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Original Research Paper

Factors associated with crash severities in built-up areas along rural highways of Nevada: A case study of 11 towns

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HIGHLIGHTS

- The study found that speeding was a major factor associated with injury crashes in built-up areas of rural highways.
- The crashes that occurred during midnight until 4 a.m. were found to be more injury crashes than the property damage crashes.
- The likelihood of occurring injury crashes on weekdays are three times more than that of weekends.

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ABSTRACT

In 2014, 32,675 deaths were recorded in vehicle crashes within the United States. Out of these, 51% of the fatalities occurred in rural highways compared to 49% in urban highways. No specific crash data are available for the built-up areas along rural highways. Due to high fatalities in rural highways, it is important to identify the factors that cause the vehicle crashes. The main objective of this study is to determine the factors associated with severities of crashes that occurred in built-up areas along the rural highways of Nevada. Those factors could aid in making informed decisions while setting up speed zones in these built-up areas. Using descriptive statistics and binary logistic regression model, 337 crashes that occurred in 11 towns along the rural highways from 2002 to 2010 were analyzed. The results showed that more crashes occurred during favorable driving conditions, e.g., 87% crashes on dry roads and 70% crashes in clear weather. The binary logistic regression model showed that crashes occurred from midnight until 4 a.m. were 58.3% likely to be injury crashes rather than property damage only crashes, when other factors were kept at their mean values. Crashes on weekdays were three times more likely to be injury crashes than that occurred on weekends. When other factors were kept at their mean value, crashes involving motorcycles had an 80.2% probability of being injury crashes. Speeding was found to be 17 times more responsible for injury crashes than mechanical defects of

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the vehicle. As a result of this study, the Nevada Department of Transportation now can take various steps to improve public safety, including steps to reduce speeding and encourage the use of helmets for motorcycle riders.

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1. Introduction

Half a century back, the number of traffic fatalities in United States (U.S.) was increasing rapidly (NHTSA, 2012). However, the number of such fatalities has been decreasing since 2005. In 2014, the number of fatalities was 32,675 compared to 43,510 in 2005 (IIHS, 2016). During this period, the fatality rate also decreased from 14.7 to 10.2 per 100,000. In Nevada, the number of fatalities had been decreasing from 2006 to 2014. In 2006, the total number of motor vehicle crash deaths was 432, yielding a fatality rate of 17.3. However, in 2014, the number of motor vehicle crash deaths was 290, yielding the fatality rate of 10.2. Despite the decrease, the number of fatal crashes per 100 million vehicle miles traveled (VMT) in Nevada still was higher than the national average in 2014 (1.15 versus 1.08).

In 2010, 51,664 crashes occurred in Nevada. Out of those crashes, property damage only (PDO), injury, and fatal crashes were 63.40%, 36.15%, and 0.45% respectively (Nevada Department of Transportation (2012)). Among all these categories of crashes that occurred in Nevada, 10% of PDO crashes, 8% of injury crashes, and 41% of fatal crashes occurred in rural areas of the state. While fewer crashes occurred in the rural areas, much higher portion of fatal crashes occurred in the rural areas. In 2014, about 31% of fatal crashes occurred in rural areas of the state. In the national context, 49% and 51% of the fatalities occurred in urban and rural areas, respectively (IIHS, 2016). Since people are traveling 1.8 times more in urban roads than rural roads, this higher number of fatalities in the rural roads is alarming (NHTSA, 2016). All these statistics about the crashes in rural areas occurred along the entire section of the rural highways. No study had been conducted to identify the number of crashes and factors affecting the crashes in built-up areas of rural highways. In order to decrease more severe crashes in these built-up areas along rural highways, factors associated with severe crashes in built-up areas should be identified.

Many studies conducted to identify the factors affecting the crash severities focus on the geometric factors, such as lane width, number of lanes, and the presence of a median and personal factors, such as age, sex, disability, and alcohol usage (Evans and Wasielewski, 1983; Jonah, 1986; Lee and Mannering, 2002; NHTSA, 2015a, b). However, in this study, the geometrics of the road sections in built-up areas along rural highways were not considered, because all the built-up areas along these rural highways had similar road geometrics. Also, the data related to drivers who were involved in the crashes were not collected. Therefore, factors such as weather, lighting, vehicle action, time, day, month, vehicle factor, and vehicle speed were analyzed for their association with crashes. One of the major reasons for not collecting the characteristics of the person involved in crashes and the road geometric was that this research aimed to investigate crashes within a certain number of miles of each town along rural highways in order to determine whether speed limits along the town played a role in the crashes. This crash analysis was a part of research conducted for Nevada Department of Transportation (NDOT) to prepare the speed limit guidelines for built-up areas along the state's rural highways (Shrestha and Shrestha, 2016). Identification of these factors, along with curtailing speeding, is expected to aid decision makers at NDOT to prepare speed limit guidelines to reduce crashes in towns along rural highways. It will help NDOT head towards their “zero fatality” goals (Nevada Department of Transportation (2015)).

In reviewing some of the studies conducted to identify various factors affecting crash severities, the focus mostly was on factors related to weather, lightning conditions, vehicle actions, the number of vehicles involved, timing, the drivers' conditions, and vehicle speed.

Xie et al. (2012) analyzed severities of crashes (no injury, possible injury, non-incapacitating injury, and fatal injury) involving a single-vehicle. The study found that 31 out of 53 predictor variables have significant correlations with crash severities. Some of the factors found to be significant were those under investigation in this study, e.g., lighting condition, speed, and the first and second harmful events. Similarly, Chen et al. (2012) analyzed the effect of various driver characteristics, vehicle features, environmental and road factors, and crash characteristics on the severity of intersection crashes (fatal or non-fatal). The study found that speed zone, time of crash, and crash type all have a significant effect on the severity of intersection crashes.

Chang and Wang (2006) studied crash data to analyze the relationship between crash severities and various temporal characteristics (e.g., time of crash) and highway/environmental characteristics (e.g., lighting condition or speed limit). The study could not find any relationship between these factors and the severity of crash injuries. Li et al. (2012) analyzed the crash data from freeways diverge areas in Florida to analyze the factors affecting crash severities in five levels – no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. The study used 37 explanatory variables, e.g., speed, light condition, weather, road surface, and crash type. They found that the freeway pavement surface conditions, lighting conditions, weather conditions, and alcohol/drug involvement significantly affected the crash severities.

Tefft (2016) compiled the data of vehicle crashes, injuries, and deaths in relation to weather conditions in the U.S. The data used were obtained from databases of the National Highway Traffic Safety Administration, the National Automotive Sampling System, the General Estimates System, and the Fatality Analysis Reporting System. From data of 2010–2014, it was found that 5137 deaths occurred annually due to adverse weather conditions, representing about 15.6% of the total crash fatalities. It was found that the crashes that occurred in adverse weather conditions were less likely to result in injuries or fatalities than crashes that occurred in clear weather. The study showed that crashes that occurred on ice-covered roads resulted in 29% fewer fatalities than crashes that occurred on dry roads. Eisenberg and Warner (2005) found that there were significantly lower numbers of fatal crashes during snowfall than during dry weather; however, there were significantly more nonfatal-injury crashes and PDO crashes.

Numerous studies were conducted to correlate crash fatalities and the speed of the vehicles. Elvik et al. (2004) stated that speed was one of the most important factors causing injury crashes. Another study showed that the crash rate increased as the speed of the vehicle increased (Aarts and Schagen, 2006; SWOV, 2016). Similarly, crash severity increased as the speed of the vehicle increased. Aarts and Schagen (2006) reviewed studies conducted to determine the relationship between speed and the risk of road crashes. They showed that most of the studies did find a correlation between speed and the risk and severity of the road crashes.

Kockelman et al. (2006) found that there was a significant relationship between an increase in the speed limit and total crash rates. The study found that an increase of the speed limit from 55 to 65 mph (88.5–104.6 kmph) increased the crash rates by around 3% and fatalities by 28%. However, the increase in speed from 65 to 75 mph (104.6–120.7 kmph) increased the crash rates and fatality only by 0.64% and 13%, respectively. Friedman et al. (2009) conducted a study on the long-term effects of repealing the national maximum speed limit in the U.S. The authors found that the fatality rate increased by 3.2% in all types of roads. However, when the fatalities were categorized based on the interstate types, it was found that the increase in fatalities in rural highways (9.1%) was higher when compared to urban interstates (4%). Therefore, their study showed that increased speed had a greater effect on rural highways in terms of crash fatalities.

National Highway Traffic Safety Administration, U.S. Department of Transportation (2015b) found that in 2013, about 10% of the total crashes occurred due to distraction. Out of those crashes, about 14% occurred due to the use of cell phones. In the same year, 3154 fatalities occurred due to the driver distraction. This distraction-related factor is believed to cause an increase in fatalities during vehicle crashes. In addition to this, 9967 people died in alcohol-impaired-driving crashes in 2014. Out of this number, 64% were the drivers, 28% were the motor vehicle occupants, and 8% were non-occupants.

Zha et al. (2016) has conducted a study to compare the Poisson inverse Gaussian (PIG) model and negative binomial (NB) model in analyzing motor vehicle crash data. The authors used 4253 vehicle crash data of Texas and 5737 crash data of Indiana rural interstate highways to determine which model has better performance in terms of goodness-of-fit, distributions of varying dispersion parameters, crash variance–mean relationship, and accuracy of prediction. This study used six geometric explanatory variables, i.e., annual average daily traffic (AADT), lane width, shoulder width, curve density, segment length, and median width, to determine the correlation with motor vehicle crashes in the rural interstate highways. The authors concluded that "the PIG model provided slightly better statistical fit than the NB model and almost the same prediction performance as the NB model."

Thus, many studies have analyzed and found multiple factors associated with the crashes. It is important to analyze crash data of built-up areas along rural highways to identify the factors that are significantly associated with the crashes in those locations of Nevada. These findings will help NDOT traffic engineers to prepare the guidelines for speed limit in these built-up areas along the rural highways.

2. Methods

This study reviews existing literature about factors affecting the crash severities. The literature review includes national (USA) as well as international studies that analyze various factors to evaluate its effect on the crash severities. Crash data is collected from NDOT. First, descriptive statistics is used to analyze the data. The data is further used to develop binary logistic regression (BLR) model to analyze the factors that affect crash severities in built-up areas along rural highways in Nevada. The results of the model are then presented.

2.1. *Data source and data cleaning*

In order to analyze crash data, 11 towns along rural highways of Nevada were identified by NDOT – technical advisory panel (TAP). The towns under study are Alamo (US 93), Austin (US 50), Beatty (US 95), Fernley (US 50A), Goldfield (US 95), Luning (US 95), McGill (US 93), Panaca (SR 319), Schurz (US 95/US 95A), Searchlight (US 95), and Tonopah (US 95/US 6). Crash data from April 2001 to April 2011 were obtained from the Nevada citation and accident tracking system (NCATS) used by NDOT. The data from only full calendar years 2002–2010 were used to identify the factors associated with the crashes. The partial year data from 2001 to 2011 were not used in order to remove any possible bias when identifying the temporal effect on the crashes. The crash data under investigation included data from 4 to 20 lane-miles (3–32 lane km) of rural highways depending upon the size of towns.

The data obtained from NDOT consists of 38 variables, out of which 16 variables were independent variables that were relevant to the study. It should be noted that some data for these variables were not recorded for a number of crashes. Also, some variables were not applicable to all the crashes. For example, variables related to the secondary vehicle, such as "secondary vehicle type" and "secondary vehicle action", were not applicable to crashes involving only one vehicle. Therefore, these variables were excluded from the analysis. Also, such variables as "factors non-motor" were recorded for a very few crashes. Those variables that had very limited data set were not used in the analysis, leaving only 12 predictor variables as listed in Table 1.

The data contained 337 crash records including 3 fatal crashes. There were no personal characteristics (e.g., age, gender, ethnicity, etc.) of the driver in the data. To develop a BLR model, 334 nonfatal crash records were used. All five crashes with "other" type of primary vehicles resulted into PDO crashes, i.e., failures were predicted perfectly in those cases. Those crash records were dropped by STATA®, leaving 329 records for final analysis. The crash data was first analyzed using descriptive analysis to obtain the summary statistics of the data.

2.2. Binary logistic regression model

A BLR model was developed to identify the factors associated with crash severities. In this case, as the dependent variable was a binary variable (injury or no injury), the binary regression model was used (Park, 2009). There are three types of BLR models, including the binary logistic regression model, the binary probit regression model, and the bivariate probit regression model. According to Park (2009), "the choice between logistic and probit models is more closely related to estimation and familiarity than to theoretical or interpretive aspects. In general, logistic models reach convergence fairly well." A number of researchers had used binary logistic model to analyze the traffic crash data (Holdridge et al., 2005; Lee and Abdel-Aty, 2008; Usman et al., 2016).

The binary logistic regression can be expressed mathematically as follow

$$\text{logit}(P) = \ln[P/(1-P)] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i$$

where P is the probability of injury crashes, β_0 is the model coefficient, x_i is the predictor variable, β_i is the model coefficient corresponding to x_i (IDRE, 2016).

In this model, each estimated coefficient was the expected change in the log odds of being an injury crashes for a unit increase in the corresponding variable holding other predictor variables constant. To get the odd ratio (OR) for each predictor variables, the coefficient of these predictor variables should be exponentiated.

Table 1 – Predictor variables.

Variable code	Variable name	Number of possible values
Weather	Weather	6
Ctype	Crash type	5
Action	Primary vehicle action	5
Lighting	Lighting	6
Vcount	Total number of vehicles	2
Tgroup	4 hourly time categorization	6
Day	Day of the week	7
Month	Month	12
v1type	Primary vehicle type	6
v1driverf	Primary vehicle driver factor	5
v1harmful	Primary vehicle most harmful event	8
v1vehiclef	Primary vehicle factor	6

The OR indicates how much one value of variable (e.g., cloudy weather) is preferred for injury crashes as compared to the base value (e.g., clear weather). If OR is higher than 1, the variable under consideration has a higher chance of being in an injury crash than the reference variable value. Only those predictor variables whose coefficient values are significant at alpha level of 0.05 were considered as reliable predictors for this model. In addition to this, the margins and marginal effects of the predictor variables were calculated. Several crash-analysis studies had used these parameters to determine the effect of independent variables on the outcome of the types of crashes (Agbelie, 2016; Leard and Roth, 2015). According to Jann (2013), "a margin is a statistic computed from predictions from a model while manipulating the values of the covariates." Similarly, the marginal effect was the difference in the levels of margins if the covariate values were changed.

STATA® software was used to analyze the data. The default logistic regression was used, in which a list-wise deletion of missing data was performed. During the analysis, over-dispersion of the model was checked by calculating the ratio of Chi square value and degrees of freedom. Also, the multicollinearity test was conducted to see whether there was a correlation between the predictor variables.

3. Results and discussions

The descriptive statistics showed that higher percentage of crashes occurred in favorable weather conditions, driver factor, roadway, etc. For example, 87% of crashes occurred on dry roadway, 70% crashes occurred during clear weather, 60% crashes occurred in daylight, 63% of crashes occurred when driver was in normal condition, and 74% of crashes occurred when primary vehicle was going straight. Further analysis of the data using BLR model provided better insight of the factors associated with injury crashes.

During BLR model development, the over-dispersion value was calculated by dividing the Chi square value (87.6) by degree of freedom (64). It was about 1.4, which is near to 1; therefore, it was assumed that there was no over-dispersion in the model. Similarly, the multicollinearity test in STATA was conducted using the linear regression with predictor variables. Regression was conducted using the variable "lightning" as the dependent variable. The collinearity test statistics values showed that none of the predictor variables had a variance inflation factor (VIF) more than 2.5 (Table 2). Generally, when the VIF value is more than 2.5, which indicates that there are multicollinearity issues with the predictor variables (Allison, 2012). In this model, there were no issues related to multicollinearity with the predictor variables.

The factors and corresponding odd ratios that were found to be significant for causing injury crashes as compared to PDO crashes are listed in Table 3. The crashes that occurred from midnight until 4 a.m., as compared to crashes that occurred at other time intervals listed in Table 3, were likely to be injury crashes rather than PDO crashes. To determine the correlation, the model was tested again with day variables coded as weekend and weekdays. The result showed that crashes that occurred on weekdays were three

Table 2 – Multicollinearity test results.

Variable	Collinearity statistic	
	Tolerance	Variance inflation factor
Weather	0.88	1.14
Crash type	0.38	2.48
Primary vehicle action	0.84	1.19
Total number of vehicles	0.38	2.48
4 hourly time categorization	0.98	1.02
Day of the week	0.97	1.04
Month	0.97	1.04
Primary vehicle type	0.95	1.05
Primary vehicle driver factor	0.91	1.10
Primary vehicle most harmful event	0.85	1.18
Primary vehicle factor	0.89	1.12

times more likely to be injury crash than crashes that occurred on weekends. Also, the crashes that occurred on January were five (1/0.209) times more likely to be injury crashes than the crashes that occurred on June. This finding is in contrast to the findings of Chang and Wang (2006), who did not find any significant correlation between crashes and the timing of the crashes. Motorcycles were found to be significantly more prone to injury crashes as compared to other types of vehicles listed in Table 3. Speeding was found to be 17 (1/0.060) times more responsible for injury crashes than mechanical defects of the vehicle. Numerous studies found that the severity of crashes was directly related to the speed of the vehicles (Aarts and Schagen, 2006; Elvik et al., 2004; Kockelman et al., 2006; SWOV, 2016; Xie et al., 2012).

The overall effects of the predictor variables were calculated for BLR model. The result showed that "day of the week", "primary vehicle type", and "primary vehicle most harmful event" had significant effect in the injury crashes. The study conducted by Xie et al. (2012) also found significant correlation between the severity of crashes and the primary vehicle most harmful event.

Margins were calculated for the BLR model developed for this study. Margins indicated the probability of causing injury crashes when all other factors were kept at their mean values. Top 12 factors that had the highest probability of causing injury crashes are provided in Table 4. This table shows that the crashes involving motorcycles had an 80.2% probability of being injury crashes when other factors were kept at their mean value. It also can be seen that crashes that occurred from midnight until 4 a.m. had a 58.3% chance of being injury crashes. Severe crosswinds, passing other vehicles, and fatigue were likely to result in severe crashes as compared to other values in their category. Similar findings were derived from other studies (Li et al., 2012; NHTSA, 2015b; Xie et al., 2012).

The marginal effects of switching values of variables from the base value to other values were also calculated. The marginal effects that were found to be significant are listed in Table 5. Assuming a hypothetic situation, in which all the crashes that occurred in clear weather occurred instead in mixed unfavorable weather, the probability of those crashes being injury crashes would decrease by 0.209. In other words, 1 out of 5 (1/0.209) such crashes would be PDO crashes instead of injury crashes. Similarly, if the time of the crashes that occurred in time interval "00:00 a.m. to 3:59 a.m." were switched to other time intervals listed in the table, the probability of such crashes being injury crashes would decrease by 0.242–0.358, depending upon the time intervals. If the day of the crashes that occurred in weekends were weekdays, the probability of those crashes being injury crashes would increase by 0.157. The table also shows that if the vehicle type were switched from motorcycles to other vehicle types listed in the table, the probability of those crashes being injury crashes would decrease. Finally, if all the crashes related to speeding were caused by mechanical defect, the probability of those crashes being injury crashes would decrease by 0.343.

The study showed that lesser crashes occurred during unfavorable conditions, such as snow, darkness, or rain, possibly because drivers are more alert in unfavorable driving conditions. This finding was similar to that of other studies (Eisenberg and Warner, 2005; Tefft, 2016). Possible explanations for fewer crashes during unfavorable driving conditions might be a difference in exposition, i.e., more vehicles miles are travelled during favorable conditions. Also, the weather in most of the towns in Nevada is favorable on most days, and fewer people drive at night.

The BLR model showed that crashes that occurred from midnight until 4 a.m. have higher chances of being in injury crashes. Noticeably, the crashes that occurred on weekdays were found to be three times more prone to the injury as compared to crashes that occurred in weekends. The

Table 3 – Odd ratios for significant factors.

Variable	Category	Odds ratio	Sig. value	95% con. interval
4 hourly time categorization (base value: 00:00 a.m. to 3:59 a.m.)	8:00 a.m. to 11:59 a.m.	0.110	0.012	0.019–0.617
	12:00 p.m. to 3:59 p.m.	0.105	0.010	0.019–0.587
	8:00 p.m. to 11:59 p.m.	0.211	0.041	0.047–0.938
Day of the week (base value: weekends)	Weekdays	3.119	0.006	1.375–7.074
Month (base value: January)	June	0.209	0.032	0.050–0.875
Primary vehicle type (base value: motorcycle)	Carry-all/utility	0.067	0.008	0.009–0.490
	Car	0.051	0.001	0.008–0.318
	Pickup/van	0.094	0.010	0.015–0.574
	Heavy	0.046	0.001	0.007–0.299
Primary vehicle factor (base value: speeding)	Mechanical defect	0.060	0.034	0.004–0.805
	Unknown/other	0.224	0.005	0.079–0.638

Table 4 – Margins of the factors likely to result in injury crashes.

Variable	Category	Margin	Sig. value	95% con. interval
Weather	Severe crosswinds	0.505	0.039	0.026–0.984
Crash type	Others/unknown	0.484	0.025	0.062–0.907
Primary vehicle action	Passing other vehicle	0.454	0.015	0.090–0.819
Lighting	Dawn/dusk	0.386	0.018	0.067–0.705
Total number of vehicles	Multiple	0.270	0.002	0.096–0.443
4 hourly time categorization	00:00 a.m. to 3:59 a.m.	0.583	0.000	0.266–0.899
Day of the week	Weekdays	0.267	0.000	0.195–0.339
Month	November	0.360	0.020	0.056–0.664
Primary vehicle type	Motorcycle	0.802	0.000	0.533–1.070
Primary vehicle driver factor	Fatigue/asleep	0.435	0.023	0.060–0.809
Primary vehicle most harmful event	Others	0.784	0.000	0.522–1.047
Primary vehicle factor	Speeding	0.399	0.000	0.241–0.558

Table 5 – Marginal effects on probability of injury by changing variables from base value.

Variable	Categorization	dy/dx	Sig. value	95% con. interval
Weather (base value: clear)	Mixed unfavorable	−0.209	0.033	−0.402–−0.016
4 hourly time categorization (base value: 00:00 a.m. to 3:59 a.m.)	8:00 a.m. to 11:59 a.m.	−0.353	0.007	−0.608–−0.097
	12:00 p.m. to 3:59 p.m.	−0.358	0.006	−0.613–−0.102
	4:00 p.m. to 7:59 p.m.	−0.242	0.043	−0.476–−0.008
	8:00 p.m. to 11:59 p.m.	−0.260	0.031	−0.497–−0.023
Day of the week (base value: weekends)	Weekdays	0.157	0.002	0.059–0.255
Month (base value: January)	June	−0.222	0.027	−0.419–−0.026
Primary vehicle type (base value: motorcycle)	Carry-all/utility	−0.448	0.002	−0.727–−0.170
	Car	−0.488	0.000	−0.732–−0.243
	Pickup/van	−0.393	0.002	−0.642–−0.145
	Heavy	−0.502	0.000	−0.751–−0.253
Primary vehicle factor (base value: speeding)	Mechanical defect	−0.343	0.000	−0.522–−0.163
	Unknown/others	−0.228	0.003	−0.379–−0.076

multicollinearity test showed that there was no correlation between day and other independent variables.

In general, one might expect that there would be more crashes and more severe crashes during weekend because most of the drivers during weekend travel might not be commuters and were not familiar with the road and roadside characteristics of the highway. A study conducted by Yu and Abdel-Aty (2013) found that there were more crashes in weekdays (6.76 per segment) than weekends (3.57 per segment). Crashes involving motorcycles were found to be much more prone to injury crashes as motorcycles have different crash injury mechanism. Speeding was associated with the injury crashes showing the importance of the proper enforcement. The BLR model supported this finding. As mentioned before, various studies showed a correlation between the severity of crashes and the speed of the vehicles. According to Elvik et al. (2004), “a variation in the mean speed of traffic by a factor of 1.35 produces a variation in the number of fatalities by a factor of 3.92.” Therefore, speed is a risk factor. This study and other study findings also showed that it is necessary to have speed limits in built-up areas along rural highways to reduce the injury crashes.

Factors associated with the fatal crashes were similar to factors associated with injury crashes. Looking at crash data in detail, one of the noticeable factors was speeding versus inattention. It was found that inattention was associated more with fatal crashes than with speeding, i.e., inattention was a riskier factor than speeding, because two out of three fatalities were due to in attention and one out of three was due to speeding. NHTSA (2015b) found that about 10% of the crashes in the U.S. occurred due to the driver's inattention, 3154 fatalities occurred due to this too.

4. Conclusions and limitations

This study analyzed the factors collected in crash scene to identify correlation between these variables and severity of crashes. BLR model shows that injury crashes are associated with factors, like weekdays, motorcycle, speeding, and occurred in time interval between midnight and 4 a.m. Those factors can be used by Nevada DOT to take steps to reduce injury crashes.

The findings of the study can be used by Nevada DOT to improve public safety as well. For example, as injury crashes were related to the motorcycles, Nevada DOT can encourage motorcycle riders to use helmets, or propose a law that mandates the use of helmets. Similarly, steps to decrease speeding by providing speed limit along these built-up areas, can be taken to reduce crash severities. The primary contribution of this paper to the body of knowledge is to identify the factors related to crashes along built-up areas of rural highways.

Crash data from only 11 towns were used for this study. Thus, the results of the analysis are applicable only to the towns under study and cannot be generalized. Also, not all the predictor variables considered for developing BLR model may have a causal effect. Some of the data that might have an effect on the severity of the crashes were not available, e.g., seat belt usages.

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