TRL) report, 20-50 million people are seriously injured in traffic crashes each year (14). Another study summarized the characteristics of rural road safety around the world, and reported that about 75,000 people are killed every year on rural roads in OECD countries and the social costs attributed to these crashes are approximately equal to $120 billion per year (15). At the international level, 75 percent of all crashes happen on the rural roads, and are defined within three main crash types: SV crash, head-on collision, and collision at intersections. Moreover, SV crashes constitute 35 percent or more of all fatal rural road crashes. These statistics on roadside-related traffic crashes indicate the need for research to develop cost-effective countermeasures to reduce the frequency and severity of such crashes. Furthermore, less attention has been paid in identifying the relationship between ROR crash frequency and key roadside features. Neuman et al (8) summarized the effects of roadside features on the severity of ROR crashes. These authors noted that objects located near the roadside may harm the errant drivers more seriously than objects located further away (as expected), especially on high-speed roads. Another study by Zegeer et al. (16) concluded that flattening a sideslope from 1:2 to 1:7 or flatter could reduce ROR crashes by about 27 percent. The authors pointed out that the benefits, although still positive, decrease as the changes become smaller (e.g., 1:5 to 1:7). Other research studies have investigated the causative factors such as pavement edge drop off, horizontal curves and grades, pavement surface and human factors on roadway departure crashes. Some other
studies have focused on knowing the impact of roadside features such as roadway guardrail systems \((17)\) and the utility poles \((18)\) on motor vehicle crashes. Additional relationships between the frequency of crashes and geometric design can be found in the HSM \((19)\). The lack of roadside data for estimating rigorous statistical models has been a major obstacle for roadside safety research for many years, making it difficult to analyze the SVROR crashes and their severity. Therefore, this paper makes use of the field data collected on 501 rural two-lane roadway segments in four districts in Texas for investigating the relationship of SVROR crash frequency and severity with roadside features such as clear zone distance and side slope conditions. Negative binomial and multinomial logit models were used in estimating the crash frequency and severity respectively.

The next section presents the methodology used in this study.

2. Methodology

This section describes the methodology and the characteristics related to the negative binomial and multinomial logit models.

2.1 Negative Binomial model

Despite its documented limitations \((20)\), the Poisson-gamma (aka negative binomial) (NB) model is the most common type of model used by transportation safety analysts. This model is preferred over other mixed-Poisson models since the gamma distribution is the conjugate of the Poisson distribution. The Poisson-gamma model has the following model structure \((21)\): the number of crashes \(Y_{it}\) for a particular \(i^{th}\) site and time period \(t\) when conditional on its mean \(\mu_{it}\) is Poisson distributed and independent over all sites and time periods

\[
Y_{it} | \mu_{it} \sim Po(\mu_{it}) \quad i = 1, 2, \ldots, I \text{ and } t = 1, 2, \ldots, T
\]  

(1)

The mean of the Poisson is structured as:

\[
\mu_{it} = f(X; \beta) \exp(e_{it})
\]  

(2)

where,

\(f(\cdot)\) is a function of the covariates \((X)\);

\(\beta\) is a vector of unknown coefficients; and,

\(e_{it}\) is the model error independent of all the covariates.

It is usually assumed that \(\exp(e_{it})\) are independent and gamma distributed with a mean equal to 1 and a variance \(\delta\) for all \(i\).

\[\exp(e_{it}) = gamma(1/\delta, 1/\delta)\]
where,
\[ \delta \text{ is the dispersion parameter (note: variance function is } \text{Var}(Y_i) = \mu_i + \delta \mu_i^2). \]

An important characteristic associated with the development of statistical relationships is the choice of the functional form linking crashes to the covariates. For this work, the functional form was as follows:

\[ \mu_i = \beta_0 \times L_i \times F_i^{\beta_1} \times y \times e^{\sum_{j} x_{ij} \beta_j} \]  

(3)

Where,
\[ \mu_i = \text{ the estimated number of crashes per year for site } i ; \]
\[ F_i = \text{ vehicles per day (ADT) for segment } i ; \]
\[ L_i = \text{ length of segment } i \text{ in miles;} \]
\[ y = \text{ number of years of crash data;} \]
\[ X_{ij} = \text{ a series of covariates (e.g., shoulder width, lateral clearance etc.) for site } i ; \]
\[ n = \text{ number of covariates; and,} \]
\[ \beta_1, \beta_2..\beta_n = \text{ estimated coefficients.} \]

2.2 Multinomial Logit model

In this study, the multinomial logit (MNL) model was used for identifying differences in factors likely to affect SVROR crash-injury severity outcomes. An individual crash severity among the given severities was considered to be predicted if the crash severity likelihood function was maximum for that particular severity. Each crash severity likelihood function, which is a dimensionless measure of the crash likelihood, was considered to have a deterministic component and an error/random component. While the deterministic part is assumed to contain variables that can be measured; the random part corresponds to the unaccounted factors that impact injury severity. The deterministic part of the crash severity likelihood was designated as a linear function of the driver, roadway, vehicle and weather characteristics as shown in Equation 4.

\[ V_{ij} = ASC_j + \sum_{k=0}^{K} \alpha_{kj} X_{ki} \]  

(4)

where,
\[ V_{ij} = \text{ Systematic component of crash severity likelihood for a segment } i \text{ and crash severity } j, \]
\[ ASC_j = \text{ Alternative specific constant for crash severity } j, \]
\[ \alpha_{kj} = \text{ Coefficient (to be estimated) for crash severity } j \text{ and variable } k, k = 1, ..K, \]
\[ X_{ki} = \text{ Independent variable } k \text{ for observation } i, \]
The logit model was derived assuming that the error components are extreme value (or Gumbel) distributed and the probability of a discrete event (severity of crash) is given by Equation 5 (22).

\[ P_{ij} = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \]  

(5)

where,

- \( P_i \) is the probability of the occurrence of crash severity \( j \) for segment \( i \) and
- \( J \) is the total number of crash severities to be modeled.

Though this assumption simplifies the probability equation it also adds the Independence from Irrelevant Alternatives (IIA) property in the MNL model. The IIA property of the MNL restricts the ratio of probabilities for any pair of crash severities to be independent of the existence and characteristics of other crash severities in the set of severities considered in the model. This restriction implies that the introduction of a new crash severity type in the set will affect all other severities proportionately.

Although the IIA property is a widely acknowledged limitation of MNL model (23) for discussion of IIA, it is still preferred because it is relatively easy to calculate and implement. The maximum likelihood method (MLE) is most commonly used for parameter estimating the parameters and it is readily available in many software programs.

3. Data collection

This section first briefly explains the data collection activities undertaken to assemble a database suitable for developing regression models for SVROR crashes. It is then followed by the summary statistics of the data used for model development.

3.1 Roadside data

Though a wide variety of site characteristics and information such as Average Daily Traffic (ADT) and shoulder width were compiled through in-office efforts, it was necessary to visit each site to determine and record specific roadside features of the roadways. The characteristics of emphasis were driveway density, side slope rating and lateral clearance which were not included in the dataset provided by Texas Department of Transportation (TxDOT). The procedure for collecting the data primarily involved a crew of three team members driving an instrumented vehicle with a Dewetron data-collection system. This system includes unique synch-clock technology to combine data from many sources into one synchronized data file, which facilitates data analysis and processing. As the vehicle traveled through the site, GPS data were recorded and synchronized with text inputs that describe
parts of the road, such as lateral clearances and location of intersections. The LIDAR gun was used to measure distances from the roadside to nearby obstructions and fixed objects, providing a record of lateral clearance. The distance measured included the shoulder, to be consistent with the definition of the roadside clearance described by AASHTO. The equipment does not measure the side slope. A screen shot showing the Dewetron data collections system is presented in the Figure 1. The lateral clearance measured is recorded into this system at the top right corner of the screen. The video signal recorded by camera is shown in the middle of the screen and the GPS signal is shown at the bottom right corner. The lateral clearance and roadside condition of certain point in a road segment can be investigated by combining these three kinds of data.

Figure 1: Screen of Dewetron software

The side slope rating is a way to estimate the hazard that the side slope area poses to a driver that runs off the road. Side slope ratings were assigned on a five-point scale in this study as follows:

- 1 – Little grade, if any; generous area to correct for vehicles leaving the traveled-way;
- 2 – Some rise or fall with low grade, but still highly correctible at highway speeds;
• 3 – Definite rise or fall with moderate grade, (e.g., drainage ditch), probably not correctible at moderate to high speeds, good possibility for non-injury
• 4 – Definite rise or fall with high grade and possible guardrail, similar to bridge over a shallow creek: not correctible, and high chance of non-incapacitating injury at highway speed; and,
• 5 – High grade and significant elevation change, such as a cut into a cliff; not correctible and high chance of fatal or incapacitating injury at highway speed.

3.2 Crash data

The crash data analyzed in this paper were extracted from the TxDOT’s Crash Records Information System (CRIS) maintained by Traffic Operations Division (TRF). The crashes available in this database covered the period from 2003 to 2008.

Crash data were collected for the following severity levels: the K=Fatal, A=Injury Type A or incapacitating injury, B=Injury Type B or non-incapacitating injury, C=Injury Type C or possible injury, O=Property Damage Only or PDO. Since it is widely-recognized that PDO crash counts vary widely on a regional basis due to significant variation in reporting threshold, only those crashes that are associated with injury or fatality (KABC) were considered in this study.

3.3 Data Summary

Table 1 provides the summary statistics of all segments on two-lane rural roads in Texas that are used in this study for model development. The final database contains 245.3 miles of roadway divided into 501 road sections. Only segments that were above 0.1 mile in length were considered in the analysis.

<table>
<thead>
<tr>
<th>Table 1: Summary Statistics of the Variables used in this Study</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>--------------------------------</td>
</tr>
<tr>
<td>Length of section(mile)</td>
</tr>
<tr>
<td>ADT</td>
</tr>
<tr>
<td>Shoulder width(ft)</td>
</tr>
<tr>
<td>Sideslope rating</td>
</tr>
<tr>
<td>Driveway density</td>
</tr>
<tr>
<td>Lateral clearance(ft)</td>
</tr>
<tr>
<td>SVROR Crashes</td>
</tr>
</tbody>
</table>

4. Modeling Results

This section first explains the results of the NB model for crash frequency followed by the results of the MNL model for crash injury severity.
4.1 Negative Binomial regression

Three separate NB models were estimated: All segments (501 horizontal curve plus tangent segments), horizontal curves only (195 segments), and tangent segments only (306 segments) in order to better investigate the relationship between SVROR crash frequency and roadside features. The latter two models were intended for examining whether the effects of roadside features on crash occurrence are different for horizontal curves when compared to tangent segments.

Table 2 shows the final result for three models. The results indicate that the SVROR crash frequency is significantly influenced by the ADT, shoulder width, lateral clearance and side slope rating. These variables are significant at 5% level. Driveway density was not found to be significant in influencing the SVROR crashes. The positive coefficients for ADT and side slope rating variables indicate that as those values increase the number of crashes also increase. The negative sign for the shoulder width and lateral clearance indicates that the number of crashes reduces as they increase, which is a desirable finding.

The annual SVROR crash frequency can be estimated by the following equations:

For all segments:
\[
\mu = e^{5.685 \times F^{0.6309} \times e(-0.192SW + 0.577SS - 0.02LC)}
\] (6)

For tangent segments:
\[
\mu = e^{5.575 \times F^{0.6506} \times e(-0.123SW + 0.570SS - 0.012LC)}
\] (7)

For horizontal curves:
\[
\mu = e^{5.302 \times F^{0.762} \times e(-0.205SW + 0.590SS - 0.024LC)}
\] (8)

\(\mu = \) the estimated number of crashes per mile;

\(F = \) vehicles per day (ADT);

\(SW = \) shoulder width in feet;

\(SS = \) side slope rating;

\(LC = \) lateral clearance in feet.
Table 2: Estimation results of the NB model

<table>
<thead>
<tr>
<th>Variable</th>
<th>All segments</th>
<th>Tangent segments</th>
<th>Horizontal curves</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std. Error)</td>
<td>Estimate (Std. Error)</td>
<td>Estimate (Std. Error)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-5.685 (0.9955)</td>
<td>-6.5748 (1.0942)</td>
<td>-5.3024 (1.7235)</td>
</tr>
<tr>
<td>ADT</td>
<td>0.6329 (0.1308)</td>
<td>0.6506 (0.1506)</td>
<td>0.7623 (0.2117)</td>
</tr>
<tr>
<td>Shoulder width</td>
<td>-0.1919 (0.048)</td>
<td>-0.1225 (0.0482)</td>
<td>-0.2047 (0.0855)</td>
</tr>
<tr>
<td>Sideslope rating</td>
<td>0.5773 (0.1084)</td>
<td>0.5706 (0.1193)</td>
<td>0.5905 (0.1946)</td>
</tr>
<tr>
<td>Lateral clearance</td>
<td>-0.0206 (0.0098)</td>
<td>-0.0123 (0.0106)</td>
<td>-0.0246 (0.0159)</td>
</tr>
<tr>
<td>Dispersion parameter</td>
<td>0.8396 (0.2567)</td>
<td>1.2604 (0.3062)</td>
<td>1.1028 (0.2817)</td>
</tr>
<tr>
<td>Goodness of fit (GOF)</td>
<td>Deviance value=327.85</td>
<td>Deviance value=241.10</td>
<td>Deviance value=112.4</td>
</tr>
<tr>
<td></td>
<td>Deviance/DF=0.661</td>
<td>Deviance/DF=0.80</td>
<td>Deviance/DF=0.59</td>
</tr>
<tr>
<td></td>
<td>AIC=715.6</td>
<td>AIC=641.7</td>
<td>AIC=221.6</td>
</tr>
<tr>
<td></td>
<td>BIC=740.8</td>
<td>BIC=664.1</td>
<td>BIC=241.3</td>
</tr>
</tbody>
</table>

Figure 2a shows the predicted number of crashes with the change in average shoulder width for different traffic flow levels. When traffic flow is very low, the effect of shoulder width on roadway departure crashes is marginal. However, with the increased flow, the increase in shoulder width has a greater effect. For example, when the ADT is equal to 3,500 vehicles per day, and if the shoulder width is increased from 0 to 10 ft one can expect a reduction in the number of SVROR crashes from 0.59 to 0.09 crashes per mile per year.

Figure 2b shows the comparison of predicted number of crashes with the change in average shoulder width on tangents and horizontal curves when the ADT is equal to 3,500 vehicles per day. An increase in shoulder width from 0 to 10 ft on tangent segments could expect a reduction in the number of SVROR crashes from 0.28 to 0.08 crashes per mile per year (71%) compared to a reduction from 2.5 to 0.32 crashes per mile per year (87%) on horizontal curves.
Figure 2: Change in SVROR crashes with shoulder width

Figure 3a shows the predicted number of crashes with the change in average lateral clearance for different traffic flow levels. Similar to the shoulder width, the increase in lateral clearance has a greater effect with the higher ADT values. For example, when the ADT is equal to 3,500 vehicles per day, for an increase in lateral clearance from 10 to 35 ft, one can expect a reduction in the number of SVROR crashes from 0.48 to 0.26 crashes per mile per year.

Figure 3b shows the comparison of predicted number of crashes with the change in average lateral clearance on tangents and curves when the ADT is equal to 3,500 vehicles per day. An increase in lateral clearance from 10 to 40 ft on tangent segments could expect a reduction in the number of SVROR crashes from 0.25 to 0.17 crashes per mile per year (32%) compared to a reduction from 0.68 to 0.33 crashes per mile per year (51%) on horizontal curves.

Figure 3: Change in SV ROR crashes with lateral clearance
Figure 4a shows the predicted number of crashes with the change in side slope rating for different traffic flow levels. The side slope rating has a greater effect for higher ADT levels. For example, when the ADT is equal to 3500 vehicles per day, a change in side slope rating from 1 to 5 could expect an increase in the number of SVROR crashes from 0.58 to 5.84 crashes per mile per year.

Figure 4b shows the comparison of predicted number of crashes with the change in side slope rating when the ADT is equal to 3500 vehicles per day. For a change in side slope rating from 1 to 5 on tangent segments, one can expect an increase in the number of SVROR crashes from 0.49 to 4.81 crashes per mile per year compared to an increase from 0.61 to 6.46 crashes per mile per year on horizontal curves. Zegeer and Council (24) also reported that roadside improvement could reduce crashes by 19 to 52 percent when flattening sideslope from 3:1 to 7:1.

4.2 Multinomial Logit regression

In order to further investigate the impact of roadside features on SVROR crashes, a MNL model was used to estimate the relationship between the roadside features and the crash severity. A dataset was created with the severity of each crash as the dependent variable and the roadside features at the location for each crash as the independent variables. There were 197 SVROR KABC crashes occurred from 2003 to 2008 on the road segments described in the previous section. Out of which 16 (8.2%) were fatal, 20 (10.1%) were incapacitating injury, 84 (42.6%) were non-incapacitating injury and 77 (39.0%) were possible injury crashes. The MNL model estimates k-1 models for k levels of the outcome variable. There are four levels of the severity variable and thus the models for three different severity levels will be estimated. During the model calibration, the “possible injury” category is set as the base scenario with coefficients restricted at zero.

Table 3 summarizes the estimation results of the MNL model. An examination of the coefficient values and their implication on the corresponding crash severity levels are documented below.
Table 3: Estimation results of the MNL model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Fatality (K)</th>
<th>Incapacitating injury (A)</th>
<th>Non-Incapacitating injury (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std. error)</td>
<td>Estimate (Std. error)</td>
<td>Estimate (Std. error)</td>
</tr>
<tr>
<td>Alternative specific constant</td>
<td>-1.3822 (0.2435)</td>
<td>-1.2265 (0.0787)</td>
<td>0.3962 (0.0867)</td>
</tr>
<tr>
<td>Shoulder width</td>
<td>-0.0793 (0.0198)</td>
<td>-0.0733 (0.0176)</td>
<td>-0.0734 (0.0176)</td>
</tr>
<tr>
<td>Side slope rating</td>
<td>0.1073 (0.0494)</td>
<td>0.0675 (0.0467)</td>
<td>0.0435 (0.0469)</td>
</tr>
<tr>
<td>Lateral clearance</td>
<td>-0.0238 (0.0129)</td>
<td>-0.0162 (0.0105)</td>
<td>-0.0072 (0.0047)</td>
</tr>
</tbody>
</table>

The coefficients in Table 3 were combined with Equation 4 to obtain the systematic component of each crash severity for SV ROR crashes. The form of each model is:

\[
V_K = -1.3822 - 0.0793 \times SW + 0.1073 \times SS - 0.0238 \times LC \quad (9)
\]

\[
V_A = -1.2265 - 0.0733 \times SW + 0.0675 \times SS - 0.0162 \times LC \quad (10)
\]

\[
V_B = 0.3962 - 0.0734 \times SW + 0.0435 \times SS - 0.0072 \times LC \quad (11)
\]

The probability of each severity category is then obtained by combining Equation 5 with Equations 9 to 11.

4.2.1 Predicted Probabilities

Shoulder width

The sign for shoulder width in Table 3 indicates that as the shoulder width increases, the chance of high severity crash goes down. Figure 5 suggests that the probability of a fatal crash changes from 8.2% for no shoulder to 5.7% for 10 ft shoulder and the probability of incapacitating injury crash changes from 9.6% for no shoulder to 7.1% for 10 ft shoulder.
Lateral clearance

The sign for lateral clearance in Table 3 indicates that as the lateral clearance increases, the chance of high severity crash goes down (as expected). Figure 6 suggests that the probability of a fatal crash decreases from 6.9% to 4% and an incapacitating injury crash decreases from 8.8% to 6.4% when the lateral clearance changes from 10.0 ft to 40.0 feet.
Side slope rating

The sign for side slope rating in Table 3 indicates that as the side slope rating increases, the chance of high severity crash goes up. Figure 7 suggests that when the side slope rating changes from 1 to 5, the probability of fatal crash increases from 8.8% to 11.6% and incapacitating injury crash increases from 9.9% to 11.1%.

![Figure 7: Severity distribution with a change in the side slope rating](image)

5. Conclusions

The objective of this paper was to develop the relationship of SVROR crash frequency and severity with roadside features. The objective was accomplished by using field data collected in four districts in Texas. The field data that were collected include lateral clearance, side slope condition and driveway density. The NB model was used to investigate the relationship between SVROR crash frequency and roadside features. The MNL model was used to model the crash severity and roadside features. The main conclusions of this study are:

1. Wider shoulder width has a significant positive impact on SVROR crash frequency and its severity and the impact increases with the increase of traffic flow. The reason is that if the driver loses the control and runs off the road then a wider shoulder increases the opportunity to return to the traveled way.

2. Similar to the shoulder width, wider lateral clearance has a significant positive impact on SVROR crash frequency and crash severity. If the lateral clearance increases then the chance of hitting an object decreases.

3. The SVROR crash frequency and severity will decrease significantly if the side slope condition is improved. One can expect a significant reduction of crashes by 90% for a given ADT when the side slope condition is changed from 5 to 1.
4. The benefits of improving the roadside conditions are more on the horizontal curves than on the tangent sections.

5. The driveway density was not found to be significantly influencing the SVROR crash frequency or severity.

By quantifying the relationship between roadside conditions and the SVROR crash frequency and severity, this study provides a basis for identifying effective ways to improve roadside feature design which will reduce the frequency and severity of SVROR crashes. As roadway departure crashes are mostly associated with human-related factors, future research should examine countermeasures that would help reduce the likelihood for these errors to occur and those that would minimize the severity when the driver leaves the traveled-way. Also, it may be worthwhile to examine how data collected from the national naturalistic study currently underway could be used for developing driver-centric countermeasures.

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DISCLAIMER

The contents of this paper reflect the views of the authors, who are responsible for the facts and accuracy of the results presented herein. The contents do not necessarily reflect the official view or policies of the Texas Department of Transportation (TxDOT).

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