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A Bayesian Approach to Examine the Impact of Pavement Friction on Intersection Safety

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Abstract: The safety of intersections has been the focus of many studies since intersections are considered hazardous zones of road networks. Identifying the main contributing factors of severe traffic crashes at intersections is crucial to implementing appropriate countermeasures. We investigated the major contributing factors to crash injury severity at intersections, particularly pavement surface friction. Nine years of intersection crash data in Wyoming have been analyzed for this study. The random forest technique was employed to identify the importance of critical variables influencing crash injury severity risk. Subsequently, a Bayesian ordinal probit model was applied to examine the relationships between crash injury severity risk and these crash contributing factors. As per the random forest model's results, pavement friction has a strong impact on crash injury severity risk along with using safety restraints, intersection type, signalized or unsignalized, reckless driving, and crash type. The results of the Bayesian model demonstrated that higher pavement surface friction levels and proper use of restraints reduced the likelihood of severe injury. Based on these findings, several countermeasures may be proposed, such as those pavement friction requirements, driver's education, and traffic law enforcement to mitigate injury severity concerns at intersections.

Keywords: crash injury severity; pavement friction; intersection safety; Bayesian ordinal probit model; random forest regression

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1. Introduction

Road traffic creates negative effects on society and is considered one of the key challenges for developing sustainable transportation. Road transportation has severe adverse impacts on the safety of road users, human health, and the environment. In 2021, traffic crashes in the US claimed nearly 43,000 lives. In addition, road traffic crashes have direct negative impacts on the environment due to gas leaks and fluids spillage, vehicle repairs and disposal, roadway repairs, and increased emissions due to crash-related congestion and detours [1,2].

Crashes generally occur as a result of human, roadway, environmental factors, or a combination of such factors. For instance, time of the day, driving under the influence, adverse weather, and road surface conditions are some of the known crash precursors [3,4]. Nationally, crashes that occur at or near intersections are responsible for 40% of all traffic-related fatalities and injuries due to the nature of connecting multiple roadways [5,6]. Furthermore, new challenges are being faced when it comes to the safety of intersections with the increasing traffic volumes and emerging technologies. Traffic control and safety at intersections can be even more challenging with multimodal operations. This presents hazards that give rise to severe crashes. The US Department of Transportation (DOT) and the Federal Highway Administration (FHWA) are continuously striving to alleviate crash severities and prevent fatalities by coordinating with the state DOTs. Therefore, improving intersection safety is one of the priorities of the Wyoming Department of Transportation (WYDOT) [7–11].

Generally, excessive speed and drivers' inattention often create an environment where friction demand is higher than that supplied by standard pavement surfaces resulting in a loss of control [12,13]. Therefore, achieving adequate levels of pavement friction enhances road safety in terms of reducing the severity of certain crash types. Pavement friction is a crucial resisting force that eliminates the relative motion between the vehicle tires and the pavement surface [14,15]. Equipped with more knowledge about pavement conditions and performance, especially pavement friction, transportation engineers can devise fundamentally safer intersections for roadway users [16,17].

Even though Bayesian modeling has been widely implemented in crash data analysis and the effect of pavement friction on road safety cannot be overemphasized, to the best of the authors' knowledge, no study has involved a Bayesian approach to examine the influence of pavement friction on intersection safety, particularly in the context of limited data. The objective of this study was to identify crash severity risk as a function of pavement friction, crash characteristics, driver characteristics, environmental characteristics, and other factors. First, the critical parameters would be identified using the variable importance charts of the random forest technique. Afterward, a Bayesian ordinal probit model would be developed to achieve the objective. That is because Bayesian models mitigate the negative consequences of processing limited data. This paper is organized as follows. Previous studies related to this work are elaborated and this study's data are presented. Subsequently, the methodology implemented for this study, analysis results, conclusions, and recommendations are discussed.

2. Background

Generally, friction levels decrease with time due to traffic volumes that polish the texture of aggregates in the pavement surface layer. As a result, it is strongly recommended that state DOTs and transportation agencies monitor the friction levels regularly. The FHWA promotes the use of continuous pavement friction measurement (CPFM) to measure pavement friction continuously through tangents, curves, and intersections [18]. Elkhazindar et al. [19] surveyed the state of the practice among State DOTs for managing pavement friction. The survey reported that 19 out of 32 states do not collect data on specific road characteristics (curves, ramps, and intersections), while 11 DOTs collect such data by request to investigate safety concerns. Increased wet pavement crashes are usually the major safety concern initiating friction data collection at specific road locations.

It is well established that skid resistance varies throughout the year and can change seasonally or occasionally due to environmental conditions (such as temperature or precipitation) or the presence of contamination on the pavement surface [20,21]. Crashes on the wet pavement are commonly related to skid resistance, as friction force is greatly reduced by wet pavement conditions. This can also be the case under dry pavement conditions if available friction is significantly less than the established design criteria for the roadway [18]. Wyoming has one of the highest snowfall rates in the nation. Therefore, more than 30% of crashes in Wyoming occur on non-dry road surfaces, this includes wet, icy, snowy, or slushy road surfaces [2].

In terms of friction levels and intersection safety, the application of pavement surface treatments plays a critical role in the potential hazards of skid-related (also known as friction-related) crashes. Pavement surface treatments include chip seals, micro-milling, thin hot-mix asphalt (HMA) overlay, open-graded friction course (OGFC), cape seals, scrub seals, and slurry seals, among others. Some of these treatments may be used as spot applications to increase the intersection friction levels where higher friction demands are required to reduce skid-related crashes. As a result, the impact of various roadway conditions and the relationship between skid resistance and traffic safety are not well investigated [18,22,23]. Moreover, High Friction Surface Treatments (HFSTs) provide significant increases in surface friction in locations with increased friction demand including intersections [18].

Various modeling approaches have been utilized over the past years to identify the main contributing factors to severe injuries. Preliminary analysis is critical to determine the significant independent variables for further modeling. The random forest technique has been frequently used in preliminary analyses of crash data. Jiang et al. [24] processed a massive dataset using the random forest technique to identify hazardous zones (hot spots) at the macro level. A series of random forest models have been applied along with cross-validation methods to identify the most contributing macro-level crash factors. Li et al. [25] utilized a random forest classifier to interpret the associations between crash injury severity and crash contributing factors.

While the random forest is a popular technique to identify the importance of critical influencing factors, it can be combined with other methodologies to examine the association between the response variable and these contributing factors. Since Bayesian methods are very powerful analytical tools, different Bayesian models have been widely utilized in crash analysis. Alarifi et al. [26] investigated the contributing factors to crash counts at signalized intersections and road segments. The authors utilized data from 255 intersections and 220 road segments to analyze different crash types including same-direction, angle, turning, opposite-direction, non-motorized, single-vehicle, and other multi-vehicle crashes. Bayesian multivariate and univariate hierarchical Poisson-lognormal (HPLN) spatial joint models have also been employed in the authors' study. The results indicated that the multivariate model outperformed the univariate model. The study demonstrated that the major explanatory variables varied across crash types. Moreover, the results highlighted the need for predicting crash counts by type by implementing the multivariate modeling structure.

Xie et al. [27] investigated the contributing factors of pedestrian crashes at urban signalized intersections in Hong Kong. A Bayesian measurement errors model was developed to account for the uncertainties in the data. Yu and Abdel-Aty [28] investigated crash injury severity likelihoods using real-time traffic and weather data. The crashes were classified as severe and non-severe crashes by utilizing Bayesian binary probit and maximum likelihood estimation binary probit models. Comparing the results of the two modeling approaches, the results showed the superiority of the Bayesian models.

Hierarchical Bayesian models are commonly employed in road safety research to draw inferences regarding crash injury severity. Huang et al. [29] employed a Bayesian hierarchical binomial logistic model to identify the major factors of severe injuries and vehicle damages incurred at signalized intersections. Xu et al. [30] developed a Bayesian hierarchical logit model with uncorrelated and spatially correlated random effects to investigate pedestrian injury severity risks at signalized intersections in Hong Kong. Li et al. [31] selected a hybrid approach by combining cluster analysis and hierarchical Bayesian models to analyze injury severity risks sustained due to intersection-related crashes. Three clusters were set by K-means cluster analysis considering environmental and road conditions. Hierarchical Bayesian random intercept models were estimated for each of the three clusters and for the whole dataset to determine the contributing factors of injuries. The model was compared to an ordinary multinomial logistic model neglecting the hierarchical characteristics of the crash data and the comparison confirmed the effectiveness of the proposed hybrid approach.

Bayesian modeling structures are shown to be superior in analyzing small datasets. Xie et al. [32] developed a Bayesian ordinal probit model to examine the injury severity likelihoods. The authors also compared the performance of this model to that of an ordinal probit model using datasets of various sizes. Both models yielded comparable results for large datasets, while the Bayesian model produced more accurate parameter estimates for smaller datasets. Zhu et al. [33] developed a Bayesian network structure to analyze the risk factors of multi-fatality crashes in China. The research team utilized data from

484 multi-fatal crash records. As per the findings, the most influential factors were driver behavior, vehicle condition, road condition, and weather characteristics.

Several studies involved the use of both the random forest technique and a Bayesian modeling framework to explore crash severity likelihoods. Yu et al. [34] developed analysis models for crash injury severity risks on a mountainous freeway. The analysis included crash data, weather, and real-time traffic data. The random forest technique was employed to select the explanatory variables with the highest importance after classifying the injury severity as severe and non-severe. Three models were developed to analyze crash injury severity risk. A Bayesian approach was selected to develop one of the models which was a fixed-parameter logit model. Lee et al. [35] explored the correlation between poor pavement conditions and crash severity. The importance of variables was interpreted using the random forest technique. The authors implemented Bayesian ordinal logit models to examine single and multiple-vehicle crashes on low, medium, and high-speed roads. As for single-vehicle crashes, the models indicated that substandard pavement conditions reduce crash severity likelihood on low-speed roads and raise them on high-speed roads. For multiple vehicle crashes, poor pavement conditions increase crash severity risks on all roads.

Incorporating the chief influential variables in the analysis is critical to acquiring noteworthy results from the study. Pavement surface friction is one of the key factors affecting the safety of road users. Adequate pavement friction is necessary for vehicle maneuvering, acceleration, and braking [14]. Intersections typically have higher friction demand as they tend to lose friction more rapidly than roadway segments. Meeting the friction demand at intersections is crucial to ensuring the safety of all road users [22,36].

Road safety studies corroborated the strong correlation between insufficient friction, crash counts, and crash severities regardless of whether the roadway surface was dry or wet. Cafiso et al. [37] indicated that increasing friction supply is associated with crash frequency reductions, especially for wet, nighttime, and run-off-the-road crashes. Ivan et al. [38] confirmed the existence of a strong association between pavement friction during wet conditions and crash frequency, particularly at curves and intersections. Sharafeldin et al. [39] demonstrated that pavement friction is a key factor influencing the risk of rear-end crashes at signalized intersections.

Najafi et al. [36] developed a regression model to evaluate the effect of friction on the rate of dry and wet crashes on urban roads. The study found that pavement friction is a significant factor in the rate of both dry and wet crashes. Smith et al. [40] reviewed many pavement safety programs and studies investigating the relationship between friction and crash. The review confirmed the relationship between friction and crashes with various considerations. The review also established the concept of friction and texture threshold levels.

This study comprised the development of a random forest model to interpret the critical variables, especially pavement surface friction, that impact intersection crash injury severity likelihoods as a preliminary task. Then, a Bayesian ordinal probit model was developed to investigate the effects of the variables on such likelihoods.

3. Data Description

Crash data were collected from the Critical Analysis Reporting Environment (CARE) package, supported by the Wyoming Department of Transportation (WYDOT). The crash records were collected by WYDOT from police crash reports and filed in the database. The data comprised records of 402 crashes at 52 intersections from January 2007 through December 2017, except for the years 2010 and 2011. The dataset was prepared such that each data point represents a crash record. In this study, the crashes are considered intersection crashes when they are located within 250 feet (76.2 m) from the center of the intersection [41]. The analyzed dataset did not include any missing or unknown data points and only considered the official data addressed in the crash report.

The friction data throughout the road network of Wyoming were collected by WYDOT personnel using the locked-wheel tester. The field data were calibrated by WYDOT at the regional calibration center. When not available directly, the friction measurement at the intersection was estimated from the friction measurements along the route of the intersection. Friction data were integrated with the obtained crash data. The friction measurements were matched to the crash records that occurred in the same year of friction measurement. Each row of the dataset represents a unique crash record with the friction number at the intersection, measured in the crash year. Table 1 present summary statistics of this study's data variables.

Table 1. Summary statistics of intersection safety data (binary variables).

Binary Variables				
Variable	**Count**		**Percent**	
Response				
Fatal, Suspected Serious Injury, or Suspected Minor Injury Crash	55		13.68	
Possible Injury Crash	58		14.43	
Property-Damage-Only Crash	289		71.89	
Crash Characteristics				
Commercial Motor Vehicle Involved	25		6.22	
Rear-End Crash	108		26.87	
Sideswipe Crash	33		8.21	
Other Crash	261		64.93	
Driver's Characteristics				
Driving under the Influence Related Crash	19		4.73	
Improper Use or Non-Use of Restraints	50		12.44	
Speed Related Crash	81		20.15	
Reckless Driving	81		20.15	
Roadway and Environmental Characteristics				
Signalized Intersection Crash	288		71.64	
Daylight, Dawn, Dusk, or Dark with Street Lighting	373		92.79	
Adverse Weather	88		21.89	
Wet, Icy, or Snowy Road Surface	144		35.82	
Continuous Variable				
Variable	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Friction	44.370	10.316	23.350	68.000

For this study, the response modeled was the crash severity. It was categorized into three classes, namely (1) fatal crashes, suspected serious injury crashes, and suspected minor injury crashes, (2) possible injury crashes, and (3) property-damage-only crashes. They are denoted as KAB, C, and O, respectively, as per the Highway Safety Manual [41]. Possible injury crashes are those in which drivers complain of pain, which may or may not be a result of the crash. As shown in the table, most crashes were property-damage-only crashes. The three crash severity levels K, A, and B were aggregated into one severity category to address the imbalance issue of the dataset in crash severity levels.

The presence of commercial vehicles variable represented 6% of the data's records. Moreover, a quarter of such intersection crashes were rear-end crashes, while sideswipe crashes comprised lower proportions of the data. All other crashes, such as head-on and left-turn crashes, among others, represented more than half of the total crash records.

Regarding the driver's characteristics, crashes involving improper use or non-use of safety restraints, over-speeding, and reckless driving comprised considerable proportions of the data. In contrast, crashes involving driving under the influence of drugs or alcohol represented less than 5% of the data.

Concerning roadway and environmental characteristics, the friction values ranged from 23 to 68 and the average value was 44. Figure 1 presents the friction data for the analyzed crash records count. In addition, unsignalized intersection crashes accounted for a minority of the crash records (28%). Adverse weather-related crashes and crashes that occurred on non-dry roads constituted 22% and 36% of the total crashes, respectively. The term "adverse weather" refers to conditions such as raining, snowing, and any other unfavorable conditions. It is well-known that precipitation and contamination are significantly affecting skid resistance of the pavement surface as they act as a coating layer and prevent direct contact between tires and the pavement surface [42]. It should be noted that Figure 1 only presents the distribution of friction numbers across the analyzed dataset. Friction data were matched to the crashes that occurred in the same year and at the same location of friction measurement.

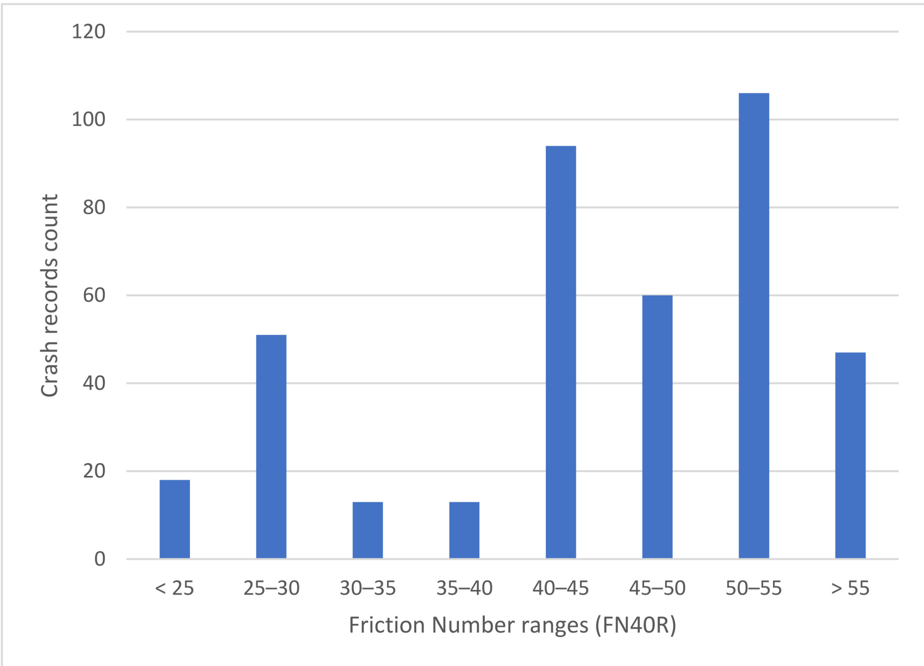

Figure 1. Friction data distribution for the crash records count.

4. Research Methodology

Two methods were employed to analyze the intersection safety data of this study. First, a preliminary analysis was conducted using the random forest machine learning technique to identify the critical independent explanatory variables influencing crash injury severity risk. Second, a Bayesian ordinal probit model was applied to gain insights into the relationships between crash injury severity risk and the crash contributing factors. The advantage of Bayesian modeling structures is that they are appropriate for conducting analyses on limited data [43–45].

The random forest technique is an extension of the decision tree machine learning technique [46]. It involves fitting a decision tree to bootstrapped datasets. A bootstrapped set consists of multiple data points sampled from the original data with replacement. The size of the bootstrapped set is equivalent to that of the original dataset. The mean of the results of the predictions outputted by each tree is the reported predictions of the random forest model. Yet, when developing each tree, the technique specifies that the tree branches are bifurcated by performing computations on data of a select subset of the total set of explanatory variables. The variables of the subset are randomly selected, and the count of those variables is equal to the square root of the total number of variables in the original dataset rounded to the nearest integer. Furthermore, the random forest technique may be used to identify the critical variables and interpret the relative importance of each variable in terms of its influence on the model's predictive power. Random forest analysis has many virtues over traditional classification and regression trees (CART), including low variance and high predictive accuracy. Therefore, many domains are replacing the use of CART with "resampling methods", such as random forests, that address CART's potential instability by averaging the results of multiple trees [47].

The reader is referred to James et al. [46] for details on decision tree methods and their variants.

Other than the random forest machine learning method that would be applied for gauging the variables' importance measures, a Bayesian ordinal probit model is developed to interpret the influence of the crash contributing factors on crash severity. Under the ordinal probit structure, a latent propensity, y^*, is defined for each crash record, i, as follows [48]:

$$y_i^* = \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_p X_{pi} + \varepsilon_i \tag{1}$$

The X's are the crash contributing factors and the β's denote their respective regression coefficients. The variable, ε_i, is the error term, which is assumed to follow the normal distribution with a mean of 0 and a standard deviation of 1, also known as the standard normal distribution. The outcome, y_i, is defined as [48]:

$$y_i = \begin{cases} O, & y_i^* < \psi_1 \\ C, & \psi_1 < y_i^* < \psi_2 \\ KAB, & y_i^* > \psi_2 \end{cases} \tag{2}$$

The variables, ψ's, are thresholds that demarcate the boundaries among injury severity categories. Note that the constant term in Equation (1), β_0, is omitted and, instead, the first threshold, ψ_1, is computed. Alternatively, β_0 may be retained and the threshold, ψ_1, is set as 0. Either formulation is equivalent to the other. The injury severity risks, $P(.)$'s, are computed using the following formulas where $F(.)$ represents the function that is used to obtain the cumulative standard normal distribution [49]:

$$P(y_i = O) = F\left(\psi_1 - \sum_{j=1}^{J} \beta_j X_{ji}\right) \tag{3}$$

$$P(y_i = C) = F\left(\psi_2 - \sum_{j=1}^{J} \beta_j X_{ji}\right) - F\left(\psi_1 - \sum_{j=1}^{J} \beta_j X_{ji}\right) \tag{4}$$

$$P(y_i = KAB) = 1 - F\left(\psi_2 - \sum_{j=1}^{J} \beta_j X_{ji}\right) \tag{5}$$

In the frequentist approach, the model's variable coefficients are obtained using the maximum likelihood estimation (MLE) method. On the other hand, in the Bayesian approach, posterior distributions of the coefficients are obtained using prior information about the current data, also known as prior distributions, or simply priors, and the crash injury severity likelihoods, estimated from the data. Under Bayes' theorem, the posterior distributions of the variables' coefficients, β's, are proportional to the products of the coefficients' prior distributions and the crash injury severity likelihoods as per the data [50]. The posterior distributions of the parameter coefficients cannot be directly computed since high dimensional integrands are involved. Instead, Markov Chain Monte Carlo (MCMC) simulation methods, including the Gibbs sampler and the Metropolis–Hastings method, were utilized to create random sampling based on the pre-defined prior distribution [50,51]. In this study, the brms package of R software was implemented to develop the model [52]. The package employs the Stan programming language to run Hamiltonian Monte Carlo simulations. Moreover, weakly informative priors were assigned to each independent variable. That is, each variable's prior was assumed to follow the standard normal distribution (N [0, 1]) as suggested by Lemoine [53]. Weakly informative priors compensate for the data's low sample size [45]. A Bayesian credible interval (CI) is typically established to assess the explanatory variables' distributions. It is interpreted as the probability that a variable's coefficient lies within the interval. On the other hand, in the frequentist approach, inferences are drawn from the confidence interval such that the explanatory variable's coefficient lies within the interval had the data collection and processing procedure been conducted repeatedly [54].

When it comes to the goodness of fit (GOF) evaluation of the Bayesian ordinal probit model, the deviance information criterion (DIC) is a widely used metric that gauges model performance. However, it has been subject to criticism [52,55,56] partly because it is descriptive of a single estimated value. In particular, it is a function of the effective number of parameters and the output deviance computed using the means of the explanatory variables' posterior distributions [57]. The study utilized the Watanabe–Akaike information criterion (WAIC), which is a measure that involves averaging the crash injury severity risks across the explanatory variables' posterior distributions [58] since it is more appropriate than the DIC [52]. Another effective measure is the leave-one-out (LOO) cross-validation measure which is used for ascertaining the predictive power of the model. Smaller WAIC and LOO cross-validation values indicate improved model performance [52]. More information about the WAIC and the LOO cross-validation measures are found in Gelman et al. [58] and Vehtari et al. [59], respectively.

The variables' results are commonly interpreted using marginal effects [60]. A marginal effect is a change in crash injury severity risks due to a change in the explanatory variable's value (i.e., from 0 to 1). Thus, for each observation, the crash injury severity risks were computed using Equation (3) through Equation (5) once assuming that the variable's value was 0 and once using a value of 1. For both conditions, the values of the other variables were as provided in the data. The variables' coefficients, inputted in the computations, were the means of their output posterior distributions. The marginal effect of the variable was computed for each observation. The average of the marginal effects across all observations was considered as the variable's marginal effect. Similarly, this procedure was repeated for all other explanatory variables.

5. Empirical Analysis

Preliminary analysis of the intersection safety data was conducted using the random forest machine learning technique and the variable importance charts were obtained. The analysis was conducted using the randomForest package [61] of R software with a preset random seed and 500 bootstrapped datasets. The variable importance charts are presented in Figures 2 and 3. Figure 2 illustrates the variables' importance in terms of the mean decrease in accuracy measure while Figure 3 depicts the variables' importance in terms of the mean reduction in the Gini index averaged across all generated trees in the random forest model. The mean decrease in accuracy is the loss in accuracy that results when removing an explanatory variable, redeveloping the model, and predicting the responses. On the other hand, the Gini index is a measure of tree node purity where a genuinely pure node is one of which all data points belong to one category of the response. The mean decrease in the Gini index measures the variable contribution to the homogeneity of the leaves and nodes of the resulting random forest, with a higher value indicating the higher importance of the variable in the model. It should be noted that the Gini impurity measure can be biased towards numeric variables as they have many split points [46].

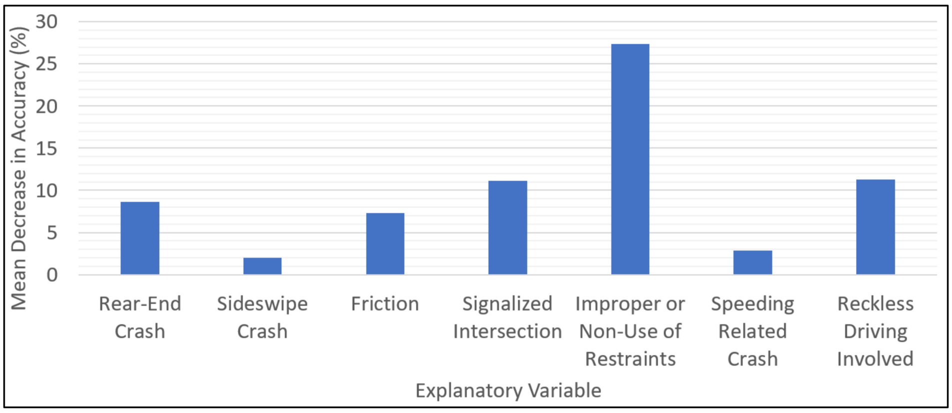

Figure 2. Variables' importance as per mean decrease in accuracy.

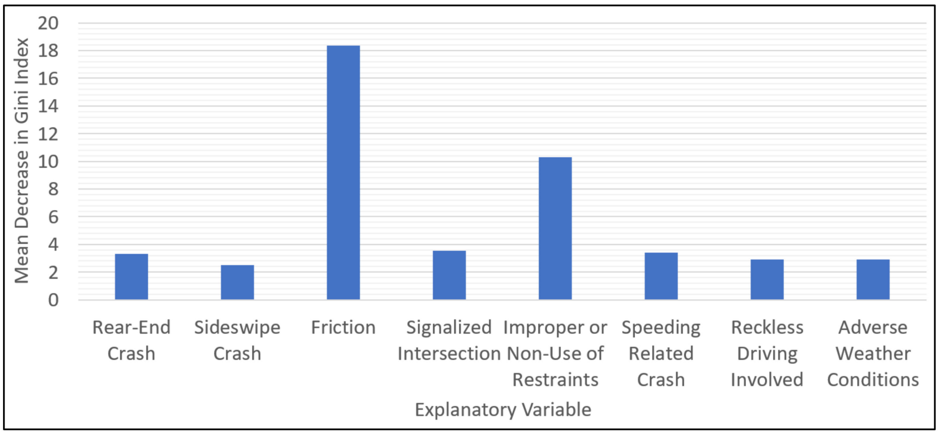

Figure 3. Variables' importance chart as per mean decrease in the Gini index.

As shown in Figure 2, the top critical explanatory variables, as per the mean decrease in accuracy metric, were the improper use or non-use of safety restraints, reckless driving, and signalized intersections. These findings are in line with Bham et al. [62], Weiss et al. [63], and McGee [64], respectively. This procedure demonstrated that these factors should be investigated in further analysis using the proposed probit model since they are the top critical explanatory variables. It should be noted that the mean decrease in accuracy demonstrated that "adverse weather" was not a significant explanatory variable.

In contrast, the pavement surface friction was the top explanatory variable influencing model performance followed by the improper use or non-use of restraints and the signalized intersection variables in terms of average loss in the Gini index. This would emphasize the importance of maintaining the pavement such that its surface friction levels provide adequate skid resistance. These findings align with Mayora and Piña [65], Bham et al. [62], and McGee [64]. The results of the Gini index emphasized the importance of including these factors in the next step of the analysis (Bayesian model) since they are the top critical predictors.

Other than the preliminary analysis, the Bayesian ordinal probit model was developed successfully using the brms package of R. Three chains, each of which entailed 10,000 iterations, were run. Moreover, the number of burn-in iterations per chain was set as 2000. Density and trace plots were outputted and, as per inferences drawn from them, the model converged. The model's results are presented in Table 2. Note that, in the table, the standard errors represent estimates of the standard deviations of the variables' posterior distributions. In addition, the 90th percentile credible interval was used instead of the 95th credible interval since the sample size was small. The variable marginal effects are presented in Table 3. In Table 3, the $\Delta P(.)$s denote the changes in crash injury severity risks. The subsequent content comprises the discussion of the results. Each variable's effect on the response was inferred assuming all else was controlled.

Table 2. Bayesian ordinal probit model results.

Variable	Mean Estimate	Standard Error	Lower 90th CI	Upper 90th CI
Crash Characteristics				
Rear-End Crash (Reference: All Other Crashes)	−0.643	0.220	−1.007	−0.284
Sideswipe Crash (Reference: All Other Crashes)	−1.037	0.339	−1.607	−0.505
Driver's Characteristics				
Improper or Non-Use of Restraints	0.921	0.182	0.619	1.220
Speed Related Crash	0.380	0.174	0.093	0.665
Reckless Driving Related Crash	0.444	0.231	0.063	0.826
Roadway and Environmental Characteristics				
Friction	−0.014	0.007	−0.026	−0.002
Signalized Intersection Crash	−0.332	0.166	−0.604	−0.062
Adverse Weather-Related Crash	−0.376	0.187	−0.686	−0.070
Goodness of Fit				
WAIC	588.566	30.315		
LOO Cross-Validation	588.654	30.325		

Notes: CI = credible interval, — = variable with credible interval containing 0 removed, WAIC = Widely Applicable Information Criterion (WAIC), LOO cross-validation = leave-one-out cross-validation.

As shown in Table 3, rear-end and sideswipe crashes were found to be less severe than all other crashes, such as head-on, left-turn, angle, and fixed-object crashes. It was estimated that, on average, a rear-end crash would have a 10% lower chance of resulting in a KAB injury relative to all other crashes except sideswipe crashes. Likewise, as per the estimated results, a sideswipe crash would have a 12% lower risk of resulting in a KAB injury relative to all other crashes except rear-end crashes. Abdel-Aty and Keller [66] inferred that signalized intersection head-on, angle, and left-turn crashes would be severe relative to both sideswipe and rear-end crashes.

Regarding the driver's characteristics, seat belt use habits were found to play a major role in influencing injury severity likelihood conditional on the occurrences of crashes. Failing to properly buckle up would raise the probability of a severe injury by an estimated 24% on average, a finding in line with Bham et al. [62]. It was also interpreted that speeding would increase the chance of incurring severe injury by 8%. Imprialou et al. [67] concluded that speeding would lead to grievous consequences. Reckless driving was also found to increase the likelihood of KAB injuries (marginal effect = 9%), a finding consistent with Weiss et al. [63]. Driving under the influence of intoxicants was not found to have an impact on injury severity risk, a finding that contradicted that of Bham et al. [62].

Table 3. Variable marginal effects.

Variable	Marginal Effects (%)		
	ΔP(y = O)	**ΔP(y = C)**	**ΔP(y = KAB)**
Crash Characteristics			
Rear-End Crash (Reference: All Other Crashes)	17.40	−6.92	−10.48
Sideswipe Crash (Reference: All Other Crashes)	22.58	−10.58	−12.00
Driver's Characteristics			
Improper or Non-Use of Restraints	−31.90	7.98	23.92
Speed Related Crash	−11.76	3.86	7.90
Reckless Driving Related Crash	−13.73	4.29	9.44
Roadway and Environmental Characteristics			
Friction	10.84	−2.93	−7.91
Signalized Intersection Crash	10.25	−3.54	−6.71
Adverse Weather-Related Crash	10.45	−4.10	−6.35

Notes: The friction variable's marginal effects were computed assuming that its value changed from 25 to 45 and that all other variable values were 0, ΔP(y = O) = change in the likelihood of incurring no injury, ΔP(y = C) = change in the likelihood of incurring possible injury, ΔP(y = KAB) = change in the likelihood of incurring fatal, suspected serious injury or suspected minor injury.

When it comes to the roadway and environmental characteristics, it was interpreted that improving pavement surface friction from 25 to 45 would reduce the risk of incurring severe injury and hence increase that of incurring no injury. The average marginal effect for this variable was computed as −7.9% assuming all other variable values were 0. Mayora and Piña [65] contended that larger friction levels indicated fewer hazards during wet pavement conditions. Signalized intersection crashes were found to be less likely to be severe (marginal effect = −7% for KAB injury). Plausibly, signalized intersections are safer than unsignalized intersections [66]. The model's results also indicated that adverse weather-related crashes would be less likely to result in severe injury possibly because drivers traveled more cautiously during such conditions and would collide at lower speeds. Kelarestaghi et al. [68] concluded that inclement weather conditions ameliorated crash severity.

6. Conclusions and Recommendations

This study entailed an investigation of the major contributing factors of severe injuries sustained as a result of intersection crashes, especially pavement surface friction. The importance of the variables was examined using the random forest method. As per its results, pavement surface friction, improper use of safety restraints, manner of collision, speeding, reckless driving, intersection traffic control type, and adverse weather all influenced crash injury severity risk substantially.

A Bayesian ordinal probit model was then developed to explore the impact of the contributing factors on crash severity risk. This study contributes to the pavement engineering literature in that it demonstrates the concept that Bayesian inference applies to pavement friction and safety data analysis when the sample size is small. The modeling results demonstrated that increasing the friction number from 25 to 45 would significantly decrease the risk of observing severe injuries and fatalities. The findings also indicated that improper use of safety restraints may increase the probability of a severe injury by 24% on average. Furthermore, according to the modeling results, signalized intersections would be less likely to experience fatal, serious injury, and minor injury crashes than unsignalized intersections. The probability of a KAB injury crash on signalized intersections is 7% less compared to unsignalized intersections.

Several recommendations are made based on this study's findings. One is to investigate safe friction thresholds by roadway functional classification and traffic volume. Another is to regularly maintain the pavement friction above acceptable levels to ensure safe traffic operations. In addition, in-depth studies ought to be conducted on intervention strategies to reduce safety restraint improper use/non-use rates, speeding, and reckless driving. These strategies pertain to drivers' educational and enforcement campaigns. When it comes to crash types, implementing countermeasures that reduce severe crashes, such as angle crashes, as documented in the Crash Modification Factors (CMF) Clearinghouse is suggested [69].

7. Study Limitations and Future Research

Although this study offered several remarkable findings, it had some limitations. One was the sample size based on Wyoming intersections only. A similar approach may be selected for a future study on larger datasets from other states. With larger data, random parameters may be incorporated to infer unobserved heterogeneity of the parameters on crash injury severity risks. Additional information about traffic volumes and traffic combinations (heavy trucks proportions) will be helpful to improve the model.

Another limitation is the identification of intersection-related crashes based on only one criterion, occurring within 250 ft for the intersection influence area. More variables can be considered to better classify intersection-related crashes. These variables can include crash location, first harmful event, driver contributing circumstances, manner of collision, and direction of travel.

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