Hindawi
Journal of Advanced Transportation
Volume 2018, Article ID 5942686, 8 pages
https://doi.org/10.1155/2018/5942686

Research Article

Determining Causal Factors of Severe Crashes on the Fort Peck Indian Reservation, Montana

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Received 20 August 2018; Accepted 9 October 2018; Published 1 November 2018

Academic Editor: Yair Wiseman

Indian reservations have been struggling with the highest rate of crashes that lead to fatal and incapacitating injuries across the United States for decades. The US government has been striving to improve roadway safety on Indian reservations to reduce such crashes. However, the rustic nature of the reservations, issues of jurisdictional coordination and collaboration, inadequate resources, and limited crash data make it challenging for the tribes to reduce the number of severe crashes. Determining factors associated with crashes is one of the most efficient and effective ways to select appropriate countermeasures for improving roadway safety and reducing crashes. Due to the unique nature of each of the reservations, factors contributing to crashes vary across the reservations as well as across the different roadways within the reservations. Only a few researches have investigated factors contributing to crashes on Indian reservations, and no studies have determined the factors separately for different roadways within the reservations. Therefore, this study was conducted to identify the contributory factors to fatal and injury crashes in the Fort Peck Indian Reservation (FPIR). The crash database covering a ten-year period from 2005 to 2014 was obtained from the Montana Department of Transportation (MDT). During this period, 940 crashes occurred on state, county, city, and tribally owned roads. Binary logistic regression models were developed to determine the factors associated with fatal and injury crashes for all roads within the FPIR and separately for the roads maintained by different agencies. The analysis identified unique contributory factors to fatal or injury crashes for different roadways, which justified separating crashes based on different road types. Impaired driving, adverse weather condition, collision with a ditch/embankment, pedestrian involvement, and overturn/rollover crashes were some of the factors that significantly contribute to increasing the risk associated with fatal and injury crashes. Impaired driving was found to be the most significant factor contributing to crash severity in all three roadways. Indian reservation roads were found to be possessing the highest risk of fatal and injury crashes due to impaired driving among the three roadway systems. The results of the study provide the Fort Peck Tribes with the opportunity to determine the countermeasures for safety improvements on their roadway systems efficiently.

1. Introduction

Lack of roadway safety on Indian reservations is one of the major concerns for the roadway systems in the United States. Indian reservations roadways have been consistently experiencing higher crash rate over the past few decades than the other roadways across the United States [1]. According to National Highway Traffic Safety Administration (NHTSA), American Indians experienced the highest fatality rate per 100,000 populations [2]. Besides poor road conditions, geographic isolations of roadways, perilous driving behaviors including reluctance to adhere to safety restraint use, speeding, and impaired driving are some of the factors that contribute to the elevated rate of fatalities on Indian reservations [3]. According to the National Tribal Transportation Safety Summit Report, impaired driving and the lack of seat belts/child safety seats usage are the highest concerns among the various safety issues on reservation roadways. NHTSA also stated that 65% of the tribes who died in motor vehicle crashes were unrestrained at the time of the fatal crash [4]. While about 40% of fatal crashes on Indian reservations were alcohol-related, alcohol accounted for 31% of total crashes

nationally during the same time period [4]. Road conditions in the reservations also contribute to the high fatal crash rates on Indian reservations. The Federal Highway Administration (FHWA) stated that only 17% of the total of the Bureau of Indian Affairs (BIA) and tribally owned roads is in acceptable condition [5].

Numerous agencies and research projects have been working to address the causes and solutions to the high crash, injury, and death rates in these areas [6]. However, issues associated with data collection and analysis practices including nonuniform crash reporting systems across different jurisdictions, lack of resources and expertise, inadequate funding, and other factors hinder efforts to determine causative factors of crashes [3]. Without a good understanding of where, when, and why crashes are occurring, accountable authorities would continue to struggle to improve safety in these areas.

There have been extensive researches determining contributing factors of crashes that concentrated on urban areas. However, only a few researches have investigated crash contributing factors on rural roadways, which is even lower for Indian reservations roadways [6]. This study attempts to identify the contributing factors affecting crash severity using binary logistic regression models for all roadways within the Fort Peck Indian Reservation (FPIR). Also, due to substantial differences among various roadways in terms of crash contributing factors, this study separately analyzed the roads under three jurisdictions: Indian reservation, city and county, and state highway agency. This study would provide the Fort Peck Tribes with the opportunity to determine the countermeasures for safety improvements on their roadway systems efficiently.

2. Background

Over the past several years there has been a steady decline in fatal crash rates across the United States, yet transportation related mortality rates continue to increase on tribal lands. The US Centers for Disease Control (CDC) reported that motor vehicle crashes are the leading cause of unintentional injury for Native American/Alaska Natives (AI/AN) ages 1 to 44. Adult (aged ≥20 years) motor vehicle-related death rates for AI/AN are more than twice that of non-Hispanic whites or blacks (CDC, 2014). The fatal crash rate for AI/AN occurring mostly in rural areas varies across the United States, and, in most reservations, the rate is higher than that of national average [5]. The CDC also stated that 5 states including South Dakota, Wyoming, Montana, North Dakota, and Arizona have a fatality rate more than twice the national average for all AI/ANs and more than 4 times the rate for the general US population [7].

According to Montana Indian Fatality Crash Information, traffic fatalities among Native Americans in Montana are nearly three times that of non-Native Americans [8]. This report stated that the death toll among Native Americans is about 15.6% of the statewide fatalities while the average Native American population of the state is only 6.1% [8]. Among the seven Indian reservations in Montana, the FPIR is home to about two federally recognized tribes with numerous bands and division. It is the ninth largest Indian reservation in the United States. There is approximately 1,500 miles of roadways in FPIR, which comprise 375 miles of the BIA system and tribally owned roads. Of the 211 miles of BIA-owned roads, more than 50% is gravel and dirt roads. Most of the roads were built a long time ago and are not maintained properly [9]. The transportation professionals of the FPIR have been trying extensively to enhance FPIR roadway safety. Identifying factors associated with crashes is one of the cost-effective and efficient ways to improve roadway safety and reduce crash rate.

Numerous studies have been conducted to identify the contributing factors to severe crashes for different roadways and vehicles characteristics using statistical models. The statistical models express a crash as a function of variables such as roadway condition, traffic characteristics, and weather conditions and help to determine significant contributing factors of crashes to identify potential countermeasures (Thakali et al., 2015). The statistical analysis enables professionals to easily extract more information about the crash databases and provides assistance to determine safety policy improvements.

Various statistical models have been employed to identify significant factors and quantify their impacts on crash injury severity. Lord and Mannering discussed the methodological issues associated with crash data analysis, as well as pros and cons of the several statistical models used in analyzing crash data [10]. In this study, the authors discussed the strength and weakness of various models such as the Poisson regression model, the negative binomial regression model, the Poisson log normal model, the zero-inflated Poisson and negative binomial model, the Conway-Maxwell-Poisson model, and the gamma model [10]. The Poisson regression model has been widely used to model crash frequency [11]. But it has issues of overdispersion which can be addressed by the negative binomial distribution [12]. The negative binomial distribution model was also used in the Highway Safety Manual (HSM) for Safety Performance Functions (SPFs) [12]. The logistic regression model has also been used in numerous studies to determine factors contributing to crashes. Bham et al. [13] developed multinomial logistic models to determine the crash contributing factors for different collision crashes on urban highways. They also developed binary logistic regression models to identify the factors contributing to crash injury severity [13]. In their study, crash severity was categorized into a severe or nonsevere crash to address the issues of underreporting of three types of nonsevere crashes by joining them together. The analysis showed that driver's drug involvement doubled the risk of crash severity for collision crash on divided highways. From the analysis, drug involvement was also significant in the single-vehicle crashes. On the other hand, Pei and Fu [14] used an ordered probit model to determine injury severity with four levels (no injury, slight injury, severe injury, and fatal injury) at unsignalized intersections. This study found that crash severity was associated with the road conditions, collision types, and highway classification [14]. However, Wang et al. found that partial proportional odds regression provides much better results than does the ordered probit model for fitting injury severity data. This study revealed that factors including curve and

grade at diverge areas, light and weather conditions, alcohol or drug involvement, heavy-vehicle involvement, number of lanes on main lines, average daily traffic, and crash type associated with injury severity at freeway diverge areas [15].

Though numerous studies have been carried out in analyzing crash data using statistical models in urban areas, only limited studies have been found on identification of contributing factors of crashes in rural roadways, especially Indian reservations roadways [6]. Wu et al. developed mixed logit models to investigate driver injury severity in single-vehicle and multivehicle crashes on rural two-lane highways. They found significant difference in causal factors of driver injury severity such as dark lighting, weather, overtaking tendency, and impaired driving between single-vehicle and multivehicle crashes [16]. Shinstine et al. performed crash severity analysis for rural highway systems including tribal roads in Wyoming using the multiple logistic model. This study showed that driver impairment, motorcycles, mean speed, and safety equipment use increased the probability of severe crashes [6]. Pollack et al. conducted a systematic review of the published literatures to identify risk factors for motor vehicle deaths and pedestrians on Indian reservations [7]. This study found impaired driving as a risk factor for both motor vehicle occupants and pedestrian death in most of the epidemiological studies. However, despite the high crash rate on Indian reservations, not much study has been conducted to determine unique contributory factors of crashes on these areas. Therefore, this study was set forward to identify the contributing factors of fatal and injury crashes on the FPIR. In this study, the logistic regression model was chosen due to its usefulness in understanding the influence of independent variables on a dichotomous dependent variable (fatal and injury crashes and PDO). The conditional distribution of the injury crashes (i.e., given that a crash has occurred) illustrates the association between the crash injury and the contributing factors. Mathematically, extreme flexibility and intuitiveness of the logistic regression model result in meaningful interpretations (Hosmer and Lemeshow, 2000). Thus, binary logistic regression modeling is used in this study to model crash severity as in Shinstine et al. and Bham et al.

3. Objectives

The objective of this study is to determine factors contributing to crash severity in the FPIR. Four binary logistic regression models were developed for all roads within the FPIR and roads under the three jurisdictions Indian Tribe, city and county highway agency, and the state highway agency to study their differences in terms of crash contributing factors that affect crash severity. Results of these models provide insight to decision-makers of different jurisdictions to determine strategies for reducing crashes by identifying the unique contributing factors of crashes in the respective roadway systems.

4. Data Description

The Montana Department of Transportation (MDT) maintains a crash analysis database for all roadways in Montana. The database includes information on every recorded crash within the state. Crash data within the FPIR was collected from the MDT. The ten-year period (2005–2014) crash data was used to develop models for all roadways within the FPIR. All the variables that matched up directly with each of the crashes were included in the analysis. Also, categorical variables were dichotomized according to whether the fatal or injury crashes were attributable to these variables or not. Later, to develop distinct models for different roads, crash data was divided into three separate datasets. The first model used the dataset containing crashes that occurred on roadways maintained by the Indian Tribe. The second and third datasets included crashes that occurred on roadways managed by the city and county highway agency and state highway agency, respectively. Once the datasets were arranged accordingly, the crash information was used to create a list of predictor variables. This study considered crash severity as the response variable for the model assigning a binary value of 0 or 1. Though initially crashes were divided into five categories based on the KABCO scale, they were categorized into two classes: fatalities and injuries and property damage only (PDO) crashes for the analysis. Fatal and injury crashes include fatalities and incapacitating, nonincapacitating, minor, and possible injuries. PDO crashes include crashes that occurred with no injuries and incurred damage to the vehicle only.

Crashes that involved fatalities and injuries were assigned a value of (1), and crashes that involved no injury were assigned a value of (0). One reason behind this categorization is that the number of fatal and injury crashes was nominal in the dataset. To address the issue of underreporting, fatal and all injury crashes were joined together. Another reason for joining fatal and injury crashes is that no injury crashes are expected to occur regardless of the severity level. This study would determine how the factors influence the fatal and injury crashes in an effort to reduce these types of crashes.

Categories of the First Harmful Event (FHE) were aggregated to generate meaningful predictors. For all roads and state highways, FHEs were aggregated and then factorized into seven categories including overturn/rollover, collision with a ditch/embankment, motor vehicle, animal, pedestrian, other fixed objects, and others. For the other three models, FHEs were again categorized based on their frequency of occurrence relative to all crashes. For Indian reservation roads, FHEs were consolidated into four categories including collision with motor vehicle, a ditch/embankment, overturn/rollover crashes, and others as baseline category. Others incorporated a variety of events such as collision with cargo, guardrail, and utility pole. For city and county roads, only collisions with fixed objects were included in the model to find out the association between this category and crash severity. In this model, collision with a ditch/embankment and overturn crashes were not included separately due to their low number of incident (two and three crashes, respectively). On these roadways, crashes that involved other motor vehicles made up the majority (around 83%) of the total crashes. Of these crashes, only 17 % resulted in fatal or injury crashes. Table 1 illustrates the FHW categories.

Other variables selected for the models included environmental condition such as weather and lighting condition, roadway characteristics including presence of intersection and traffic control, geometric characteristics such as alignment and profile, temporal characteristics, and impaired driving. Indian reservations have high prevalence of alcohol-impaired driving and the highest alcohol-related motor vehicle death rate of all races [17]. FPIR is no exception with 24% of the crashes occurring with a driver under the influence of a substance. Of these 216 crashes due to impaired driving, around 75% were fatal or injury crashes. Drivers' information such as gender, age, and seat belt usage was not included in the models because these data were not available to match up directly with each crash. To better understand the variables, frequency and percentage distribution of all initial variables for the four models is presented in Table 1.

5. Methodology

The logistic regression model has been commonly used in many studies involving binary crash outcomes. In this study, binary logistic regression models were developed to investigate the relationship between fatal and injury crashes and potential contributing factors. This study considered crash severity as the response variable for the model. This study presumed a Bernoulli distribution because the response variable, crash severity, is binary. In this discrete probability distribution, the outcome 1 indicates a "success" with probability π, and the outcome 0 denotes a "failure" with probability 1- π.

The logistic regression model is represented by (1). Here, x denotes a q ×1 vector of p predictor variables and β denotes the regression coefficients of the corresponding q ×1.

$$X'\beta = \beta_0 + \sum_{j=1}^{p} \beta_j X_j. \tag{1}$$

Logit links of the logistic regression model are expressed as the following form [18]:

$$\begin{aligned} X'\beta &= \ln\left[\frac{\pi}{(1-\pi)}\right] \\ \pi &= \frac{\exp\left(X'\beta j\right)}{1+\exp\left(X'\beta j\right)}. \end{aligned} \tag{2}$$

Here, odds = $\pi/((1-\pi))$ denote the odds of fatal and injury crashes, which is defined as the probability of the fatal and injury crashes divided by the probability of the no injury crashes. $\exp(\beta_j)$ indicates an increase in odds resulting from a one unit increase in the *jth* independent variable, considering the other independent variables constant.

The model results were interpreted in terms of the odds ratio (OR). A predictor with an OR greater than 1 is an indication that the variable increases the likelihood of the fatal and injury crashes. On the contrary, predictors with OR less than 1 (or negative estimate of coefficients) are likely to be involved in property damage only crashes.

6. Variable Selection

Selecting the predictors and interaction terms is an essential step in developing models. Variable selection for models depends on several factors such as the quality of the data, the purpose of the variables, and the significance of the variables [13]. Since backward and forward selection have several drawbacks, p values were used manually as screening criteria for initial variable selection in this study. A variable was removed if its p value was greater than a significance value of 0.10. This procedure was repeated until all variables with large p values were removed, and then a final model was selected and is shown in Table 3.

Interaction terms were inspected for inclusion into the logistic regression models. Since the effect of a particular risk factor upon crash severity may depend on the values of other risk factors, interaction terms need to be considered. Statistical and practical consideration are required in incorporating the interaction terms into the model [19]. In the practical sense, interactions may be expected among the variables such as lighting condition, impaired driving, weather condition, overturn, and collision with a ditch/embankment. Table 2 shows the list of interaction terms tested in this analysis. After selecting the realistic potential interaction terms, interaction terms were removed through an iterative process starting with removing interaction terms having Wald chi-square p values greater than 0.05. The analysis found no significant interaction terms whose p values <.05 in any of the four models.

7. Model Adequacy

Model adequacy can be examined by the goodness of the fit test which measures how well the observed data correspond to the fitted model. Since all the predictors in these models were categorical, the Hosmer-Lemeshow test would not be appropriate in this study. The Pearson chi-square test and deviance test were carried out to assess the adequacy of the models. For all roads within the FPIR, the p values for the deviance and Pearson chi-square test were 0.37 and 0.77, respectively. The p values for deviance for the roads maintained by the Indian reservation and city and county highway agency were 0.78 and 0.97, respectively. For state highway agency, the p value for deviance test was 0.002. The small p values for deviance of models for state highway agency could be attributed to the unbalanced distribution of the predictors in the models. However, the p values for the Pearson chi-square test for the roads maintained by the Indian reservation, city and county highway agency, and state highway agency were 0.92, 0.53, and 0.58, respectively. The high p value for the Pearson chi-square test and deviance test denotes the good fit data.

Model adequacy can also be assessed by its predictive ability. The Receiver Operating Characteristics (ROC) curve enables the predictive power of the model to be assessed. The higher the area under the curve, the better the predictive power the model has. The ROC of the four models (0.82, 0.82, 0.74, and 0.71, respectively) indicate the good predictive power of the models.

Table 1: Initial variables and their frequency and percentage.

Variables	Categories	All Roads Freq	All Roads %	IRR* Freq	IRR* %	County Freq	County %	State Highways Freq	State Highways %
Response variables									
Crash Severity	Fatal +Injury	388	41.28	101	72.14	50	19.38	229	44.81
	PDO*	552	58.72	39	27.86	108	41.86	282	55.19
Temporal Characteristics									
Day of Week	Weekend	281	29.8	49	35.00	77	29.84	146	28.57
	Weekday	659	70.1	91	65.00	181	70.16	365	71.43
Geometric Characteristics									
Alignment	Curve	90	9.57	33	23.57	9	3.49	47	9.20
	Straight	850	90.43	107	76.43	249	96.51	464	90.80
Profile	Grade	155	16.49	32	22.86	25	9.69	94	18.40
	Level	785	83.51	108	77.14	233	90.31	417	81.60
Environmental Factor									
Weather Condition	Clear	623	66.28	83	59.29	189	73.26	327	63.99
	Not Clear	317	33.72	57	40.71	69	26.74	184	36.01
Lighting Condition	Daylight	707	75.21	83	59.29	235	91.09	362	70.84
	Dark	233	24.79	57	40.71	23	8.91	149	29.16
Driver Characteristics									
Impaired Driving	Yes	252	26.81	64	45.71	46	17.83	135	26.42
	No	688	73.19	76	54.29	212	82.17	376	73.58
First Harmful Events									
Overturn/Rollover	140	14.89	58	41.43	2		0.78	77	15.07
Collision with Motor vehicles	508	54.04	26	18.57	212		82.17	250	48.92
Collision with a Ditch/ Embankment	63	6.70	23	16.43	1		0.39	36	7.05
Collision with an Animal	56	5.96	1	0.71	0		0.00	53	10.37
Collision with Pedestrians	23	2.45	2	1.43	7		2.71	12	2.35
Collision with other fixed objects	106	11.28	18	12.86	28		10.85	57	11.15
Others	44	4.68	12	8.57	8		3.10	26	5.09
Roadway Characteristics									
Presence of intersection	Intersection	264	28.09	21	15.00	84	32.56	155	30.33
	No intersection	676	71.91	119	85.00	174	67.44	356	69.67
Traffic controls system	Traffic control	665	70.74	106	75.71	186	72.09	347	67.91
	No traffic control	275	29.26	34	24.29	72	27.91	164	32.09

IRR= Indian Reservation Roads
PDO= Property Damage Only crashes

8. Results

The results obtained for all roadways within the FPIR and individual roadway systems are presented in Table 3. The table includes the coefficient estimates, error terms, p value, odds ratios, and 95% confidence intervals for the odds ratio of those predictors that had p values less than 0.05.

8.1. All Roadways within the FPIR. The first model included all the roadways within the FPIR. For this model, different government agencies which maintain the roadway systems were included in the model as a predictor to check whether different roads have significant impact on crash severity.

For all roadways within the FPIR, impaired driving, adverse weather condition, and roadway system (Indian reservation roads and state highway) were found to be predominant predictors of fatal and injury crashes. Impaired driving had a positive coefficient and estimated odds ratio of 6.23. This indicates that impaired driving increased the likelihood of fatal and injury crashes by 6.23 times compared with sober driving (95% CI 4.34–9.00).

Adverse weather condition has an estimated odds ratio of 1.42, which means vehicles are more likely to be involved in fatal and injury crashes during adverse weather conditions by 1.42 times compared with clear weather (95% CI 1.01–1.97).

Rollover/overturn crashes had a coefficient of 1.63 (OR=5.09 [95% CI 3.17–8.34]) indicating that the rollover/overturn crashes increased the likelihood of fatal and injury crashes by 5.09 times compared with other crashes.

Table 2: List of possible interaction terms.

Lighting condition and impaired driving
Lighting condition and weather condition
Lighting condition and overturn
Lighting condition and collision with a ditch/embankment
Weather condition and impaired driving
Weather condition and overturn
Weather condition and collision with a ditch/embankment
Impaired driving and overturn
Impaired driving and collision with a ditch/embankment

The estimated odds ratios for collision with a ditch/embankment reflected that vehicles are more likely to be involved in fatal and injury crashes when run into a ditch/embankment by 3.12 times compared with other crashes (95% CI 1.67–5.99).

The results also indicated that traffic crashes that involved pedestrians increase the odds of severe crashes more than 19.12 (95% CI 5.97–85.82).

The model also revealed that roads maintained by the Indian reservation had a positive coefficient and OR of 4.36 (95% CI 2.50–7.69), which means IRR roads had the higher likelihood of fatal and injury crashes by 4.36 times than county roads. Moreover, the risk of fatal and injury crashes was increased by 2.54 (95% CI 1.74–3.76) times when crashes occurred on state highways compared with county roads. This significant association between roadway systems and crash severity inspired the development of three other models to determine the contributing factors of crash severity for each roadway system.

8.2. Roads Maintained by the Indian Tribe Nation. In case of Indian reservation roadways, impaired driving, collision with a ditch/embankment, and overturn/rollover type of crashes had significant impacts on crash severity. The results of OR indicated that impaired driving increases the odds of injury and fatal crashes by 13.88 times (OR=13.88 [95% CI 4.86–50.94]) compared with sober driving. Shinstine et al. also found impaired driving as one of the significant factors that contribute to crash severity [6].

Again, a positive coefficient of estimate and OR of 4.82 (95% CI 1.85–13.53) denotes that overturn/rollover crashes increased the likelihood of fatal and injury crashes by 4.82 times compared with other crashes. The risk of fatal and injury crashes attributable to collision with a ditch/embankment was 3.47 (95% CI 1.05–13.00) times compared with other FHE categories.

8.3. Roads Maintained by the City and County Highway Agency. For city and county roads, impaired driving, collision with fixed objects, and road alignment were the significant factors that impact crash severity. Impaired driving increased the likelihood of fatal and injury crashes by 5.04 (95% CI 2.28–11.14) times compared with driving under no influence. Moreover, collision with fixed objects increased the odds of fatal and injury crashes by 2.54 times compared with other crashes (OR=2.55 [95% CI 1.12–5.65]). The risk of fatal and injury crashes was also increased by 8.20 (95% CI 1.96–36.18) times on roads with curves compared with straight roads.

8.4. Roads Maintained by the State Highway Agency. For the roads maintained by the state highway, three factors including impaired driving, overturn/rollover crashes, and collision with a ditch/embankment significantly contributed to crash severity. The estimated odds of fatal and injury crashes due to impaired driving were 4.82 (95% CI 3.08–7.66) times higher than that of the fatal and injury crashes due to driving under no influence. Furthermore, overturn/rollover crashes increased the likelihood of fatal and injury crashes by 4.12 (95% CI 2.37–7.39) times compared with other crashes. Collision with a ditch/embankment also increased the risk of fatal and injury crashes by 2.95 (95% CI 1.38–6.65) times compared with other crashes.

9. Conclusions and Recommendations

Native Americans have been struggling with the highest rate of fatal and serious injury crashes of any other ethnicity across the United States. Extreme topography, speeding, impaired driving, and longer response time for emergency vehicles make rural reservation roads more vulnerable to higher fatality rates. The objective of this study was to develop statistical models to determine the factors contributing to crash severity in the FPIR.

A binary logistic regression model was first developed for all roads within the FPIR and then refined for the roads under the three jurisdictions, to study their differences in terms of crash contributing factors. For all roadways within the FPIR, 15 predictors were considered for the model including physical and behavioral factors. Among them, impaired driving, adverse weather condition, pedestrians, collision with a ditch/embankment, and overturn contributed to fatal and injury crashes. The model also revealed that roads being maintained by different agencies had an association with crash severity. This significant association between roadway systems and crash severity inspired the development of three other models to determine the contributing factors of crash severity for each roadway system.

For Indian reservation roadways, impaired driving, overturn/rollover crashes, and collision with a ditch/embankment increased the risk of fatal and injury crashes. Again, for city and county roads, impaired driving, collision with fixed objects, and curved roads increased the likelihood of fatal and injury crashes. Finally, for roads maintained by the state highway agency, impaired driving, overturn/rollover crashes, and collision with a ditch/embankment were found to be the contributing factors of crash severity.

This study revealed that crashes attributed to impaired driving were predominant on all roadways within the FPIR. This is one of the leading concerns for the Indian reservations across the country. Enforcement and educational programs

Table 3: Logistic regression: parameter estimates and odds ratios for all roadways.

Variables	Estimate	Std. Error	*p* value	Odds ratio	Confidence interval	
					2.50%	97.50%
All roads						
(Intercept)	2.118	0.183	< 0.001			
Impaired driving	1.829	0.185	< 0.002	6.23	4.35	9.00
Adverse Weather	0.346	0.169	0.041	1.41	1.01	1.97
Overturn	1.627	0.247	< 0.001	5.09	3.17	8.34
Ditch	1.138	0.324	< 0.001	3.12	1.67	5.99
Pedestrians	2.951	0.658	< 0.001	19.12	5.97	85.82
IRR	1.473	0.287	< 0.001	4.36	2.50	7.69
State Highway	0.932	0.197	< 0.001	2.54	1.74	3.76
Indian Reservation Roads						
(Intercept)	-0.637	0.344	0.06			
Impaired driving	2.630	0.587	< 0.001	13.88	4.86	50.94
Overturn	1.572	0.504	< 0.001	4.82	1.85	13.53
Ditch	1.245	0.633	< 0.001	3.47	1.05	13.00
Roads maintained by city and county highway agency						
(Intercept)	-2.177	0.233	< 0.001			
Impaired driving	1.618	0.402	< 0.001	5.04	2.28	11.14
Fixed Objects	0.935	0.411	0.023	2.55	1.12	5.65
Curve	2.104	0.723	< 0.01	8.20	1.96	36.18
Roads maintained by state highway agency						
(Intercept)	-0.902	0.122	< 0.0001			
Impaired driving	1.572	0.232	< 0.0001	4.82	3.08	7.66
Overturn	1.417	0.289	< 0.0001	4.12	2.37	7.39
Ditch	1.082	0.398	< 0.0001	2.95	1.38	6.65

such as promoting safe driving, strengthening law enforcement, increasing the number of sobriety checkpoints, and sponsoring events to increase awareness about the danger of impaired driving should be enhanced to address this issue. Moreover, since autonomous vehicles address the impaired driving issue, permitting these vehicles in the Fort Peck Indian Reservation in Montana can be an ideal solution for reducing impaired driving related crashes [20]. The models also identified that overturn/rollover crashes and crashes related to collision with a ditch/embankment, fixed objects, or curves had a positive association with fatal or injury crashes. Appropriate countermeasures including chevrons, widening of shoulders, and adding rumble strips can be provided to areas with high prevalence of rollover road crashes. However, it is recommended that drivers' information such as age, gender, and behavioral issues such as safety restraint usage be incorporated into the model for better assessments of crash severity.

This study can be a useful resource to other Indian Nations across the country to identify the factors associated with fatal and injury crashes in their areas through developing distinct logistic regression models for different roadways within the reservation. By selecting countermeasures which address the contributing factors identified from the analysis, tribes would be able to improve their roadway safety and reduce the severity of crashes.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The WYT^2/LTAP Center at the University of Wyoming provided extensive resources to assist in performing this study. Special acknowledgement goes to MDT and FHWA that provided the resources to make this research possible.

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