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Utah Department of Transportation - Research Division
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INVESTIGATION OF RURAL ROADWAY DEPARTURES

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DISCLAIMER

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16. Abstract

Roadway fatalities are a major priority in the transportation sector. UDOT has noted that fatalities increased in 2020 with the leading cause, by a substantial margin, being rural roadway departures. Knowledge about the specific characteristics of rural roadway departure crashes can help UDOT to develop proper mitigation strategies. This research was performed with the goal of investigating temporal and spatial characteristics associated with rural roadway departure fatalities and other crashes to identify action steps to reduce roadway departure fatalities. Study into potential methods of reducing crashes was performed to answer the following questions: Where do these crashes occur? When are roadway departures most common? What are the primary contributing factors? The identified answers to these questions will help develop methods of working through public outreach, education, engineering, and design to reduce rural roadway departure crashes and provide reference for future research and development. Through this research, patterns relating to the occurrence of these roadway departures that can be used to mitigate problems in the future were identified and highlighted. Key factors include high-risk behaviors such as drowsy driving, DUI and wrong-way driving, barriers, shoulder width, etc.

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LIST OF ACRONYMS

AADT	Annual Average Daily Traffic
ANOVA	Analysis of Variance
FHWA	Federal Highway Administration
ML	Maximum Likelihood (regression)
MLE	Maximum Likelihood Estimation
MNL	Multinomial Logistic (regression)
OLS	Ordinary Least Squares
UDOT	Utah Department of Transportation

EXECUTIVE SUMMARY

The top priority for UDOT is safety, with Zero Fatalities leading the department to search for ways to eliminate fatalities. The leading cause of fatalities on Utah roads is rural roadway departures (UDOT, 2021). This research seeks to address the largest source of fatalities on Utah roadways. This research highlights patterns relating to the occurrence of these roadway departures that can be used to mitigate problems in the future.

The results from this research will be used by UDOT to create a program for reducing rural roadway departures, including possible education and engineering solutions in the areas that prove to be the most prone to roadway departures; specific geographic locations or locations with specific characteristics.

Typical crash summaries can only provide so much insight—and they often unceremoniously unveil a very wide range of factors—so UDOT has turned to a deeper dive of the issue. This in-depth study, including statistical analysis, aims to identify common threads among roadway fatalities that UDOT can tackle head-on to mitigate the fatality increase. This chapter will first present a literature review on related topics, followed by a discussion on the research methods to be presented in this report.

Crash data from years 2010 to 2021 was obtained for this study, and afterwards filtered so that only rural roadway departure crashes were left. From the crash database 131 different crash fields were downloaded as well, with expectation that these fields would allow for variables to be effectively assigned to crashes as needed. Several variables of roadway and location data not included with the crash data were also desired, and eventually sourced from UDOT data, UDOT contacts, and ESRI files. This roadway data was then assigned to each crash using ESRI GIS software processing. The spatial join tool was used to extract information from one dataset to the other, in order to join crash IDs with roadway details. This process prepared the data for evaluation, and a total of 43,928 crashes were selected for inclusion in the statistical analysis portion of the research.

Several characteristics of each of those 43,928 rural crashes (19,489 of which were roadway departure crashes) were examined. These characteristics were broken down into three categories: travel behavior characteristics, natural and built environmental characteristics, and an evaluation of crash severity. The findings from each category are described and discussed below.

Nearly all travel behavior categories were more likely to occur in roadway departure crashes than non-roadway departure crashes in rural areas. This confirms the hypothesis that negative travel behaviors are common contributors or are associated with roadway departure crashes. Poor personal decisions contributed significantly to the likelihood of a roadway departure crash. Behaviors such as alcohol suspected, distracted driving, drowsy driving, drugs suspected, DUI involved, speed involved, and wrong-way driving can all be addressed using education.

An examination of natural and built environment characteristics found that work zones and barriers are more prevalent in roadway departure crashes. In fact, rural roadways with barriers are 35% more likely to exhibit roadway departure crashes. However, areas with fencing and barriers were significantly correlated with a decrease in crash severity. Specific land cover types were also significantly associated with a reduced likelihood of roadway departure crashes. These include trees (-6%), flooded vegetation (-57%), crops (-23%), scrub/shrub (-65%), and built areas (-23%). Additionally, the results show that compared to non-roadway departure crashes, roadway departure crashes occur in locations with more through lanes, narrower lane widths, lower elevations, narrower shoulder widths, and shorter sight distances. Of note, each additional foot of shoulder width results in a significant decrease (14%) in roadway departure crashes.

Lastly, an evaluation of severe crashes found that more severe crashes are happening on roadways with fewer through lanes. More specifically, as the capacity of the roadway decreases, the severity of crashes significantly increases. All negative driver behaviors were significantly associated with an increase in crash severity. Those with the greatest increase in crash severity were drowsy driving, DUI involved, and wrong-way driving (on freeways or divided highways). Finally, some characteristics of rural roadway departure crashes are correlated with more severe outcomes. For example, data has shown that work zone crashes are on the rise and that crashes occurring in work zones are often more severe than non-work zone crashes.

1.0 INTRODUCTION

1.1 Problem Statement

Roadway fatalities are a major priority in the transportation sector. UDOT has noted that fatalities increased in 2020 with the leading cause of fatalities in Utah that year being rural roadway departures—by a substantial margin (UDOT, 2021). Knowledge about the specific characteristics of rural roadway departure crashes can help UDOT to develop proper mitigation strategies. The Safe Systems Approach, endorsed by the United States Department of Transportation, recognizes that people make mistakes and that the design, education, and crash response need to take this into consideration (USDOT, 2022). This research would help UDOT pave the way for a strategic plan for public outreach and education as well as engineering and design by answering the following questions: Where do these crashes occur? When are roadway departures most common? What are the primary causes? Knowing the answers to these questions will enable UDOT to find a solution to the number-one cause of traffic fatalities.

1.2 Objectives

Investigate temporal and spatial characteristics associated with rural roadway departure fatalities and other crashes to identify action steps to reduce roadway departure fatalities. Specific characteristics include:

- Where rural roadway departures occur
- Primary causes of rural roadway departures
- Which travel behavior and environmental characteristics are correlated to roadway departure crashes

1.3 Scope

As defined in this research, a roadway departure crash is when a vehicle leaves the roadway and crashes on the roadside. The vast majority of these crashes involve a single vehicle, though it is possible to have a multi-vehicle roadway departure crash where one or more vehicles leaves the roadway. This research highlights patterns relating to the occurrence of rural roadway departures that can be used to mitigate problems in the future. The results from this research will be used to inform a program for reducing rural roadway departures. This program could include possible education and engineering solutions in the areas that prove to be the most prone to roadway departures (specific geographic locations or locations with specific characteristics) and toward demographics that prove to be the most at risk from rural roadway departures.

1.4 Outline of Report

The report is organized into five sections, as follows: Section 2 provides a brief literature review examining existing research and study on rural roadway departures and related information. Section 2 also includes a description of the study methods and justifications. Section 3 presents the data collection methods utilized within this research and provides summary characteristics of collected data on rural roadway departure crashes. Section 4 presents a qualitative and quantitative analysis of the crash data to effectively analyze data and create an overall evaluation of the study. Section 5 provides conclusions based on the data analysis and evaluation.

2.0 RESEARCH METHODS

2.1 Overview

Roadway departure fatalities are an important issue in discussions on roadway safety. UDOT has noted that roadway departure fatalities have been on an increasing trend, with 2021 having the highest numbers seen in over a decade (UDOT, 2022). Typical crash summaries can only provide so much insight—and they often unceremoniously unveil a very wide range of factors—so UDOT has turned to a deeper dive of the issue. This in-depth study, including statistical analysis, aims to identify common threads among roadway fatalities that UDOT can tackle head-on to mitigate the fatality increase. This chapter will first present a literature review on related topics, followed by a discussion on the research methods to be presented in this report.

2.2 Literature Review

This section outlines existing literature on the topic of injury and fatal rural roadway departure crashes. The focus of this literature review is to determine existing research relating to the following three questions:

- Who is at the most risk for these types of crashes?
- When and where do these types of crashes most often occur?
- What mitigation strategies have been successfully used to reduce the number and severity of these crashes?

2.2.1 At-Risk Drivers

In a two-lane rural roadway departure study performed for the state of Texas, Lord et al. (2011) found that 52% of fatal and injury crashes involved unsafe speeds, 24% involved driver inattention, and 20% involved an errant evasive action such as overcorrecting. In addition, 14% of crashes involved drivers who failed to heed a warning sign, 12% involved fatigued or sleeping drivers, and 12% involved drivers that were under the influence of alcohol. Similarly, in a study performed for the state of Washington, Lee and Mannering (1999) found that a higher severity of roadway departure crashes was associated with driver inattention, speeding, driving under the influence, lack of driving experience, ignorance of safety hazards, and less roadside recovery space. Additionally, Rahman et al. (2021) found that distracted drivers, driving under the influence of drugs or alcohol, younger drivers aged 25-34 years, motorcyclists, older vehicles, and drivers with an out-of-state license are more likely to be factors in roadway departure crashes than in other types of crashes.

Fatal crashes in Utah show similar trends to those discussed above. For Utah fatal crashes cited as “roadway departure” during the years 2016-2020, UDOT reports that 48% of crashes involved drivers that were under the influence of alcohol or drugs, 36% involved unsafe speeds, 12% involved teenage drivers, 8% involved drowsy drivers, and 6% involved distracted drivers (UDOT, 2021). These insights show that there are several driver-related factors that may be quite influential in roadway departure fatalities.

2.2.2 External Factors of Most Occurrences

Unsurprisingly, Lord et al. (2011) (who used a dataset that excluded property damage only crashes) found that more roadway departure crashes occur on curves compared to straight sections of highway. They also found that narrower lanes and shoulders, more frequent curves and driveways, higher daily traffic volumes, shorter lateral clearances, and more severe side slopes are all correlated with an increase in rural roadway departure crashes. Additionally, they found that narrower shoulder widths were highly correlated with an increase in crashes on segments with sharper curves and higher volumes (Lord et al., 2011). Similarly, Lee and Mannering (1999) found that narrower lanes, shoulders, medians, bridge approaches, greater numbers of hazardous roadside objects, steeper side slopes, and medians significantly correlate with increases in roadway departure crash frequencies. A study in Virginia also found that an increase in daily traffic, greater curve severity, less textured pavement, and a decrease in shoulder width were significantly correlated with an increase in roadway departure crashes (Appiah and Zhao, 2020). This study also states that higher speed limits were correlated with an increase in roadway departure, much unlike the findings from Texas that showed lower speed limits were correlated with an increase (Lord et al., 2011). The study suggested that areas with lower speed limits may have more crashes because a lower speed limit indicates stretches that are more difficult to traverse. However, similarly to the results of Appiah and Zhao (2020), Rahman et al. (2021) found higher speed limits (50-55 mph sections in particular) to be associated with more roadway departure crashes compared to other types of crashes. However, like the other studies, Rahman et al. (2021) found roadway departure crashes are more likely to occur than other types of crashes on locations with curves, narrower shoulders, and narrower lanes.

Donnell et al. (2019) found that tighter curves are associated with more roadway departure crashes, but also considered design consistency in relation to the number of these crashes in Utah and Washington. They found that a curve tends to see more crashes when the curves before and after have larger radii. Additionally, they found that these curves see more crashes when the tangent sections before and after these curves are longer. These findings suggest that drivers become accustomed to a lack of tight curves and are unprepared when a tight curve does exist on their route. The same research team performed a similar study for crashes in Pennsylvania and Indiana, finding that the data from Pennsylvania showed the same trends as the data from Utah and Washington.

In addition to geometry factors, weather and pavement conditions were found to also influence the number of roadway departure crashes. Lee and Mannering (1999) found that crashes are more likely to be injury-causing on dry pavement compared to wet pavement as well as in daylight compared to in dark conditions. They suggest that daylight and dry roads promote overconfidence in drivers and thus more severe crashes occur. Lord et al. (2011) also found that fatal crashes make up a higher percentage of crashes on dry roads than of crashes on wet roads. In agreement with Lee and Mannering (1999), Lord et al. (2011) suggests that drivers tend to exercise more caution in bad weather and thus fewer fatal crashes occur in wet conditions. Even if more roadway departure crashes occur in daylight and on dry roads, it is still important to note that a study by Rahman et al. (2021) determined that roadway departure crashes are of the most common type of crash in wet weather and at night.

2.2.3 Mitigation Strategies

The results of the studies previously discussed (particularly Lee and Mannering, 1999; Lord et al., 2011; and Appiah and Zhao, 2020) suggest that geometric changes in crash-prone highways could reduce the number of future crashes and fatalities, including:

- Widening shoulders, lanes, medians, and clear zones
- Flattening side slopes
- Broadening curves

Further discussion of these and other potential countermeasures are given in each of the reports.

Other research efforts have studied the effects of specific countermeasures. Donnell et al. (2019) performed a cross-sectional study examining the relationship between crashes and combinations of guardrails and delineators (post-mounted and/or triangle type) in Pennsylvania. They found that the presence of guardrails paired with delineators was associated with a decrease in total, fatal and injury, roadway departure, and nighttime crashes when placed on tight curves. A guardrail alone, however, was found to increase roadway departure and nighttime crashes on tight curves as a whole, while still decreasing the number of fatal and injury crashes. The research teams suggest that these results are potentially due to guardrails presenting a roadside hazard that is more likely to be hit without any delineation, though these crashes appear to be less harmful than those without guardrails (Donnell et al., 2019). The same research group also performed a before-after study on the use of horizontal curve warning pavement markings on Pennsylvania roads. The particular pavement marking for which they performed the study was that of an arrow supplemented by “slow” or the advisory curve speed painted in the travel lane. Their results showed that pavement markings can reduce injury and fatality-related crashes by 30.7%, roadway departure crashes (all severities combined) by 23.1%, and nighttime roadway departure crashes (all severities combined) by 25.5% (Donnell et al., 2019).

Additional publications offer insights into countermeasures that agencies across the United States have implemented and subsequently seen benefits from. For example, six states participated in a peer exchange in 2013 where positive feedback was given about using high friction surface treatments, rumble strips, SafetyEdge, and curve delineation (FHWA, 2015). Kentucky has particularly seen great benefit from installing rumble strips and applying high friction surface treatments. They report the benefit-cost ratio for rumble strips to be 65.7 and experienced more than double their target decrease in fatalities by using a variety of treatments. These include median barrier installations, horizontal curve alignments, and signing improvements, in addition to high-friction surface treatments and rumble strips (Cheung and

Lovell, 2019). Furthermore, the Moving FoRRRwD program supported by FHWA offers strategies to reducing roadway departure fatalities. The program includes strategies for identifying problem locations, recommends proven countermeasures, and offers advice on how to implement chosen countermeasures effectively and efficiently. The suggested countermeasures highlighted by the program include signs and markings, rumble strips, high-friction surface treatments, SafetyEdge, and roadside design (more adequate shoulders, slopes, ditches, clear zones) (Satterfield and Albin, 2021).

2.2.4 Literature Review Summary

Overall, the literature reviewed provides a list of factors in roadway departure crashes that other research teams and agencies have found to be influential. These mostly include characteristics of the roadway and roadside features (such as curve geometry, clear zone depth, and presence of barriers), but also include a few driver behaviors and characteristics (such as driving under the influence of drugs or alcohol, speeding, distracted driving, overcorrecting, and driver age and experience). These insights prepare the research team to consider these factors as they perform their study of rural roadway departure fatalities in Utah. Additionally, the literature is full of suggestions on countermeasures for increasing the safety of the built environment (such as widening shoulders, flattening curves, adding signage, and implementing rumble strips) and mitigating the influence of nature (such as using high-friction surface treatments), but it is lacking in suggested countermeasures for improving driver behavior. The research presented in this study aims to shed light on influential factors in Utah – particularly driver behavior and characteristics – and provide reasonable countermeasures to reduce Utah rural roadway departure fatalities.

2.3 Analysis Methods

This study incorporates multiple analysis methods including summary statistics, chi-square, and maximum likelihood regression models. These methods were selected based on the dataset compiled and the specifications required to identify significant correlations and relationships.

2.3.1 Summary Statistics

Summary Statistics are used to provide a quick and simple description of the data without any predictive component or significance testing. They may include mean (average), median (center point of data), mode (most frequently occurring value), minimum value, maximum value, value range, standard deviation, and frequency percentages. Summary statistics were used in this analysis to provide context for the crash data and demographics.

2.3.2 Pearson's Chi-Square Test

A Pearson's Chi-Square Test is used on categorical data to compare an observed distribution to a theoretical one (measuring goodness of fit) for one or more categories. The events included must be mutually exclusive (e.g., weather cannot be clear and raining at the same time) and have a total probability of 1 (Greene, 2018).

Model:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

where

χ^2 is the chi-square value

Σ is the summation sign

O is the observed frequency

E is the expected frequency

2.3.3 Independent Samples T-Tests

An independent samples t-test compares the means of two independent groups (fatal crashes vs. non-fatal crashes) to determine whether there is statistical evidence that the associated population means are significantly different. The independent samples t-test is a parametric test, and can compare the means for two and only two groups. It cannot make comparisons among more than two groups (which would require an Analysis of Variance (ANOVA)).

Model:

When the two independent samples are assumed to be drawn from populations with identical population variances (i.e., $\sigma_1^2 = \sigma_2^2$), the test statistic t is computed as:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\left[\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}\right]\left[\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}\right]}}$$

where

x_1 = Mean of first sample
x_2 = Mean of second sample
n_1 = Number of observations in the first sample
n_2 = Number of observations in the second sample
s_1^2 = Variance of first sample
s_2^2 = Variance of second sample
s_p = Pooled standard deviation

The calculated t value is then compared to the critical t value from the t distribution table with degrees of freedom $df = n_1 + n_2 - 2$ and chosen confidence level. If the calculated t value is greater than the critical t value (≈1.7-2.0 depending on the sample size), then we reject the null hypothesis (Greene, 2018).

Assumptions:

- Dependent variable must be continuous (e.g., interval or ratio level)
- Independent variable is categorical
- Cases have values on both the dependent and independent variables
- Independent samples/groups
- There is no relationship between the subjects in each sample
- No influence between groups or subjects
- Random sample of data from the population
- Normal distribution (approximately) of the dependent variable for each group
- Homogeneity of variance across groups
- Few outliers

The independent samples t-test will be used to compare rural roadway departure crashes to rural non-roadway departure crashes for several study variables. The goal of the t-test analysis is to identify significant differences between the two groups. Subsequent analyses will identify how specific variables impact roadway departures and crash severity by using more complex regression techniques described below; these regression models are able to quantify the sign and magnitude of each independent variable's effect on the dependent variable.

2.3.4 Maximum Likelihood Regression

Maximum likelihood regression is used to predict a nominal dependent variable given one or more independent variables. It is sometimes considered an extension of binomial logistic regression to allow for a dependent variable with more than two categories. As with other types of regression, multinomial logistic regression can have nominal and/or continuous independent variables and can have interactions between independent variables to predict the dependent variable (Greene, 2018). Dependent variables with M categories require the calculation of M-1 equations, one for each category relative to the reference category, to describe the relationship between the dependent and independent variables.

Model:

If the first category is the reference, then, for M=2,…,M,

$$\ln \frac{P(Yi = m)}{P(Yi = 1)} = \alpha_m + \sum_{k=1}^{K} \beta_{mk} X_{ik} = Z_{mi}$$

Hence, for each case, there will be M-1 predicted log-odds, one for each category relative to the reference category. When there are more than 2 groups, for m=2,…,M,

$$P(Y_i = m) = \frac{exp(Z_{mi})}{1 + \sum_{h=2}^{M} exp(Z_{hi})}$$

For the reference category,

$$P(Y_i = 1) = \frac{1}{1 + \sum_{h=2}^{M} exp(Z_{hi})}$$

Assumptions:

- The dependent variable is measured at the nominal level
- There are one or more independent variables that are continuous, ordinal, or nominal (including dichotomous variables)
- Observations are independent and have mutually exclusive and exhaustive categories
- There is no multicollinearity

- There is a linear relationship between any continuous independent variable and the logit transformation of the dependent variable
- There are no outliers, high leverage values, or highly influential points

When interpreting a maximum likelihood regression model, one of the response categories is used as a baseline or reference cell, log-odds are then calculated for all other categories relative to this baseline, and then the log-odds become a linear function of the predictors. In this research, the crash severity of a roadway departure crash will be predicted based on driver behavior and characteristics of the built environment.

2.3.5 Binary Logistic Regression

Binary logistic regression is used to estimate the odds or probability that a characteristic is present given the values of explanatory variables (Greene, 2018). In this research, the probability of a rural roadway departure crash occurring will be predicted based on the presence of environment characteristics (e.g., functional class, presence of barriers, number of through lanes, land cover type, etc.) and travel behavior characteristics (e.g., aggressive driving, drowsy driving, speeding, etc.). The statistical model is derived as follows:

Variables:

Y_i = 1 if a specific type of crash (*i*) occurred
Y_i = 0 if a specific type of crash (*i)* did not occur
$X = (X_1, X_2, ..., X_k)$ will be a set of explanatory variables which can be discrete, continuous, or a combination (outlined in Table 1). x_i is the observed value of the explanatory variables for observation *i*.

Model:

$$\pi_i = Pr(Y_i = 1|X_i = x_i) = \frac{exp(\beta_0 + \beta_1 x_i)}{1 + exp(\beta_0 + \beta_1 x_i)}$$

or,

$$logit(\pi_i) = log\left(\frac{\pi_i}{1 - \pi_i}\right)$$
$$= \beta_0 + \beta_1 x_i$$
$$= \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k + \beta_k x_{ik}$$

Assumptions:

- The data Y_1, Y_2, ..., Y_n are independently distributed (cases are independent)
- Distribution of Y_i is $Bin(n_i, \pi_i)$, i.e., binary logistic regression model assumes binomial distribution of the response. The dependent variable does NOT need to be normally distributed, but it typically assumes a distribution from an exponential family (e.g., binomial, Poisson, multinomial, normal, etc.)
- Does NOT assume a linear relationship between the dependent variable and the independent variables, but it does assume linear relationship between the logit of the response and the explanatory variables; $logit(\pi) = \beta_0 + \beta X$
- Independent (explanatory) variables can even be the power terms or some other nonlinear transformations of the original independent variables.
- The homogeneity of variance does NOT need to be satisfied. In fact, it is not even possible in many cases given the model structure.
- Errors need to be independent but NOT normally distributed.
- It uses maximum likelihood estimation (MLE) rather than ordinary least squares (OLS) to estimate the parameters, and thus relies on large-sample approximations.
- Goodness-of-fit measures rely on sufficiently large samples, where a heuristic rule is that not more than 20% of the expected cells counts are less than 5 (Greene, 2018).

2.3.6 Multinomial Logistic Regression

Multinomial logistic regression (MNL) is used to predict a categorial dependent variable given one or more independent variables. It is sometimes considered an extension of binomial logistic regression to allow for a dependent variable with more than two categories. As with other types of regression, multinomial logistic regression can have nominal and/or continuous independent variables and can have interactions between independent variables to predict the dependent variable (Greene, 2018). Dependent variables with M categories require the calculation of M-1 equations, one for each category relative to the reference category, to describe the relationship between the dependent and independent variables.

Model:

If the first category is the reference, then, for M=2,…,M,

$$\ln \frac{P(Yi = m)}{P(Yi = 1)} = \alpha_m + \sum_{k=1}^{K} \beta_{mk} X_{ik} = Z_{mi}$$

Hence, for each case, there will be M-1 predicted log-odds, one for each category relative to the reference category. When there are more than 2 groups, for m=2,…,M,

$$P(Y_i = m) = \frac{exp(Z_{mi})}{1 + \sum_{h=2}^{M} exp(Z_{hi})}$$

For the reference category,

$$P(Y_i = 1) = \frac{1}{1 + \sum_{h=2}^{M} exp(Z_{hi})}$$

Assumptions:

- The dependent variable is measured at the nominal level
- There are one or more independent variables that are continuous, ordinal, or nominal (including dichotomous variables)
- Observations are independent and have mutually exclusive and exhaustive categories
- There is no multicollinearity
- There is a linear relationship between any continuous independent variable and the logit transformation of the dependent variable
- There are no outliers, high leverage values, or highly influential points

When interpreting an MNL model, one of the response categories is used as a baseline or reference cell, log-odds are then calculated for all other categories relative to this baseline, and then the log-odds become a linear function of the predictors. MNL models are used in this research to identify any significant relationships between crash severity and non-ordinal categorical variables such as weather and lighting condition.

Table 2.1 Parameters and Meaning of Statistical Tests

Statistics Test/Model	Parameters	Meaning
Summary Statistics	• Mean • 95% confidence interval lower and upper bounds	• Average • The lowest and highest value the mean could be (with 95% confidence)
Pearson's Chi-Square Test	• Chi-Squared	• Measurement of fit measured on a scale of 1 to 10, where a higher number indicates that the statistical model more accurately represents the data
Independent Samples t-Test	• t-statistic	• Measurement of fit measured on a scale of negative infinity to infinity, where a number closer to zero indicates poor accuracy

Maximum likelihood regression	• Unstandardized coefficients
	  o B
	  o Std. Error
	• Standardized coefficients
	  o B
	• t-statistic
		• Unstandardized coefficients
		  o Slope of the regression line
		  o Precision of estimates, 95% of observations should be within +/- 2 standard errors of the regression line
		• Standardized
		  o Adjusts data so that the variances of dependent and independent variables are equal to 1
		• t-statistic (>1.8 or <-1.8 = significance)

Binary logistic regression	• Unstandardized coefficients
	  o B
	  o Std. Error
	• Standardized coefficients
	  o Exp(B)
	• Wald
		• Unstandardized coefficients
		  o Slope of the regression line
		  o Precision of estimates, 95% of observations should be within +/- 2 standard errors of the regression line
		• Standardized
		  o Adjusts data so that the variances of dependent and independent variables are equal to 1
		• Wald is used to determine if a certain predictor (x) is significant as a chi-square distribution

Multinomial logistic regression	• Unstandardized coefficients
	  o B
	  o Std. Error
	• Standardized coefficients(?)
	  o Exp(B)
		• Unstandardized coefficients
		  o Slope of the regression line
		  o Precision of estimates, 95% of observations should be within +/- 2 standard errors of the regression line
		• Standardized
		  o Standardized slope of adjusted data

2.4 Summary

A literature review as provided describing existing research relating to who is at the most risk for being involved in rural roadway departure crashes, when and where these types of crashes most often occur, and what mitigation strategies have been successfully used to reduce the number and severity of these crashes. Additionally, analysis methods were introduced based on the dataset compiled and the specifications required to identify significant correlations and relationships.

3.0 DATA COLLECTION

3.1 Overview

As there is currently little known about characteristics of rural roadway departure crashes, effective mitigation techniques are not able to be developed. By gathering data on these crash types and performing effective analysis, more knowledge on the characteristics of rural roadway departure crashes can be discovered and utilized. Data on crashes can be used to reveal trends such as who is most likely to be involved in these crashes, where these crashes most commonly occur, and what mitigation strategies already exist that can be used to reduce these crashes. As a result, effective crash data collection formed a core part of this study.

The crash reports alone, however, do not provide an entirety of the context to a crash. Additional data needed to be collected to obtain information such as elevation, presence of barriers, Annual Average Daily Traffic (AADT), and surrounding landscape type, to name a few. The roadway files and variables obtained will be explained in this chapter, along with the process of linking the roadway data to the crash data.

3.2 Crash Data

Crash data from years 2010 to 2021 was obtained from the UDOT AASHTO Safety crash database (UDOT, 2021). The crash data was filtered so that only crashes that had an urban/rural value of “Rural” or blank were included, leaving 73,657 total crashes. Of the 228 crash data fields available in the crash database, 131 were downloaded. The project team did not anticipate that all 131 selected fields would be used, but rather they desired to have a variety of variables from which to choose. The columns used in the analysis will be provided in Chapter 4.

3.3 Roadway Data

As previously explained, roadway data was also collected to reveal more context to the location characteristics of the crashes. The UDOT Open Data Portal, Esri files, and UDOT contacts were used to search for files that had useful roadway characteristics information or that could be used to calculate any additional desired fields. Several useful files were found and were downloaded as CSVs, shapefiles, or raster imagery datasets.

Because the crash data spanned more than a decade and construction projects at any point during that time span could have changed the roadway data, it was desirable to obtain the most recently documented roadway data as well as any older files available. For this reason, files published in mid-2017 that were available on the UDOT Open Data Portal were downloaded in addition to the most recently uploaded file. For roadway files that had both a recent and a file from 2017, the 2017 roadway data was linked to crashes that occurred in 2017 or earlier, and the most recent roadway data files were linked to crashes that occurred in 2018 or later. For all roadway data files that did not have an available 2017 version, the most recent version was linked to all crashes regardless of year.

The list of files downloaded, their file type, and the variables obtained from them are shown in Table 3.1. Source information for these files is found in Appendix A.

Table 3.1 Roadway Data Files Used

File Name	File Type	Variables Obtained
AADT Rounded	Shapefile	AADT for each year 2010-2022
Barriers[1]	Shapefile	Presence of barrier(s)
Curves	CSV	Degree of curvature, curve radius
Esri 2020 Land Cover	Raster	Landscape type code; landscape type description
Fencing Inventory OMS	Shapefile	Presence of fencing
Intersections	Shapefile	Control type of nearest intersection
Lanes[1]	CSV	Number of through lanes; presence of turning lanes[2]; width of a through lane; total width of all through lanes[2]; total number of lanes (including turn lanes)[2]
Pavement Striping[1]	Shapefile	Status of permitted passing
Roadway Utilities[1,3]	CSV	Number of utility poles
Route Elevations	Shapefile	Elevation
Route Grades	Shapefile	Roadway grade; cross slope
Rumble Strips[1]	Shapefile	Presence & location (center, shoulder) of rumble strips
Shoulders[1]	Shapefile	Shoulder width
Sign Faces[1]	Shapefile	Number of signs
UDOT Speed Limits (2019)	Shapefile	Posted speed limit

Notes:
1. Also has a 2017 version
2. Added to the file through calculation
3. Filtered to only include type "Utility" (thus excluding types "Manhole," "Catch Basin," and "Monument")

3.4 GIS Work

To assign roadway data to crash data, Esri software ArcGIS Pro was used. ArcGIS Pro can chart many datasets together on a single map, and processing tools within the software can then link information from one dataset to another based on their spatial relationship. For example, the spatial join tool can use a search radius around points of a specified dataset to find points or lines (called features) of another specified dataset and extract information from them. The spatial join tool can also document how many features were found within the search radius, though the extracted information only comes from one (e.g., the nearest) feature per search radius.

Before beginning to join roadway data to the crashes, a spatial check was performed to search for any crashes incorrectly marked as rural and to identify if any crashes marked blank in the urban/rural field were located in urban areas. This check was done by using ArcGIS Pro to compare the crash locations with urban boundaries created from the 2010 census (Esri et al.). A total of 799 crashes were found to be in urban areas and were subsequently removed from the dataset, leaving a total of 72,858 crashes for further analysis.

The spatial join tool was used to link information from each roadway data file to Crash IDs. Crash locations and all the roadway data were mapped onto the same map and search radii extending from the crash points were applied. Table 3.2 specifies what search radii were used and if the spatial join tool was used to extract information (from the nearest feature within the radius) or to obtain the count of features within the search radius.

Table 3.2 Spatial Join Specifications Used

File Description	Search Radius	Extracting Count?	Extracting Roadway Information?	Fields (if extracting roadway information)
Barriers	50 ft	X		
Curves	30 ft		X	Radius Degree
Elevations	30 ft		X	Elevation
Fencing	50 ft	X		
Grades	30 ft		X	Grade Cross slope
Intersections	250 ft, 1 mi		X	Traffic control type
Land cover*	N/A		X	Land cover type Land cover code
Lanes	30 ft		X	Total number of lanes Number of through lanes Presence of turning lanes Width of one through lane Total width of through lanes
Pavement Striping	30 ft		X	Passing permitted type
Rumble Strips	30 ft		X	Type
Shoulders	30 ft		X	Shoulder width
Sign Faces	100 ft	X		
Speed Limits	30 ft		X	Speed limit
Utilities	100 ft	X		

* Land cover is of type Raster (made of grid-like map data instead of lines or points) and thus does not need a search radius.

After the spatial joins were all completed, a CSV file was exported with all the extracted count and roadway information data linked to the Crash IDs.

3.5 Data Cleanup

When the joined data was reviewed in its CSV format, it was evident that many crashes (particularly those not on state routes) were either joined to features from a different route or not joined to hardly any features at all. This was due to the lack of roadway data for non-state routes. Nearly all of the roadway data obtained was complete for state and federal aid routes, but information on local routes were not included in most files. Additionally, when multiple routes meet, sometimes the spatial join would pick data from the crossroad and not the route on which the crash occurred. To verify that the joined roadway data was from the same route as the crash data, the route numbers were obtained for the joined fields and were compared to that of each crash. The number of matching routes were summed up for each crash for the roadway files with continuous route data (i.e., Grade, Elevation, Curve, Speed Limit, AADT, Rumble Strips, Lanes, Shoulders, and Pavement Markings). Those that had matching routes for all of these data files were selected to move onto the analysis portion of the research. In total, 43,929 crashes were selected for analysis.

3.6 Additional Data Processing

Five additional variables were also added to the spreadsheet, calculated from the roadway data that was joined to the crash data:

- *Assumed sight distance (for permitted passing locations)* – the minimum sight distance required for a permitted passing zone on the roadway at the crash (based on the speed limit)

- *Crash year AADT* – the AADT of the year that the crash occurred (before the creation of this field, each crash had all AADT values assigned to it – from year 2010 to the year 2020)

- *Poles within a 100-ft radius* – the sum of the sign faces and utilities count

- *Has Barriers* – a yes/no field where yes means at least one barrier feature was found within the search radius

- *Has Fencing* – a yes/no field where yes means at least one fencing feature was found within the search radius

3.7 Summary

Crash data from years 2010 to 2021 was obtained for this study, and afterwards filtered so that only crashes of types desired for research purposes were left. 131 different crash fields from the same database as the crashes were then downloaded as well, with expectation that these fields would allow for variables to be effectively assigned to crashes as needed. Several variables of roadway and location data not included with the crash data were also desired, and eventually sourced from UDOT data, UDOT contacts, and Esri files. This roadway data was then assigned to each crash using Esri GIS software processing. The spatial join tool was used to extract information from one dataset to the other, in order to join crash IDs with roadway details. This process prepared the data for evaluation, and a total of 43,928 crashes were ready to begin the statistical analysis portion of the research.

4.0 DATA EVALUATION

4.1 Overview

This chapter provides an overview of data analysis and preliminary findings. Summary crash and roadway statistics are described, followed by a presentation of more quantitative statistical analysis of roadway departure crashes and driver behavior / environmental characteristics.

4.2 Summary Tables/Charts

It is important to have a high-level understanding of the data trends prior to performing a statistical analysis. This section will provide summary statistics of the data through charts and tables that explore various fields acquired during the data collection process.

Table 4.1 shows the breakdown of crash severity between roadway departure and non-roadway departure crashes.

Table 4.1 Crash Severity and Roadway Departure Summary

	Roadway Departure Involved		
Crash Severity	Yes	No	Total
Fatal	417	161	578
Suspected Serious Injury	11,925	21,144	33,069
Suspected Minor Injury	2,937	1,407	4,344
Possible Injury	3,041	1,335	4,376
No Injury/PDO*	1,169	392	1,561
Total	19,489	24,439	43,928

*PDO = Property Damage Only

The variance in the distribution resulted in a significant chi-square value (374.202) which shows that crash severity is not randomly distributed and is correlated to the 19,489 roadway departure crashes.

Table 4.2 shows the number and percent of crashes in the dataset, organized by crash severity. Note that the number of severe (fatal and suspected serious injury) crashes makes up approximately 5% of the dataset, with a total of 2,139 crashes. The remaining tables and figures in this section will compare summaries for all crashes combined and for severe crashes only.

Table 4.2 Crash Severity Summary

	Crash Severity					
	Fatal	Suspected Serious Injury	Suspected Minor Injury	Possible Injury	No Injury / PDO*	Total
COUNT	578	1,561	4,376	4,344	33,069	43,928
PERCENT	1%	4%	10%	10%	75%	100%

*PDO = Property Damage Only

Figure 4.1 shows the percent of crashes for ranges of AADT. Approximately 46% of severe crashes occurred on roads with AADTs of less than 2,500. While 7% of all crashes occurred on roads with an AADT of 20,000 or higher, none of those were severe crashes.

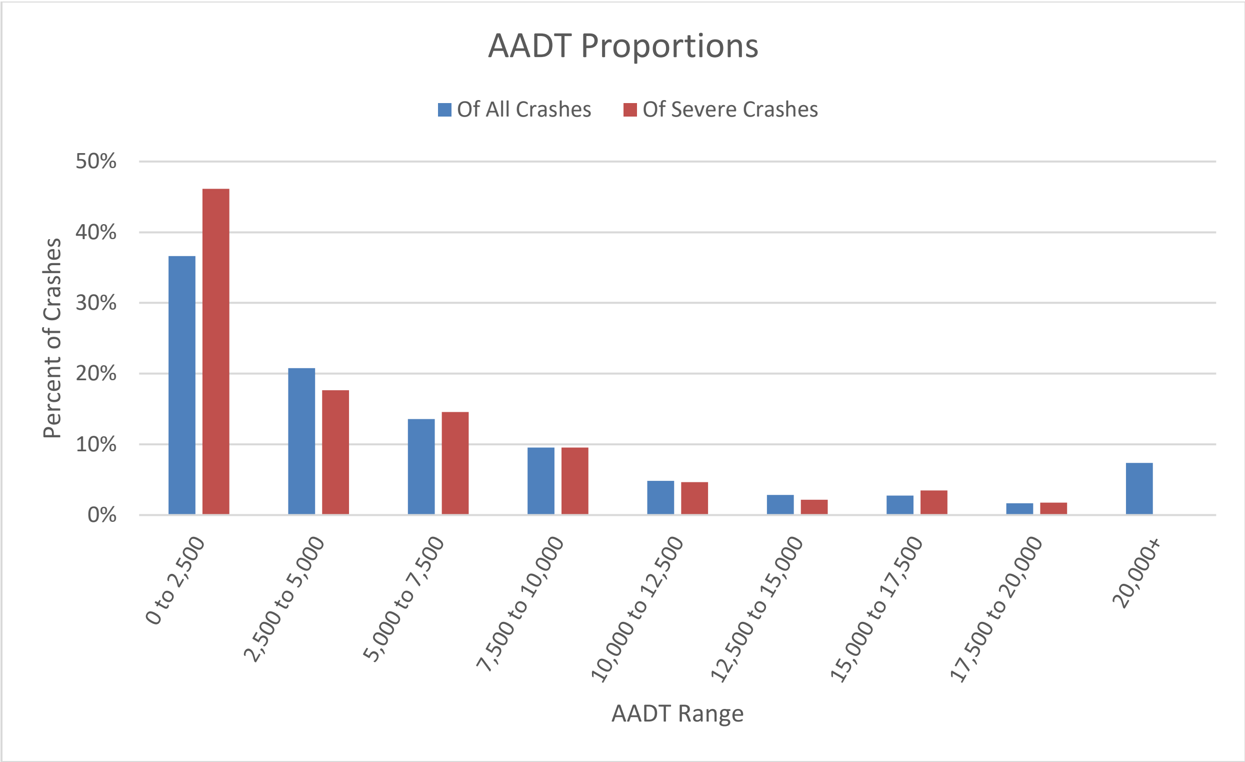

Figure 4.1 AADT Summary

Figure 4.2 shows the proportion of crashes occurring during each hour of the day. The most common hours for severe rural roadway departure crashes are in the afternoon – between 1 PM and 6 PM. Unlike severe crashes, the non-severe crashes peak during the morning (6 AM to 8 AM) and evening (6 PM to 10 PM) hours.

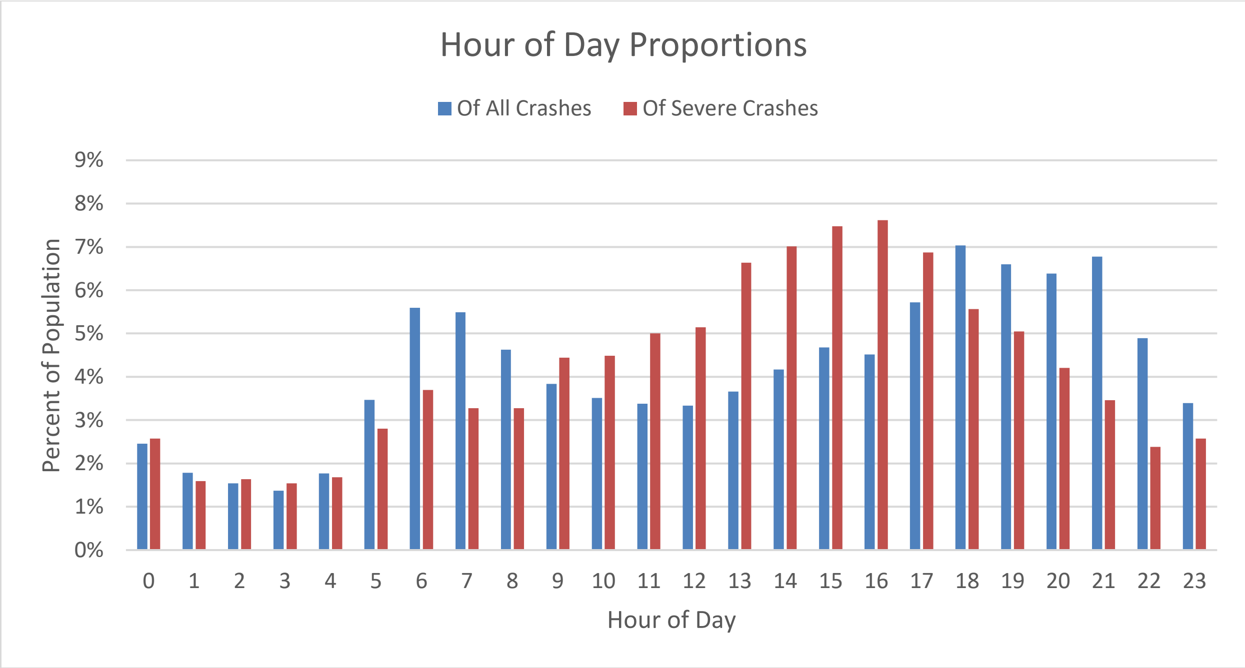

Figure 4.2 Hour-of-Day Summary

Figure 4.3 shows the percent of crashes that occurs during each documented light condition. While the non-severe crashes are split nearly 50-50 between occurring in dark or light conditions, a two-thirds majority of the severe crashes occur during daylight.

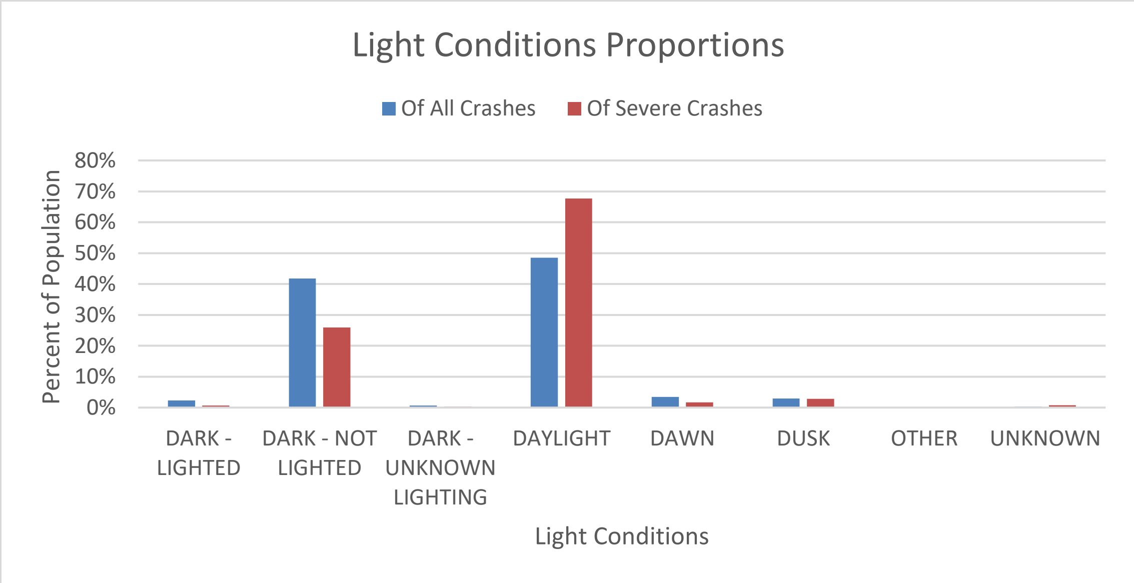

Figure 4.3 Light Conditions Summary

Figure 4.4 shows the proportion of crashes occurring on state routes of different functional classifications. Approximately 18% of severe crashes in the dataset were on an interstate or other freeway/expressway, 34% on another principal arterial, 28% on a minor arterial, and 20% on a major collector. Minor collectors and local roads make up less than 1% of the crashes; this is unsurprising due to the rarity that a road classified as local is a state route. Non-severe crashes show similar trends to that of the severe crashes.

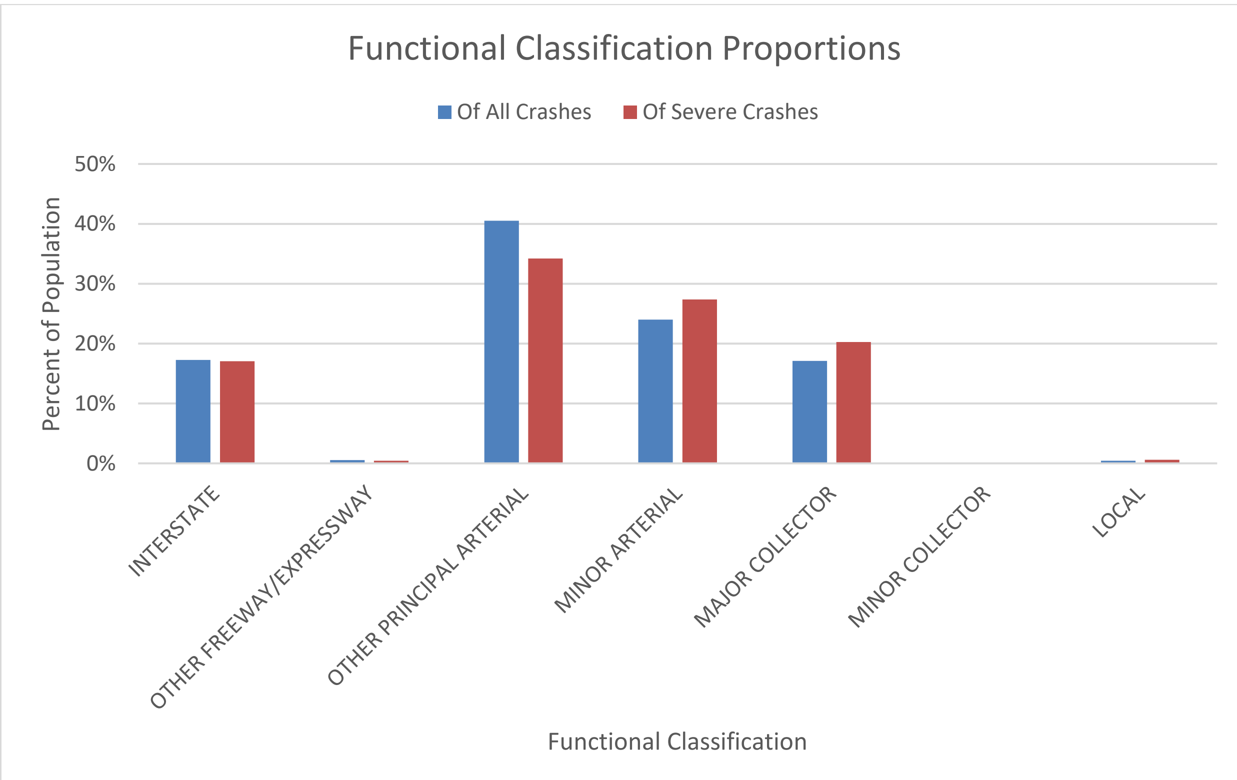

Figure 4.4 Functional Classification Summary

Figure 4.5 shows the proportion of crashes that occurred in the varying landscapes of Utah. The most common surrounding landscape is "scrub/shrub," making up 65% of all crashes and 70% of severe crashes. "Bare ground," "built area," "crops," and "trees" each make up between 5% and 10% of severe crashes.

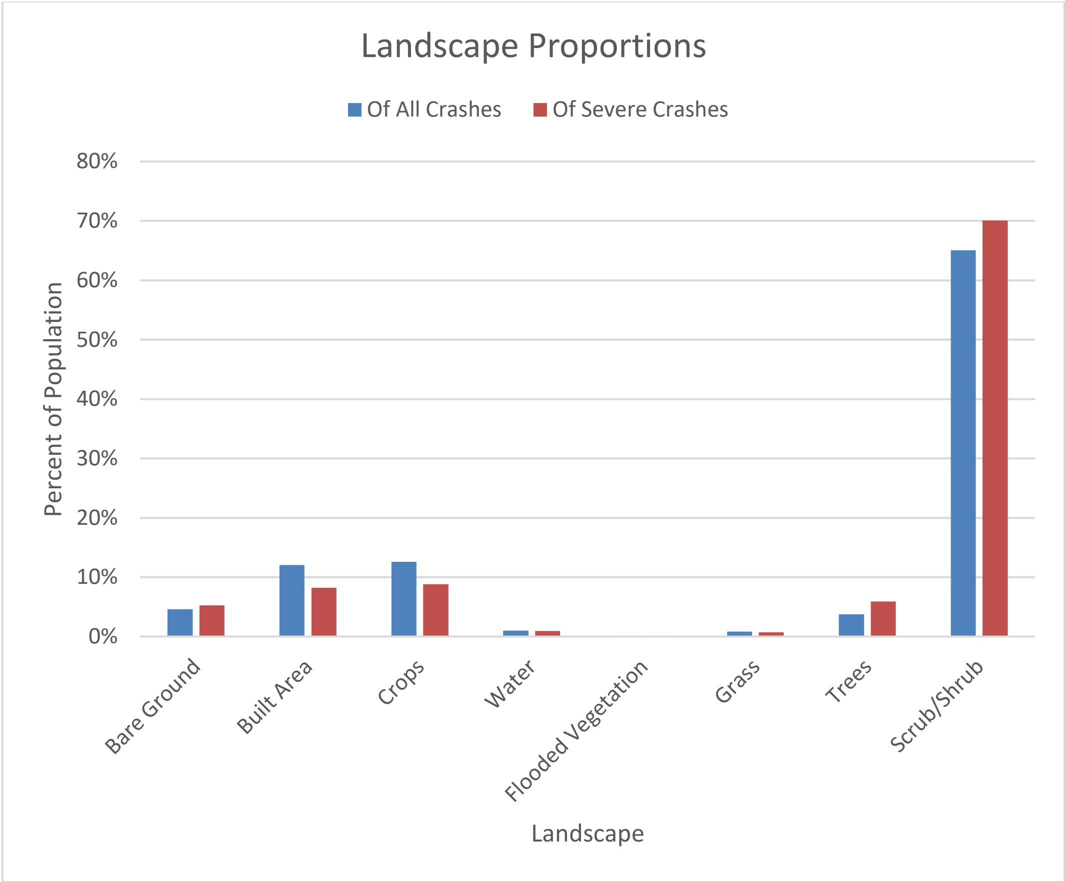

Figure 4.5 Landscape Summary

Figure 4.6 shows the proportion of crashes that occurred near a roadside barrier (within 100 feet of one). The proportions for severe crashes are nearly identical to that of the non-severe crashes. Approximately 24% of crashes were within 100 feet of a roadside barrier and 76% were not.

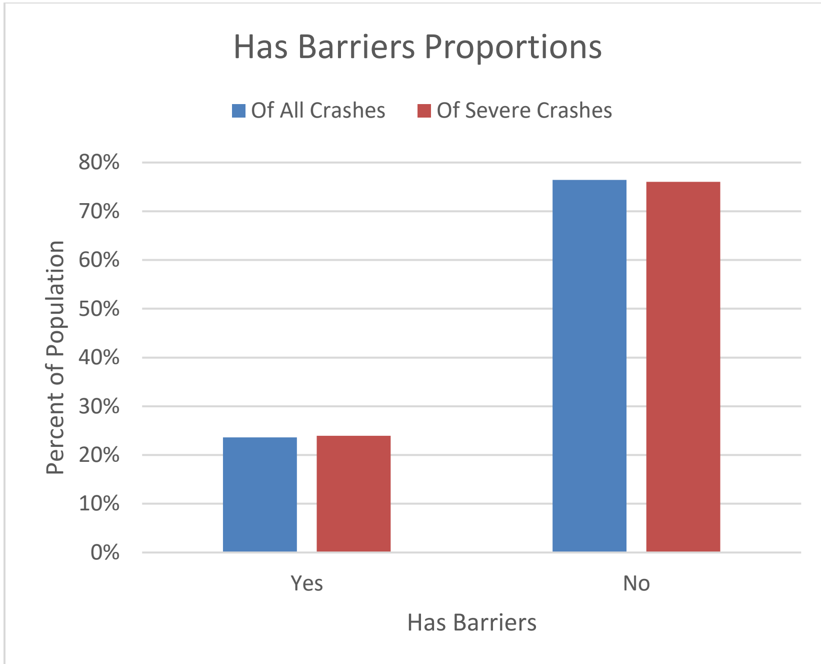

Figure 4.6 Presence of Barriers Summary

Table 4.3 shows the percent of crashes that occurred in or not in a passing zone. Implications of sight distance may be drawn based on the permissiveness of passing. Increased sight distance means drivers have additional distance/time to react to oncoming hazards. In 66% of all crashes and 70% of severe crashes, passing was not permitted which may imply limited sight distance and/or the presence of winding roads or precarious road conditions.

Table 4.3 Passing Permitted Summary

	Passing Permitted		
	Not Permitted	Permitted	Permitted – One Direction Only
Of All Crashes	66%	19%	15%
Of Severe Crashes	70%	17%	14%

Table 4.4 shows the percent of crashes occurring on curves of varying radii. 60% of severe crashes occurred on curves with radii of at least 5,500 feet.

Table 4.4 Curve Radius Summary

		Curve Radius (absolute value)										
Lower Limit (inclusive)		0	100	250	500	750	1,000	1,500	2,000	4,000	5,500	Total
Upper Limit (exclusive)		100	250	500	750	1,000	1,500	2,000	4,000	5,500	∞	
Of All Crashes	Count	45	266	969	1,090	1,407	3,203	2,177	3,422	860	30,489	43,928
	Percent	0%	1%	2%	2%	3%	7%	5%	8%	2%	69%	100%
Of Severe Crashes	Count	4	23	105	97	105	190	117	177	41	1,280	2,139
	Percent	0%	1%	5%	5%	5%	9%	5%	8%	2%	60%	100%

4.3 Data Analysis

Statistical methods were used to further identify relationships within the data. First, two independent samples t-tests and two binary logistic regression models were used to evaluate any significant differences between rural crashes that involve a roadway departure versus those that do not. Then, two maximum likelihood regression models and two multinomial logistic regression models were used to evaluate any significant differences between rural roadway departure crashes that resulted in serious injury versus those that resulted in fatality.

4.3.1 Roadway Departure Crashes versus Non-Roadway Departure Crashes

An independent sample t-test was employed to identify significant differences in the built environment between crashes that result in a roadway departure and those that do not. Results are shown in Table 4.5. For clarification, the table provides a value for "mean difference." This difference in means calculates the absolute difference between the mean value of a variable for roadway departure and non-roadway departure crashes.

$$Mean\ Difference = \frac{\sum x_1}{n} - \frac{\sum x_2}{n}$$

Where:

X_1= Variable Value for Non-Roadway Departure Crashes

X_2= Variable Value for Roadway Departure Crashes

n = Sample Size

If the mean difference is negative, it implies that the mean value for the variable is higher for roadway departure crashes than the variable's mean value for non-roadway departure crashes. The results indicate that work zones and barriers were significantly more prevalent in roadway departure crashes compared to non-roadway departure crashes. Additionally, the results indicate that compared to non-roadway departure crashes, roadway departure crashes occur in locations with more through lanes, narrower lane widths, lower elevations, narrower shoulder widths, and shorter sight distances.

Table 4.5 Built Environment Conditions and Roadway Departure Crashes: t-test

Variable	Significance*	t-statistic	Mean Difference	95% Confidence Interval	
				Lower Bound	Upper Bound
Presence of a Work Zone (y/n)	0.013	-2.212	-0.003	-0.006	0.000
Percent Grade (absolute value)	0.388	0.286	0.007	-0.046	0.062
Curve Radius (ft)	<0.001	-5.657	-3,810.5	-5,130.7	-2,490.3
Presence of Fencing (y/n)	0.101	1.274	0.035	-0.019	0.089
Presence of Barriers (y/n)	<0.001	-29.086	-0.189	-0.22	-0.176
Number of Poles Within 100-ft Radius	0.352	-0.379	-0.005	-0.033	0.022
Cross Slope (%)	0.084	1.381	0.035	-0.0148	0.086
Number of Through Lanes	0.012	-2.269	-0.012	-0.022	-0.002
Through Lane Width (ft)	<0.001	5.072	0.041	0.025	0.057
Number of lanes, including turn lanes	0.442	0.145	0.001	-0.012	0.013
Elevation (ft)	<0.001	8.889	92.509	72.110	112.908
Curve Degree	0.157	1.007	0.048	-0.045	0.142
Shoulder Width (ft)	<0.001	3.785	0.119	0.057	0.181
Sight Distance (ft)	<0.001	32.956	60.921	57.298	64.662
			N=43,928		

*Significant p-values (<0.05) are highlighted in gray

A second independent samples t-test was run to identify significant differences in travel behavior between roadway departure and non-roadway departure crashes in rural areas, and the results are shown in Table 4.6. The test identified that nearly all travel behavior categories were more likely to occur in roadway departure crashes than non-roadway departure crashes in rural areas. Uniquely, crashes involving older drivers were less likely to involve roadway departure. The most impactful travel behavior characteristics were speed involved, drowsy driving, DUI involved, and alcohol suspected. While collision with a fixed object was strongly correlated with roadway departure crashes, this is likely due to the nature of roadway departure crashes which often result in a collision with a fixed object as a part of the crash. All the variables shown below are yes/no (coded 1/0) so the mean values represent an elasticity or directional lean.

Table 4.6 Travel Behavior Characteristics and Roadway Departure Crashes: t-test

Variable	Significance*	t-statistic	Mean Difference	95% Confidence Interval	
				Lower Bound	Upper Bound
Aggressive Driving Involved	<0.001	-9.889	-0.007	-0.008	-0.005
Alcohol Suspected	<0.001	-30.471	-0.049	-0.052	-0.046
Collision with Fixed Object	0.000	-204.64	-0.682	-0.688	-0.675
Commercial Vehicle Involved	<0.001	-4.507	-0.012	-0.017	-0.007
Disregard Traffic Control Device Involved	<0.001	-5.655	-0.003	-0.004	0.002
Distracted Driving Involved	<0.001	-35.922	-0.071	-0.075	-0.067
Drowsy Driving Involved	0.000	-48.006	-0.099	-0.103	-0.095
Drugs Suspected	<0.001	-22.655	-0.026	-0.028	-0.024
DUI Involved	<0.001	-38.183	-0.073	-0.077	-0.068
Older Driver Involved	<0.001	8.178	0.023	0.018	0.029
Teenage Driver Involved	<0.001	-28.077	-0.080	-0.350	-0.36
Speed Involved	0.000	-94.508	-0.343	-0.350	-0.336
Wrong-Way Driving Involved**	<0.001	-4.706	-0.004	-0.005	-0.002
					N=43,928

*Significant *p*-values (<0.05) are highlighted in gray
**Wrong-way driving is only applicable on freeways and divided highways

To further investigate the differences between rural roadway departure crashes and rural crashes not involving roadway departures, a binary logistic regression model was employed to examine the magnitude and sign of correlations between the built/natural environment and travel behavior characteristics and roadway departure crashes. As shown in Table 4.7, several functional classes were significantly negatively correlated with roadway departure crashes. Crashes occurring on other freeways, minor arterials, major collectors, and minor collectors in rural areas were significantly unlikely to involve a roadway departure. Rural roadways with barriers are 35% more likely to exhibit roadway departure crashes, while each additional foot of shoulder width results in a significant decrease (14%) in roadway departure crashes.

Specific land cover types were significantly associated with a reduced likelihood of roadway departure crashes. These include trees (-6%), flooded vegetation (-57%), crops (-23%), scrub/shrub (-65%), and built areas (-23%). Insignificant land cover variables are not shown in the table below, but include water, grass, and bare ground. Lastly, sight distance was significantly associated with the likelihood of roadway departure crashes; each additional foot of sight distance on the roadway resulted in a 1% reduction in the likelihood of a roadway departure crash.

Table 4.7 Environment and Roadway Departure: Binary Logistic Regression

Variable	Unstandardized Coefficients		Standardized Coefficients	Wald	Significance*
	B	Std. Error	Exp(B)		
(Constant)	4.136	0.248	62.568	277.20	<0.001
Functional Class**				232.82	<0.001
Other Freeway	-0.820	0.060	0.440	188.65	<0.001
Minor Arterial	-0.779	0.064	0.459	147.16	<0.001
Major Collector	-0.784	0.068	0.457	132.35	<0.001
Minor Collector	-0.540	0.256	0.583	4.434	0.035
Presence of a Work Zone	0.164	0.084	1.178	3.803	0.051
Percent Grade (absolute value)	-0.006	0.004	0.994	2.855	0.091
Curve Radius (ft)	0.000	0.000	1.000	1.500	0.221
Presence of Fencing	-0.005	0.004	0.995	1.500	0.221
Presence of Barriers	0.299	0.019	1.349	253.55	<0.001
Number of Poles within 100-ft Radius	-0.012	0.007	0.988	2.707	0.100
Cross Slope (%)	-0.001	0.004	0.999	0.034	0.854
Number of Through Lanes	0.011	0.048	1.011	0.055	0.815
Through Lane Width (ft)	-0.022	0.014	0.978	2.598	0.107
Number of lanes, including turn lanes	0.047	0.037	1.049	1.624	0.203
Elevation (ft)	0.000	0.000	1.000	175.65	<0.001
Curve Degree	-0.001	0.002	0.999	0.174	0.676

Shoulder Width (ft)	-0.036	0.004	0.965	73.926	<0.001
Land Cover**				525.65	<0.001
Trees	-0.785	0.165	0.943	22.635	<0.001
Flooded Vegetation	-0.841	0.122	0.431	47.267	<0.001
Crops	-0.394	0.118	0.674	11.070	<0.001
Scrub/Shrub	-1.039	0.122	0.354	72.388	<0.001
Built Area	-0.265	0.134	0.767	3.930	0.047
Sight Distance (ft)	-0.002	0.000	0.998	927.61	<0.001
	X^2=1,985 (0.000)				N=43,928

*Significant *p*-values (<0.05) are highlighted in gray
**Functional Class and Land Cover values are shown if significant ($p < 0.05$)

Next, travel behavior characteristics were correlated to the likelihood of a crash involving roadway departure. Using a binary logistic regression model and as shown in Table 4.8, analysis found that rural crashes involving several travel behavior characteristics were correlated to a significant increase in the likelihood of a roadway departure. These include alcohol suspected (96%), collision with a fixed object (2,700%), commercial vehicle involved (34%), distracted driving involved (763%), drowsy driving involved (2,053%), drugs suspected (259%), DUI involved (531%), teen driver involved (85%), speed involved (733%), and wrong-way driving involved (45%).

Table 4.8 Travel Behavior and Roadway Departure: Binary Logistic Regression

Variable	Unstandardized Coefficients		Standardized Coefficients	Wald	Significance*
	B	Std. Error	Exp(B)		
(Constant)	-2.251	0.023	0.105	9,742.4	0.000
Aggressive Driving Involved	0.136	0.215	1.145	0.398	0.528
Alcohol Suspected	0.677	0.128	1.969	28.011	<0.001
Collision with Fixed Object	3.305	0.032	27.262	10703	0.000
Commercial Vehicle Involved	0.293	0.051	1.340	32.894	<0.001
Disregard Traffic Control Device Involved	0.023	0.233	1.024	0.010	0.920
Distracted Driving Involved	2.033	0.075	7.635	739.05	<0.001
Drowsy Driving Involved	3.022	0.090	20.533	1,123.9	<0.001
Drugs Suspected	0.953	0.163	2.593	33.987	<0.001
DUI Involved	1.671	0.116	5.316	209.10	<0.001
Older Driver Involved	0.063	0.050	1.065	1.634	0.201
Teenage Driver Involved	0.615	0.049	1.850	156.02	<0.001
Speed Involved	1.993	0.037	7.337	2,834.7	0.000
Wrong-Way Driving Involved**	0.374	0.165	1.453	5.138	0.023
	X^2=29,755 (0.000)				N=43,928

*Significant *p*-values (<0.05) are highlighted in gray
**Wrong-way driving is only applicable on freeways and divided highways

4.3.2 Crash Severity

A series of maximum likelihood (ML) regression models were used to evaluate the relationship between crash severity and characteristics of driver behavior and the built environment for all roadway departure crashes that occurred in rural areas. For both models, an elasticity was employed to represent crash severity based on each increased level of suspected injury. Low values (1-3) indicate no injury and higher values indicate suspected serious injury or fatality (4-5) based on the KABCO severity scale.

The first ML model, shown in Table 4.9, evaluated negative driver behaviors and crash severity. According to the model, all negative driver behaviors were significantly associated with an increase in crash severity. These behaviors included: aggressive driving, alcohol suspected, disregard for traffic control device, distracted driving, drowsy driving, drugs suspected, DUI, speeding, and wrong-way driving. Additionally, rural crashes involving a teen driver or older driver and those involving commercial vehicles were correlated to a more severe injury outcome. The driver behaviors with the greatest increase in crash severity were drowsy driving, DUI involved, and wrong-way driving.

Table 4.9 Driver Behaviors and Crash Severity

Variable	Unstandardized Coefficients		Standardized Coefficients	t-statistic	Significance*	95% Confidence Interval for B	
	B	Std. Error	B			Lower Bound	Upper Bound
(Constant)	1.265	0.006		215.487	0.000	1.253	1.276
Aggressive Driving Involved	0.471	0.059	0.037	7.991	<0.001	0.356	0.587
Alcohol Suspected	0.155	0.032	0.029	4.826	<0.001	0.092	0.219
Collision with Fixed Object	0.124	0.010	0.066	13.040	<0.001	0.105	0.143
Commercial Vehicle Involved	0.058	0.015	0.017	3.801	<0.001	0.028	0.088
Disregard Traffic Control Device Involved	0.190	0.070	0.012	2.718	0.007	0.053	0.326
Distracted Driving Involved	0.272	0.020	0.063	13.658	<0.001	0.233	0.311
Drowsy Driving Involved	0.467	0.019	0.113	24.298	<0.001	0.430	0.505
Drugs Suspected	0.307	0.038	0.041	8.067	<0.001	0.233	0.382
DUI Involved	0.824	0.029	0.183	28.183	<0.001	0.767	0.881

Older Driver Involved	0.164	0.014	0.054	11.770	<0.001	0.137	0.192
Teenage Driver Involved	0.049	0.014	0.016	3.498	<0.001	0.021	0.076
Speed Involved	0.141	0.011	0.065	13.022	<0.001	0.120	0.162
Wrong-Way Driving Involved**	1.023	0.051	0.090	19.885	<0.001	0.922	1.124
							N=43,928

*Significant *p*-values (<0.05) are highlighted in gray
**Wrong-way driving is only applicable on freeways and divided highways

The second ML model evaluated the relationship between rural roadway departure crash severity and the built and natural environment around the crash site. As shown in Table 4.9, as the capacity of the roadway decreases, the severity of crashes significantly increases. Additionally, rural roadway departure crashes occurring in work zones or areas with a larger curve radius are significantly more severe. Areas with fencing, barriers, more through lanes, wider through lanes, wider shoulders, and larger sight distance were significantly correlated with a decrease in crash severity.

Table 4.10 Built Environment Characteristics and Crash Severity

Variable	Unstandardized Coefficients		Standardized Coefficients	t-statistic	Significance*	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	1.382	0.012		114.76	0.000	1.358	1.405
Functional Class	0.025	0.003	0.035	7.320	<0.001	0.018	0.031
Presence of a Work Zone	0.160	0.036	0.023	4.475	<0.001	0.090	0.230
Percent Grade (absolute value)	0.002	0.002	0.005	1.004	0.315	-0.001	0.004
Curve Radius (ft)	1.21 5E-7	0.000	0.00	1.971	0.049	0.000	0.000
Presence of Fencing	-0.003	0.002	-0.010	-1.993	0.046	-0.006	0.000
Presence of Barriers	-0.016	0.006	-0.012	-2.491	0.013	-0.028	-0.003
Number of Poles Within 100-ft Radius	0.004	0.003	0.006	1.244	0.214	-0.002	0.009
Cross Slope (%)	0.001	0.002	0.003	0.532	0.595	-0.002	0.004
Number of Through Lanes	-0.069	0.019	-0.040	-3.563	<0.001	-0.107	-0.031
Through Lane Width (ft)	-0.038	0.005	-0.036	-7.476	<0.001	-0.048	-0.028

Number of lanes, including turn lanes	-0.015	0.016	-0.011	-0.968	0.333	-0.045	0.015
Elevation (ft)	1.471E-6	0.00	0.002	0.369	0.712	0.000	0.000
Curve Degree	-7.31 2E-5	0.001	0.000	-0.079	0.937	-0.002	0.002
Shoulder Width (ft)	-0.015	0.001	-0.052	-9.995	<0.001	-0.018	-0.012
Sight Distance (ft)	0.000	0.000	-0.059	-11.271	<0.001	0.000	0.000
							N=43,928

*Significant *p*-values (<0.05) are highlighted in gray

Next, a multinomial logistic regression (MNL) model was utilized to identify the relationship between weather and crash severity. As shown in Table 4.11, crashes resulting in suspected serious injuries are more likely than "no injury" crashes to occur in clear or cloudy weather, rain/sleet/snow, or severe crosswinds. Crashes involving a fatal crash were not significantly correlated to weather conditions.

Table 4.11 Weather and Crash Severity: Suspected Serious and Fatal Crashes

Severity/Weather*	Unstandardized Coefficients		Significance**	Exp B	95% Confidence Interval for B	
	B	Std. Error			Lower Bound	Upper Bound
Suspected Serious Crash	-3.531	0.383	<0.001			
Clear	0.817	0.276	0.003	2.264	1.319	3.886
Cloudy	0.998	0.278	<0.001	2.713	1.574	4.675
Severe Crosswinds	1.461	0.352	<0.001	4.309	2.162	8.588
Blowing Sand	0.891	0.676	0.187	2.439	0.649	9.169
Rain	0.805	0.286	0.005	2.236	1.277	3.916
Sleet / Hail	1.250	0.330	<0.001	3.492	1.828	6.671
Snowing	0.551	0.280	0.049	1.734	1.001	3.003
Blowing Snow	0.453	0.339	0.181	1.572	0.810	3.053
Fog, Smog	0.502	0.358	0.160	1.652	0.820	3.329
Other	-17.145	0.000	.	3.583E-8	3.583E-8	3.583E-8
Fatal Crashes	-2.341	0.218	<0.001			
Clear	0.534	0.385	0.165	1.706	0.803	3.626
Cloudy	0.700	0.388	0.071	2.014	0.941	4.313
Severe Crosswinds	0.688	0.569	0.227	1.989	0.652	6.063
Blowing Sand	1.179	0.833	0.157	3.252	0.635	16.655
Rain	0.272	0.408	0.505	1.312	0.590	2.918
Sleet / Hail	0.925	0.479	0.054	2.522	0.986	6.451
Snowing	-0.328	0.400	0.413	0.721	0.329	1.578
Blowing Snow	-0.395	0.563	0.483	0.674	0.224	2.032
Fog, Smog	0.453	0.502	0.366	1.573	0.589	4.206
Other	2.144	1.182	0.070	8.536	0.842	86.563
						N=43,928

*Reference Category is "no injury" crashes
**Significant *p*-values (<0.05) are highlighted in gray

A second MNL model was utilized to identify the relationship between lighting and crash severity. Table 4.11 shows the regression coefficients for the model. Crashes resulting in a suspected serious injury were significantly more likely than non-injury crashes to happen during other "lighting" conditions. On the other hand, crashes resulting in a fatality were significantly more likely than non-injury crashes to occur in all lighting conditions.

Table 4.12. Lighting Condition and Crash Severity: Suspected Serious and Fatal Crashes

Severity/Light Condition*	Unstandardized Coefficients		Significance**	Exp B	95% Confidence Interval for B	
	B	Std. Error			Lower Bound	Upper Bound
Suspected Serious Crash	-3.374	0.723	<0.001			
Daylight	0.819	0.724	0.258	2.269	0.549	9.372
Dawn	-0.238	0.744	0.749	0.788	0.183	3.386
Dusk	0.186	0.740	0.801	1.205	0.282	5.137
Dark-Lighted	-0.460	0.761	0.546	0.631	0.142	2.807
Dark-Not Lighted	-0.171	0.725	0.813	0.843	0.204	3.488
Dark- Unknown	-0.515	0.863	0.551	0.598	0.110	3.246
Other	-20.736	0.000	0.000	9.870E-10	9.870E-10	9.870E-10
Fatal Crashes	0.411	0.170	0.016			
Daylight	-4.034	0.177	<0.001	0.018	0.013	0.025
Dawn	-5.245	0.361	<0.001	0.005	0.003	0.011
Dusk	-4.446	0.292	<0.001	0.012	0.007	0.021
Dark-Lighted	-5.490	0.472	<0.001	0.004	0.002	0.010
Dark-Not Lighted	-4.894	0.187	<0.001	0.007	0.005	0.011
Dark- Unknown	-4.458	0.538	<0.001	0.012	0.004	0.033
Other	-24.857	0.000	0.000	1.603E-11	1.603E-11	1.603E-11
						N=43,928

*Reference Category is "no injury" crashes
**Significant *p*-values (<0.05) are highlighted in gray

4.4 Summary

This chapter provided an overview of data analysis and preliminary findings. Summary crash and roadway statistics are described, followed by results from maximum likelihood regression and multinomial logistic regression models which were used to evaluate any significant differences between rural roadway departure crashes that resulted in serious injury versus those that resulted in fatality. Roadway departure crashes occur in locations with more through lanes, narrower lane widths, lower elevations, narrower shoulder widths, and shorter sight distances. Crashes involving older drivers were less likely to involve roadway departure. The most impactful travel behavior characteristics were speed involved, drowsy driving, DUI involved, and alcohol suspected. Rural roadways with barriers are 35% more likely to exhibit roadway departure crashes, while each additional foot of shoulder width results in a significant decrease (14%) in roadway departure crashes.

An evaluation of crash severity determined that rural crashes involving a teen driver or older driver and those involving commercial vehicles were correlated to a more severe injury outcome. The driver behaviors with the greatest increase in crash severity were drowsy driving, DUI involved, and wrong-way driving, and as the capacity of the roadway decreases, the severity of crashes significantly increases. Areas with fencing, barriers, more through lanes, wider through lanes, wider shoulders, and larger sight distance were significantly correlated with a decrease in crash severity.

5.0 CONCLUSIONS

5.1 Summary

Knowledge about the specific characteristic of rural roadway departure crashes helps UDOT to develop proper mitigation strategies. This research was performed with the goal of investigating characteristics associated with rural roadway departure crashes to identify action steps to reduce roadway departure fatalities.

5.2 Findings

We examined a dataset of 43,928 rural crashes including 19,489 roadway departure crashes and 2,139 severe crashes. Several characteristics were examined for each crash. These were broken down into three categories: travel behavior characteristics, natural and built environment characteristics, and an evaluation of crash severity. The findings from each category are described and discussed below.

5.2.1 Travel Behavior

Nearly all travel behavior categories included in this analysis were more likely to occur in roadway departure crashes than non-roadway departure crashes in rural areas. This confirms the hypothesis that negative travel behaviors are common contributors or are associated with roadway departure crashes. While many researchers or policy makers assume that older drivers have higher risks of crashes, in this analysis crashes involving older drivers were less likely to involve roadway departure. Advanced statistical models confirmed that several travel behavior characteristics were correlated to a significant increase in the likelihood of a roadway departure. These include collision with a fixed object (2,700%), drowsy driving involved (2,053%), distracted driving involved (763%), speed involved (733%), DUI involved (531%), drugs suspected (259%), alcohol suspected (96%), teen driver involved (85%), wrong-way driving involved (45%), and commercial vehicle involved (34%).

While collision with a fixed object was strongly correlated with roadway departure crashes, this is likely due to the nature of roadway departure crashes which often result in a collision with a fixed object as a part of the crash. It is unlikely that the fixed object caused the crash, but rather the fixed object was involved after the roadway departure (See Figure 5.1).

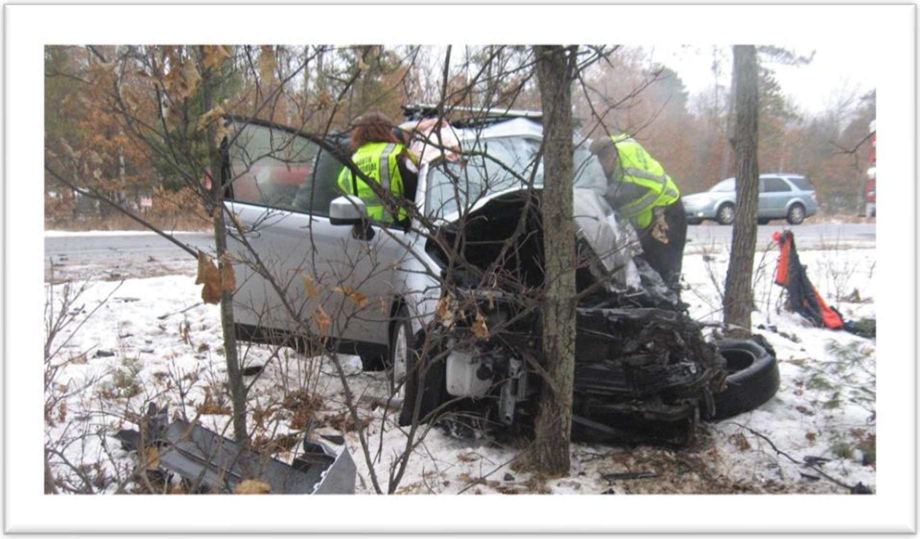

Figure 5.1 Collision with a Fixed Object After Roadway Departure (Source: www.pewtrusts.org)

Based on the analysis results, poor personal decisions contributed significantly to the likelihood of a roadway departure crash. Behaviors such as alcohol suspected, distracted driving, drowsy driving, drugs suspected, DUI involved, speed involved, and wrong-way driving can all be addressed using education. Additionally, commercial vehicles and teen drivers could provide opportunities for education to those specific groups.

5.2.2 Natural and Built Environment

An examination of natural and built environment characteristics found that work zones and barriers are more prevalent in roadway departure crashes. In fact, rural roadways with barriers are 35% more likely to exhibit roadway departure crashes. This could be because areas without barriers can provide a runoff area for vehicles that leave the roadway as shown in Figure 5.2 below. This would allow them to slow to a stop without crashing. While the Federal

Highway Administration (2015) states that “the purpose of a guardrail is first and foremost, a safety barrier intended to shield a motorist who has left the roadway,” these barriers can also create a scenario where a vehicle is forced into oncoming traffic. For example, if a vehicle is losing control and is headed for the barrier, they may swerve or overcorrect into oncoming traffic to avoid a barrier on the right shoulder resulting in a head- on type crash, or crash with the barrier on the opposite side (Figure 5.3). However, areas with fencing and barriers were significantly correlated with a decrease in crash severity. Therefore, barriers and guardrails should only be used in areas where the area adjacent to the barrier would create a greater risk if the driver were to depart the roadway (e.g., steep slope, forested area, large boulders, buildings, etc.). This lines up with the UDOT Roadway Design Manual which states “Use barrier to shield existing and proposed obstacles when the preferred mitigations described in AASHTO [Roadside Design Guide] Section 1-2 have been explored and determined infeasible.” Section 1-2 of the AASHTO RDG lists those preferred strategies, stating that “Design options for reducing roadside obstacles, in order of preference, are as follows:

- Remove the obstacle.
- Redesign the obstacle so it can be safely traversed.
- Relocate the obstacle to a point where it is less likely to be struck.
- Reduce impact severity by using an appropriate breakaway device.
- Shield the design obstacle with a longitudinal traffic barrier designed for redirection or use a crash cushion.
- Delineate the obstacle if the previous alternatives are not appropriate.”

It can be expensive for a DOT to provide clear zones sufficiently wide to address roadway departure crashes. The DOT must weigh the benefits and costs of the options discussed in the UDOT Roadway Design Manual and AASHTO Roadway Design Guide, including providing a wider clear zone, redesigning obstacles, and implementing barriers.

Figure 5.2. Rural Roadway with No Barrier (Source: FHWA, 2023)

Figure 5.3. Rural Roadway with Barrier (Source: Ayres Associates, 2021)

Results of the statistical tests showed that compared to non-roadway departure crashes, roadway departure crashes occur in locations with more through lanes, narrower lane widths, lower elevations, narrower shoulder widths, and shorter sight distances. The results pertaining to shoulder width are of particular note—each additional foot of shoulder width results in a significant decrease (14%) in roadway departure crashes. As described previously, additional traversable area on the roadside provides a runoff area for vehicles to slow to a stop without hazards. The results related to sight distance are also worth a further mention—each additional foot of sight distance on the roadway resulted in a 14% reduction in the likelihood of a roadway departure crash and a reduction in crash severity because drivers have additional distance/time to react to oncoming hazards.

Specific land cover types were significantly associated with a reduced likelihood of roadway departure crashes. These include trees (-6%), flooded vegetation (-57%), crops (-23%), scrub/shrub (-65%), and built areas (-23%). The reason for this is similar to the discussion above. Areas with flatter vegetation types (Figure 5.4) provide space for vehicles in cases where a vehicle departs the roadway. These likely include areas such as scrub/shrub (shown below) or crop-covered areas (e.g., corn fields, etc.).

Figure 5.4. Rural Roadway near Scrub/Shrub Landcover (Source: www.PXhere.com)

Built areas and areas with tree cover also show a reduction in the likelihood of experiencing roadway departure crashes. Existing research has shown that urban areas benefit from such roadside conditions because “buildings and trees that are adjacent to the sidewalk (or roadway) create a “street wall’’ that frames the street and narrows the driver’s field of vision” (Burden, 1996). A similar effect might be happening in rural areas where the presence of roadside trees or small towns narrows a driver’s field of view. It is possible the narrower field of view caused by roadside trees leads drivers to feel the crash risk is higher and change their behaviors to try to compensate for the inferred higher crash risk. However, this conclusion is in direct contrast to other conclusions that the research presented in this study has found, specifically that shorter sight distances and narrower roadside clear zones are both correlated with higher numbers of roadway departure crashes. The reason for this contradiction in results is unclear and would be a good candidate for further research. Likewise, the correlation between built areas and fewer roadway departure crashes may be due to the effect of a narrower field of view, but there may be other factors at play. For example, the presence of a developed area, no matter how rural, may suggest to drivers that additional safety hazards could be present (e.g., pedestrians, vehicles turning on or off the road, livestock or pets) or that the likelihood of police enforcement of factors such as speed or distraction may be higher than in undeveloped areas.

5.2.3 Crash Severity

Lastly, an evaluation of severe crashes found that more severe crashes are happening on roadways with fewer through lanes. More specifically, as the capacity of the roadway decreases, the severity of crashes significantly increases. This could be a direct result of rural areas having limited funds for investment and improvements on local roads.

Additionally, speed and other negative travel behaviors can be an issue on rural roadways with lower volumes and fewer vehicles as discussed previously. All negative driver behaviors were significantly associated with an increase in crash severity. These behaviors included: aggressive driving, alcohol suspected, disregard for traffic control device, distracted driving, drowsy driving, drugs suspected, DUI, speeding, and wrong-way driving. Similarly, rural crashes involving a teen driver or older driver and those involving commercial vehicles were correlated to a more severe injury outcome. The driver behaviors with the greatest increase in crash severity were drowsy driving, DUI involved, and wrong-way driving.

Some characteristics of rural roadway departure crashes are correlated with more severe outcomes. Data has shown that work zone crashes are on the rise (see Figure 5.5) and that crashes occurring in work zones are often more severe than non-work zone crashes. This is because not only is there a larger presence of barricades and hazards in work zone areas, but there is also a higher likelihood of pedestrians/workers in the roadway who are vulnerable to more serious injuries when involved in a crash (National Work Zone Safety, 2020).

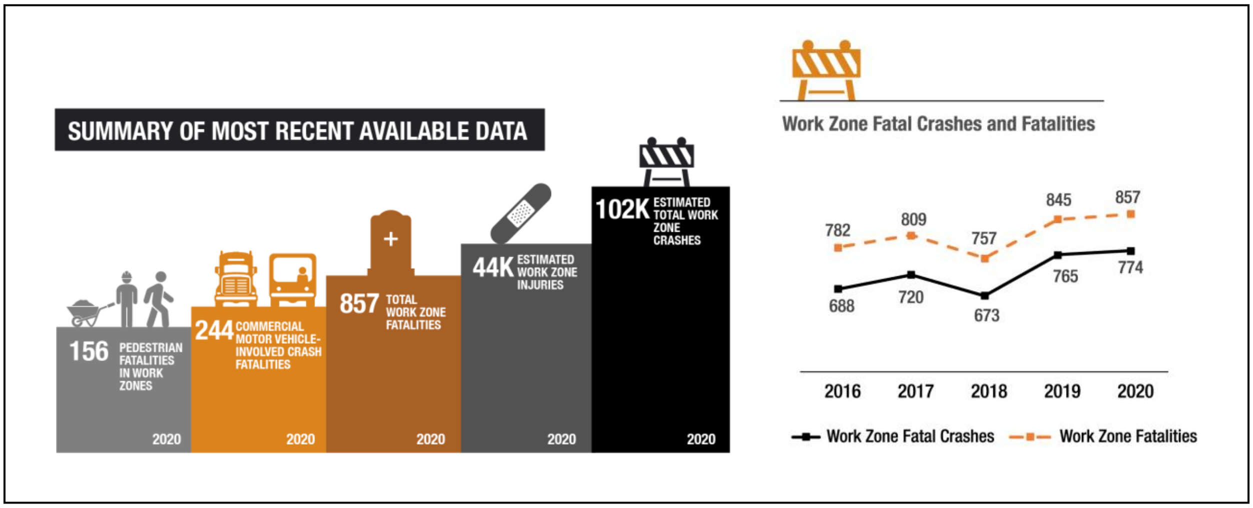

Figure 5.5. Work Zone Crash Statistics (Source: www.workzonesafety.org)

5.3 Limitations and Challenges

There were several limitations and challenges within this study. First, we were unable to determine from the data which direction vehicles were traveling. This limited our ability to identify if vehicles were traveling down or upgrade, as well as identifying which direction the roadway turned for crashes that occurred on a curve.

Next, the sight distance variable used in the analysis is questionable and not necessarily accurate. Sight distance was only provided in the database if the location was within a passing zone. Because of this we only know sight distance for locations where passing is permitted. This likely limits areas with poor sight distance artificially skewing the analysis.

Lastly, we were unable to acquire reliable data on side slope (the slope beyond the shoulder). There was data available for a sample of locations, but it was not deemed to be reliable enough to analyze. Likewise, we are unable to identify data for clear zones. Data on these variables would have increased the robustness of the analysis and provided additional insight into the contributing circumstances to roadway departure crashes.

6.0 RECOMMENDATIONS AND IMPLEMENTATION

6.1 Recommendations

Based on the research provided above, the following recommendations have been identified:

- Identify appropriate educational opportunities for high-risk travel behaviors, including drowsy driving, DUI involved, and wrong-way driving.

- Identify appropriate locations for barriers and guardrail with particular consideration for locations where the area adjacent to the barrier would create a greater risk if the driver were to depart the roadway (e.g., steep slope, forested area, large boulders, buildings, etc.).

- Identify opportunities to expand shoulder widths where possible.

- Work with rural jurisdictions to identify smaller, lower volume rural roadways that could use additional funding for improvements.

6.2 Implementation Plan

To be identified by the Project Champion.

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APPENDIX A: Roadway Data Sources

This appendix lists the roadway data file names and their source links.

Dataset Name: AADT Rounded

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::aadt-rounded/about

Date Accessed: January 20, 2022

Dataset Name: Barriers

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::barriers/about

Date Accessed: January 24, 2022

Dataset Name: Barriers (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::barriers-2017/about

Date Accessed: August 1, 2022

Dataset Name: Curves

Owner: UDOT

Source: Obtained directly from UDOT Highway Performance Monitoring System (HPMS) personnel

Date Accessed: August 1, 2022

Dataset Name: Esri 2020 Land Cover

Owner: Esri

Source URL:https://www.arcgis.com/home/item.html?id=d6642f8a4f6d4685a24ae2dc0c73d4ac

Date Accessed: January 20, 2022

Attribution: This dataset is based on the dataset produced for the Dynamic World Project by National Geographic Society in partnership with Google and the World Resources Institute.

Dataset Name: Fencing Inventory OMS

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::fencing-inventory-oms/about

Date Accessed: January 21, 2022

Dataset Name: Intersections

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::intersections/about

Date Accessed: January 24, 2022

Dataset Name: Lanes

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::lanes/about

Date Accessed: January 24, 2022

Dataset Name: Lanes (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::lanes-2017/about

Date Accessed: August 1, 2022

Dataset Name: Pavement Striping

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::pavement-striping/about

Date Accessed: January 24, 2022

Dataset Name: Pavement Striping (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::pavement-striping-2017/about

Date Accessed: August 1, 2022

Dataset Name: Roadway Utilities

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::roadway-utilities/about

Date Accessed: January 24, 2022

Dataset Name: Roadway Utilities (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::roadway-utilities-2017/about

Date Accessed: August 1, 2022

Dataset Name: Route Elevations

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::route-elevations/about

Date Accessed: January 24, 2022

Note: This file appears to no longer exist. Date of removal is unknown.

Dataset Name: Route Grades

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::route-grades-1/about

Date Accessed: January 20, 2022

Dataset Name: Rumble Strips

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::rumble-strips/about

Date Accessed: January 20, 2022

Dataset Name: Rumblestrips (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::rumblestrips-2017/about

Date Accessed: August 1, 2022

Dataset Name: Shoulders

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::shoulders/about

Date Accessed: January 20, 2022

Dataset Name: Shoulders (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::shoulders-2017/about

Date Accessed: August 1, 2022

Dataset Name: Sign Faces

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::sign-faces/about

Date Accessed: January 20, 2022

Dataset Name: Sign Faces (2017)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::sign-faces-2017/about

Date Accessed: August 1, 2022

Dataset Name: UDOT Speed Limits (2019)

Owner: UDOT

Source URL: https://data-uplan.opendata.arcgis.com/datasets/uplan::udot-speed-limits-2019-1/about

Date Accessed: January 21, 2022

Note: This file was the most recent UDOT Speed Limits file when accessed. On September 21, 2022 it was replaced by an updated file called UDOT Speed Limits (2021) which can be accessed at https://data-uplan.opendata.arcgis.com/datasets/uplan::udot-speed-limits-2021/about