

Article

Exploring Risk Factors for Crash Severity During Thailand's Holiday Travel: Machine Learning Exploration Compared to Heterogeneity Modeling

Savalee Uttra ¹, Thanapong Champahom ^{2,*}, Sajjakaj Jomnonkwao ³, Chamroeun Se ⁴, Panuwat Wisutwattanasak ³ and Vatanavongs Ratanavaraha ³

¹ Department of Logistics Engineering and Transportation Technology, Faculty of Engineering and Industrial Technology, Kalasin University, Kalasin 46000, Thailand; savalee.ut@ksu.ac.th

² Department of Management, Faculty of Business Administration, Rajamangala University of Technology Isan, Nakhon Ratchasima 30000, Thailand

³ School of Transportation Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand; sajjakaj@g.sut.ac.th (S.J.); panuwat.w@g.sut.ac.th (P.W.); vatanavongs@g.sut.ac.th (V.R.)

⁴ Department of Civil Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangkok 10140, Thailand; chamroeun.se01@kmutt.ac.th

* Correspondence: thanapong.ch@rmuti.ac.th

Abstract

Thailand's Western New Year and Songkran festivals witness a surge in traffic crashes due to increased travel volume. This study explores risk factors influencing crash injury severity during these holidays (2017–2019). Crash data is analyzed using both the Random Parameters Ordered Logit Model with Means Heterogeneity (RPOLHM) and machine learning techniques (Multilayer Perceptron (MLP), Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost), Random Forest). Crash severity is categorized as property damage only (PDO), minor injury, and severe/fatal injury. The results reveal that factors like motorcycle or pedestrian involvement, adverse weather, speeding, drunk driving, fatigue, nighttime conditions, improper overtaking, and urban location all significantly increase the risk of severe/fatal crashes. Notably, the XGBoost model outperforms both RPOLHM and other machine learning methods, achieving a validation accuracy of 83.8%. While machine learning approaches demonstrate superior predictive capability, RPOLHM provides interpretable coefficient estimates and marginal effects essential for understanding causal mechanisms. This complementarity suggests that concurrent application of both paradigms offers comprehensive insights: machine learning for prediction-oriented objectives and econometric models for policy formulation. These findings provide valuable guidance for policymakers, highway engineers, and researchers to develop targeted road safety interventions during these high-risk periods.

Keywords: random parameters; ordered logit model; multi-layer perceptron neural network; unobserved heterogeneity; festival crashes

Academic Editors: Zihe Zhang and Yonggang Wang

Received: 7 January 2026

Revised: 28 January 2026

Accepted: 3 February 2026

Published: 4 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Although road traffic is crucial, it is responsible for the highest number of crashes compared to other modes of transportation [1]. Reckless driving and the increasing

number of vehicles on the road contribute to the growing impact of crashes. According to the World Health Organization [2], crashes are the leading cause of injury, death, permanent disability, and property loss worldwide [3]. Thailand has one of the highest road fatality rates globally, with 32.7 fatalities per 100,000 people. The goal of reducing the fatality rate from road crashes in Thailand is gaining attention. Historical crash statistics from 2017 to 2019 provided by the Department of Highways of Thailand showed that during the New Year and Songkran festivals, which last for only 14 days out of 365, 17.94% of all crashes in Thailand occurred, accounting for 9.27% and 8.67% of all crashes during the two festivals, respectively [4]. This proportion is concerning due to the increased travel volume and changes in driver behavior during this period, which result in more crashes and higher severity [5–7]. Speeding, drunk driving, fatigue, and other dangerous driving behaviors are the primary causes of these crashes [8].

Addressing the urgent need to mitigate road fatalities requires a multifaceted approach. Effectively reducing crash severity and fatalities depends on two key strategies: (1) comprehensive crash frequency analysis aimed at reducing the overall number of road crashes, thereby decreasing fatalities; and (2) meticulous examination of crash severity, focusing on transforming incidents that would result in fatalities into outcomes of lesser injury severity or, ideally, property damage only (PDO). The latter approach also contributes significantly to reducing road crash effects.

Given these considerations, the primary objective of this study is to analyze factors closely associated with road crash severity, particularly those leading to fatalities. This analytical focus is based on the premise that such examination can unveil causative factors attributable to either driver behaviors or specific road environment conditions. However, the application of a crash frequency model requires specific data: segmented road sections and crash frequencies within each segment. While this approach proves valuable for identifying factors related to the road environment and its physical attributes, it falls short in capturing driver-related factors. Furthermore, when comparing crashes during normal versus festival periods, a notable observation emerges: crashes during both periods occur on the same roadways across Thailand (roadway characteristics remain constant). However, during festival periods, crashes exhibit a significantly higher proportion and more severe outcomes. This suggests that crash causes and severity may be more closely linked to driver-specific factors rather than roadway characteristics. The present study analyzes factors specifically associated with crash injury severity during festival periods to provide relevant authorities with actionable findings that can inform policy development aimed at reducing crash injury severities.

Nowadays, numerous types of machine learning (ML) have been applied in crash severity studies [9,10], including Multilayer Perceptron (MLP) [11–14], Decision Tree [15–17], Support Vector Machine (SVM) [18–20], Random Forest [21,22], K-Nearest Neighbors [23–25], Naïve Bayes [13,26], (Extreme) Gradient Boosting [27,28], and Adaptive Boosting (AdaBoost) [26,28,29]. Some studies have compared the statistical performance of two or more methods. For example, Sarkar et al. [11], Aghayan et al. [30], and Abdelwahab and Abdel-Aty [31] found that Artificial Neural Networks (ANNs), specifically the MLP model, provide higher accuracy and minimum errors compared to other models in classifying vehicular crash severity. Conversely, Lee et al. [22] found that Random Forest provided the best results compared to other methods such as Artificial Neural Networks and Decision Tree. Several other studies also found the superiority of the Random Forest model over other methods considered in their respective studies [16,21,32]. However, the XGBoost model was found to outperform Random Forest in studies by Lin et al. [33] and Mokoatle et al. [27], whereas another study found that AdaBoost produced the best results compared to Decision Tree, K-Nearest Neighbors, and Naïve Bayes. Although data-driven approaches have limitations, such as being unable to identify the impact of explanatory

variables on outcome probability [34,35], researchers still prefer using them for statistical analysis due to their ability to handle large amounts of data and better predict outcomes compared to econometric methods [36].

Furthermore, the logit model is a widely adopted approach for crash prediction, offering valuable insights into comparing characteristics across different severity levels. For instance, Champahom et al. [37] analyzed crash severity on urban and rural roads in Thailand. Similarly, Chen et al. [38] studied injury severity among truck drivers, and Huang et al. [39] explored driver injury severity and vehicle damage in traffic congestion scenarios at intersections in Singapore. Despite its widespread use, the traditional logit model has limitations when applied to datasets with numerous variables. To address these limitations, researchers have developed the random parameter model, designed to capture the nuances inherent in complex datasets [40,41]. This model extends the traditional logit framework, enabling a description of the relationship between fixed parameters and the inherent variability within the model. Moreover, recent research has introduced the concept of unobserved heterogeneity, encompassing variations in means and variances, which can be effectively integrated with the random parameters (probit) logit model for analyzing traffic crash injury severity [42,43]. This concept introduces a latent layer of influence that can impact the direction of the model's random parameters. The incorporation of unobserved heterogeneity enhances the model's ability to account for complexity and hidden factors, offering a nuanced perspective on crash severity analysis.

In assessing the capabilities and merits of two analytical paradigms—the logit model and machine learning techniques—it is essential to consider their respective strengths in prediction accuracy and result interpretation. Notably, a gap exists in the literature: no studies have systematically compared four distinct machine learning models—Multilayer Perceptron (MLP), AdaBoost, XGBoost, and Random Forest—against the random parameters logit model. This gap underscores the unique and timely contribution of this study.

The objectives of this research are threefold: First, it conducts a comparative analysis, examining the strengths and weaknesses of these analytical methods. Through this comparison, the study provides critical insights into the advantages and disadvantages of each method, along with an evaluation of their predictive accuracy. Second, the study identifies the most suitable analytical approaches for analyzing crashes during Thailand's long vacation periods. This is a notable contribution given the distinct dynamics of these extended holidays. Third, the study examines factors associated with crash injury severity during Thailand's long vacation periods. This aspect has received limited attention in prior research and holds the potential to uncover crucial insights into road safety dynamics during festive seasons.

The research's contribution extends beyond academia. The findings can guide relevant authorities in formulating informed road safety policies and interventions tailored to the unique challenges of extended vacation periods. By doing so, this study aims to prevent fatalities and mitigate severe injuries, particularly during Thailand's festive long vacation periods.

2. Literature Review

The primary causes of road crashes predominantly stem from human factors, encompassing high-risk behaviors such as speeding, alcohol consumption, traffic violations, fatigue, and drowsiness [44,45]. These dangerous behaviors can originate from drivers, passengers, or other road users, all potentially exposing themselves to danger [46]. Drivers often commit errors due to factors like excessive speeding, fatigue from prolonged journeys, emotionally charged driving, alcohol consumption, or lack of driving

experience. Passengers also increase crash risks by diverting the driver's attention from the road [47].

Moreover, previous research has shown that road and environmental factors are responsible for approximately 5–10% of road crashes [48,49]. Consequently, comprehensive risk assessment requires holistic examination of the road's physical environment, including adherence to standard engineering design, rigorous maintenance, and diligent inspection of road infrastructure. Research findings have consistently shown heightened crash risks associated with poor road maintenance and non-standardized or defective road conditions [50]. Various components of a road environment significantly influence crash probabilities, including lane and shoulder width, available field of vision, number of lanes, presence of roadside barriers, placement and visibility of traffic signs and lights, provision of pedestrian facilities, and overall road surface conditions. Beyond the road's immediate parameters, environmental conditions further contribute to crash dynamics. Factors such as lighting, prevailing weather conditions, visibility, and the presence of objects near the road all impact crash probabilities [51]. A summary of the categories encompassing significant factors from prior research is presented in Table 1.

Table 1. Significant variables used in previous studies.

Variable	Variable Used in Studies
Cause	Harith et al. [52], Anvari et al. [53], Chen et al. [54], Pervez et al. [55]
Collision Diagram	Connor et al. [47], [56], Bachani et al. [57], Harith et al. [52], Chen et al. [54], Kim et al. [58], Se et al. [59], Abdulazeez et al. [60]
Curve	Mahajan and Kaur [61], Klinjun et al. [62], Zhang et al. [50]
Light	Klinjun et al. [62], Harith et al. [52], Uchida et al. [63], [51], [64], Wang et al. [65]
Median	Asare and Mensah [66], Zhang et al. [50]
Opened Median	Zhang et al. [50], Somchainuck et al. [67]
Period	Li et al. [68], Sangkharat et al. [69], Bullard et al. [70]
Road Spare	Solah et al. [71], Klinjun et al. [62], Zhang et al. [50], Ulak et al. [72]
Slope	Al-Ghamdi [73], Lardelli-Claret et al. [74], Li et al. [68], Lankarani et al. [75], Pervaz et al. [76]
Surface	Lardelli-Claret et al. [74], Ismail et al. [77], Zhang et al. [50], Li et al. [68], Zhao et al. [78]
Weather	Lardelli-Claret et al. [74], Ismail et al. [77], Zhang et al. [50], Lankarani et al. [75], Bachani et al. [57], Klinjun et al. [62], Xiao et al. [79]

3. Materials and Methods

Building upon the comprehensive reviews discussed earlier, the primary objective of this study is to examine the factors influencing crashes during holiday festivals in Thailand. To achieve this, the research employs a combination of statistical and machine learning methodologies. This section provides a detailed description of the data collection, sample statistics, and modeling techniques used in this study.

3.1. Data Collection

This study utilized nationwide crash data obtained from the Highways Accident Information Management System (HAIMS) under the Department of Highways of Thailand, which is responsible for collecting crash data in the country. This study used secondary data from recorded crashes that occurred during the New Year and Songkran festivals from 2017 to 2019, excluding data from previous years due to mismatched variables. Festival crash data from previous years were considered but found to have limited and outdated variables. However, during 2017–2019, road crashes during festival periods in Thailand increased and became more severe, prompting related agencies (police) to collect more detailed and comprehensive data. In Thailand, New Year is on 1 January and Songkran is on 13 April every year; however, the government monitors

crashes for three days before and after each festival, known as the “7-Day Danger” period. The 7-Day New Year Danger period runs from 29 December to 4 January, and the Songkran period runs from 10 April to 16 April (a total of 14 days each year).

Crash severity depends on the extent of property damage and rehabilitation needs. Property damage refers to crashes that only affect property without causing injuries, while minor injuries require treatment for full recovery within three weeks. Serious injuries require hospitalization for more than three weeks, and fatalities include those who died at the scene, during transport, or after being hospitalized within 24 h [4]. The three levels of crash severity used in this study were property damage only (PDO), minor injury, and severe/fatal injury. The decision to combine severe injury and fatal injury into a single category was based on multiple considerations encompassing statistical requirements, theoretical justification, and empirical verification.

From a statistical perspective, the original dataset contained 2198 severe injury cases (26.3%) and only 390 fatal injury cases (4.7%) out of the total 8346 crash records. This substantial imbalance, with fatal crashes representing less than 5% of observations, poses significant challenges for model estimation stability, particularly for the Random Parameters Ordered Logit Model where reliable parameter estimation requires adequate sample sizes within each outcome category. Sparse cell counts in discrete outcome models can lead to inflated standard errors, unstable coefficient estimates, and convergence difficulties during maximum likelihood estimation. The machine learning models similarly benefit from more balanced class distributions, as extreme minority classes often result in poor predictive performance for the underrepresented category despite potentially high overall accuracy metrics [80].

From a theoretical standpoint, severe injuries and fatalities share fundamental similarities in terms of crash dynamics and contributing factors. Both outcomes typically result from high-energy impacts involving similar mechanisms such as high collision speeds, vulnerable road user involvement, or absence of protective infrastructure. Previous research has demonstrated that the factors distinguishing fatal crashes from severe injury crashes are often related to post-crash medical response and victim characteristics rather than crash-level variables typically available in police-reported crash databases [81]. Consequently, combining these categories allows the analysis to focus on distinguishing high-severity outcomes from lower-severity outcomes, which aligns with the primary objective of identifying factors that elevate crash consequences to levels requiring hospitalization or resulting in death.

This categorical specification is consistent with established practices in the crash severity literature. Numerous studies have adopted similar approaches when analyzing crash injury outcomes, merging severe and fatal categories to address sample size constraints while maintaining meaningful severity distinctions [82]. The three-level severity classification (PDO, minor injury, severe/fatal injury) has been widely employed in transportation safety research and provides sufficient granularity to capture the spectrum of crash outcomes while ensuring robust model estimation.

To verify the appropriateness of this specification, preliminary sensitivity analyses were conducted comparing models with three-level (merged) and four-level (separate) severity classifications. The four-level specification exhibited convergence difficulties for several random parameters and produced unstable coefficient estimates for the fatal injury category, with standard errors exceeding coefficient magnitudes for multiple variables. Furthermore, likelihood ratio tests comparing the explanatory power of significant variables across severe and fatal categories indicated that the majority of contributing factors exhibited similar directional effects and comparable magnitudes for both outcomes, supporting the theoretical basis for combining these categories. Based on

these statistical and theoretical considerations, the three-level severity classification was adopted for all subsequent analyses.

Prior to analysis, systematic data preprocessing procedures were implemented to ensure data quality and analytical validity. The original dataset obtained from the Highways Accident Information Management System (HAIMS) contained 8712 crash records. Missing data assessment revealed that 366 records (4.2%) contained incomplete information for one or more explanatory variables. Given the relatively small proportion of missing data and to maintain analytical integrity, records with missing values were excluded from the analysis using listwise deletion, resulting in a final analytical sample of 8346 complete crash records.

Regarding normalization and scaling procedures, all explanatory variables in this study were coded as binary indicators (0 or 1) representing the presence or absence of specific crash characteristics, as shown in Table 2. Consequently, feature scaling techniques such as min-max normalization or standardization were not required, as all variables already existed on the same scale. This binary coding approach is consistent with standard practices in crash severity modeling using both econometric and machine learning methods, as it facilitates straightforward interpretation of variable effects and avoids potential issues associated with continuous variable transformation [83]. For the machine learning models, the binary nature of input features ensured that no single variable dominated the learning process due to scale differences, thereby eliminating the need for additional normalization procedures.

Table 2. Descriptive statistic of the explanatory variables.

Variable	Description	Mean	S.D.
Main lane	1 if crash occurs on main lane, 0 otherwise	0.05	0.219
Frontage lane	1 if crash occurs on frontage lane, 0 otherwise	0.01	0.114
Work zone	1 if crash occurs in work zone, 0 otherwise	0.02	0.144
2_lane	1 if crash occurs on 2-lane road, 0 otherwise	0.35	0.478
4_lane	1 if crash occurs on 4-lane road, 0 otherwise	0.45	0.498
No median	1 if crash occurs on road without median, 0 otherwise	0.39	0.487
Flush median	1 if crash occurs on road with flush median, 0 otherwise	0.09	0.280
Raised median	1 if crash occurs on road with raised median, 0 otherwise	0.21	0.407
Depressed median	1 if crash occurs on road with depressed median, 0 otherwise	0.24	0.429
Barrier median	1 if crash occurs on road with barrier median, 0 otherwise	0.07	0.257
Concrete pavement	1 if crash occurs on concrete road, 0 otherwise	0.11	0.312
Curve	1 if crash occurs curve, 0 on straight road)	0.15	0.360
Slope	1 if crash occurs at road with slope > 3%, 0 otherwise	0.04	0.202
Intersection	1 if crash occurs at intersection, 0 otherwise	0.09	0.284
U-turn	1 if crash occurs at median opening area, 0 otherwise	0.06	0.239
Bride	1 if crash occurs on bridge, 0 otherwise	0.01	0.107
Wet road	1 if road surface is dry, 0 otherwise	0.1	0.305
Adverse weather	1 if crash occurs during rain, 0 otherwise	0.11	0.311
Lit road	1 if crash occurs at nighttime with light condition, 0 otherwise	0.29	0.454
Unlit road	1 if crash occurs at nighttime without light condition, 0 otherwise	0.13	0.332
Exceeding speed limit	1 if cause of crash is exceeding speed limit, 0 otherwise	0.62	0.486
Sudden crossing	1 if driver hits a sudden-crossing object, 0 otherwise	0.16	0.370
Improper overtaking	1 if driver overtakes illegally/improperly, 0 otherwise	0.01	0.113
DUI	1 if driver is under the influence of alcohol, 0 otherwise	0.07	0.253
Fatigue	1 if driver is fatigued, 0 otherwise	0.07	0.251
Pedestrian	1 if crash involves a pedestrian	0.04	0.193
Rear-end	1 if collision is a rear-end crash, 0 otherwise	0.27	0.444
Sideswipe	1 if collision is a sideswipe, 0 otherwise	0.13	0.338

Single crash	1 if collision is a single crash or run-of-road crash, 0 otherwise	0.44	0.497
Head-on	1 if collision is a head-on crash, 0 otherwise	0.05	0.217
Motorcycle	1 if crash involves a motorcycle, 0 otherwise	0.46	0.498
Car	1 if crash involves a car, 0 otherwise	0.37	0.482
Pickup truck	1 if crash involves a pickup truck, 0 otherwise	0.42	0.493
Large truck	1 if crash involves a large truck, 0 otherwise	0.07	0.268
Urban	1 if crash occurs in an urban area, 0 rural	0.15	0.357
Pre-festival	1 if crash occurs pre-festival, 0 otherwise	0.51	0.500

Note: S.D. = standard deviation.

Outlier detection and management were carefully considered during the preprocessing phase. Traditional outlier identification techniques based on statistical distributions (such as z-scores or interquartile range methods) are primarily applicable to continuous variables and are not directly transferable to binary categorical data. Therefore, data quality verification focused on logical consistency checks rather than conventional outlier removal. Specifically, each crash record was examined to ensure that mutually exclusive categories were correctly coded (for example, a crash could not simultaneously occur on both a curved and straight road segment), and that the combination of coded variables represented plausible crash scenarios. Records exhibiting logical inconsistencies were flagged for review and corrected based on original crash report documentation where possible, or excluded from analysis when verification was not feasible. Additionally, frequency distributions of all variables were examined to identify potential data entry errors, such as implausible combinations of crash characteristics. Through these validation procedures, 27 records were identified with logical inconsistencies and subsequently removed, contributing to the total of 366 excluded records mentioned previously.

Over a span of three years, Thailand recorded a total of 8346 crashes during extended holiday periods nationwide. Among these, 1989 (23.8%) were categorized as property damage only (PDO), 3769 (45.2%) as minor injuries, and 2588 (31%) as severe or fatal crashes. Table 1 provides a summary of the descriptive statistics for the explanatory variables used in the analysis. The study employed Nlogit Version 6 for analyzing the random parameter model and the R program for analyzing the machine learning models.

3.2. Descriptive Statistics

The distribution of vehicles involved in crashes (Figure 1) shows motorcycles comprising 33.82%, cars at 27.21%, pickup trucks at 30.88%, pedestrians at 2.94%, and large trucks at 5.15%. The high incidence of motorcycle-related crashes highlights the urgent need for targeted safety measures, while the prominence of cars and pickup trucks emphasizes the importance of responsible driving behaviors. This distribution demonstrates the necessity of a comprehensive road safety strategy tailored to the distinct challenges posed by various vehicle types to reduce crashes and their severity.

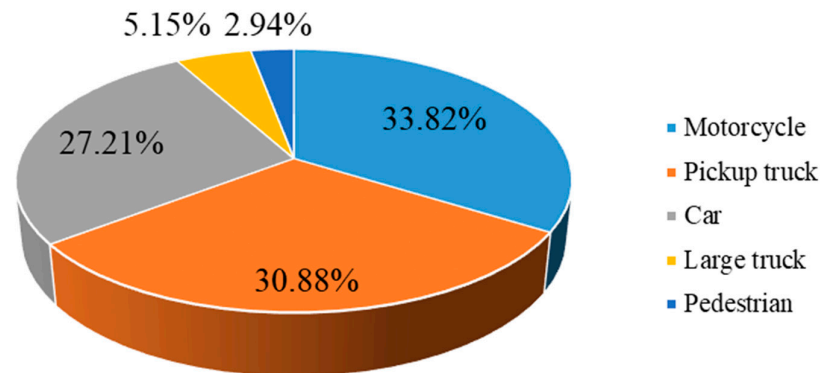


Figure 1. Percentage of vehicle types in crashes occurring between 2017 and 2019 in Thailand.

In the preliminary data analysis, as indicated by the descriptive statistics in Table 2, several noteworthy patterns emerge. A significant majority of cases, 62%, were attributed to speeding, while 16% resulted from sudden crossing incidents. Moreover, 52% of the crashes occurred before the commencement of the holiday or festival period. In terms of road configurations, 4-lane roads constituted 45% of the total cases, with 2-lane roads accounting for 35%. Regarding road medians, 24% of the incidents occurred on depressed median roads, 21% on raised median roads, and 39% on roads without a median, marked only by a yellow line dividing the directions. Additionally, 29% of crashes occurred during nighttime on illuminated roadways, while 13% occurred on unlit roadways. Lastly, 15% of cases occurred on curved roads within urban areas.

3.3. Random Parameters Ordered Logit Model with Heterogeneity in Means (RPOLHM)

This study adopted the Random Parameters Ordered Logit Model with Heterogeneity in Means (RPOLHM) for the model analysis. The model begins by defining the severity function S_{jm} of crash m sustaining injury severity j as follows [84]:

$$S_{jm} = \beta_j X_{jm} + \varepsilon_{jm} \quad (1)$$

where X_{jm} is a vector of the crash-level factors (independent variables) with β_j acting as a vector of estimable parameters, and ε_{jm} is an error term which is assumed to be normally distributed with a mean of 0 and variance of 1. For crash m , the resulting injury severity function S_{jm} sustaining injury severity j can be written as follows:

$$S_{jm} = j, \text{ if } \mu_{j-1,m} < S_{jm} \leq \mu_{j,m} \quad (2)$$

where $j = 0, 1$, or 2 , respectively, for PDO, minor injury, and severe/fatal injury. μ_j is the threshold that defines S_{jm} which corresponds to the integer-ordered injury outcome level such that $\mu_{j-1} < \mu_j$. Next, the ordered probability function $P(S = j)$ of the j -th injury severity level for each crash observation can be written as follows:

$$P(S = j) = \Phi(\mu_j - \beta_m X_m) - \Phi(\mu_{j+1} - \beta_m X_m) \quad (3)$$

where Φ denotes the standard logistic cumulative distribution function. To allow for a more flexible approach in capturing the underlying unobserved heterogeneity, the model estimation also allows the effect of the explanatory variables to influence the means and variances of the significant random parameters. To do this, heterogeneity in the mean and variance of random parameters β_{jm} in latent injury risk propensity function can be computed as [85]:

$$\beta_{jm} = \beta_j + \Psi_{jm} \Omega_{jm} + \sigma_{jm} e^{(\nu_{jm} \Psi_{jm})} \omega_{jm} \quad (4)$$

where β_j is the mean value of the random parameter vector, Ω_{jm} is a vector of attributes that captures heterogeneity in the mean, Ψ_{jm} is the corresponding vector of estimable parameters, Ψ_{jm} is a vector of attributes that captures heterogeneity in the standard deviation σ_{jm} with the corresponding parameter vector γ_{jm} , and ω_{jm} is a disturbance term.

In terms of model interpretation, it is commonly recommended to compute the average marginal effect (AME) for each explanatory variable and each injury outcome category across the crash population. For a binary variable (or indicator variable), the AME is computed as the difference in the estimated probabilities $P(S = j)$ with the indicator variable X_i changing from zero to one, while all other variables $\bar{X}_i$ are equal to the average values over sample observations [85]. The computation of the AME can be defined as:

$$AME = P(S = j | \bar{X}_i, X_i = 1) - P(S = j | \bar{X}_i, X_i = 0) \quad (5)$$

The identification of random parameters and heterogeneity terms followed a systematic specification search procedure. Initially, all explanatory variables were estimated as fixed parameters in a standard ordered logit model. Subsequently, each variable was individually tested as a random parameter by allowing its coefficient to vary across observations following a normal distribution. A variable was retained as a random parameter if two conditions were satisfied: the estimated standard deviation of the random parameter was statistically significant at the 90% confidence level or higher, and the inclusion of the random parameter improved overall model fit as assessed by the Akaike Information Criterion (AIC) and likelihood ratio tests [86]. This iterative process was repeated for all candidate variables, and the final model specification retained only those random parameters that demonstrated both statistical significance and meaningful improvement in model performance. Through this procedure, two variables were identified as random parameters: personal car involvement and pickup truck involvement, both exhibiting statistically significant standard deviations indicating substantial variation in their effects across crash observations.

Following the identification of random parameters, heterogeneity in means was assessed by examining whether observed crash characteristics could explain systematic variation in the mean values of the random parameters. For each identified random parameter, all other explanatory variables were tested as potential sources of heterogeneity in the mean by including interaction terms in the parameter distribution specification as shown in Equation (4). A variable was included as a source of heterogeneity in means if the corresponding coefficient was statistically significant and the interaction was theoretically justifiable based on the traffic safety literature. The results indicated that main lane, roads without median, and roads with flush median significantly influenced the mean values of the random parameters associated with personal car and pickup truck involvement. These findings suggest that the effects of vehicle type on crash severity systematically vary depending on roadway characteristics.

Heterogeneity in variances was similarly assessed by testing whether observed variables affected the variance of the random parameters. Each candidate variable was included in the variance function as specified in Equation (4), and statistical significance was evaluated. Despite comprehensive testing across all explanatory variables, no statistically significant heterogeneity in variances was identified in this study. Consequently, the final model specification reverted to the Random Parameters Ordered Logit Model with Heterogeneity in Means (RPOLHM) rather than the full heterogeneity in means and variances specification. This finding indicates that while the mean effects of vehicle type vary systematically with roadway characteristics, the degree of unobserved variation around these means remains relatively consistent across different crash contexts.

The absence of variance heterogeneity is consistent with several previous crash severity studies that have similarly found heterogeneity in means to be more prevalent than heterogeneity in variances [87].

3.4. Machine Learning Approaches

3.4.1. Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) represents a potent and adaptable machine learning algorithm that resides within the domain of Artificial Neural Networks [88]. The core architecture of an MLP consists of multiple interconnected layers of nodes, commonly known as neurons. These neurons are distributed across an input layer, one or more hidden layers, and an output layer [89]. Each connection between neurons is associated with a weight, which is systematically adjusted during the training process to optimize the model's performance. One of the distinguishing features of MLP is its capacity to capture intricate patterns and relationships within the data, thanks to the presence of multiple hidden layers. The training process of an MLP is often guided by optimization techniques like gradient descent, where the model learns to minimize a defined loss function by iteratively adjusting the weights [90]. Backpropagation, a key element of MLP training, facilitates the propagation of errors backward through the network, thereby fine-tuning the model's weights. The specific formulas are as follows:

Input:

$$X = \sum_{i=1}^n w_{ij}x_i + b_i, \quad i = 1, 2, 3, \dots, n \quad (6)$$

Hidden layer (using sigmoid function):

$$h_j = \frac{1}{(1+e^{-x})}, \quad j = 1, 2, 3, \dots, m \quad (7)$$

Output layer (using SoftMax activation function for multi-class classification):

$$S(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}} \quad (8)$$

Moreover, its flexibility allows for customization by adjusting hyperparameters like the number of hidden layers, the number of neurons in each layer, and the activation functions used. In practice, implementing an MLP begins by importing essential R packages “neuralnet” (version 1.44.2) for constructing the model [91] and “caret” (version 7.0-1) for supplementary evaluation tools [92].

3.4.2. Adaptive Boosting (AdaBoost)

The Adaptive Boosting algorithm, often referred to as AdaBoost, constitutes a formidable and versatile machine learning technique that falls under the ensemble learning umbrella [93]. AdaBoost is esteemed for its proficiency in enhancing the performance of weak learners, ultimately culminating in robust and highly accurate predictions. The fundamental principle behind AdaBoost revolves around iteratively assigning higher weights to those data points that are persistently misclassified by the weak learners in the ensemble. This strategic emphasis on the “hard” instances effectively directs the learning process towards improved classification accuracy. Every instance is weighted in the training dataset. At first, the weight is set to [23]:

$$Weight, W_i = \frac{1}{n} \quad (9)$$

where W_i is the i -th training instance weight and n is the number of training instances. More weight is given where hard to predict, whereas less weight is given where easy to predict [93]. One of the distinguishing features of AdaBoost is its adaptability to various base classifiers, including Decision Trees, which are frequently employed as weak

learners. By sequentially incorporating multiple weak learners into the ensemble, AdaBoost progressively refines its prediction capabilities. The final prediction is derived through weighted majority voting, where each weak learner's influence on the final decision is proportionate to its performance. In practice, the implementation of AdaBoost begins with loading essential “adabag” (version 5.1) package in R for constructing the model [94]. The Model Training phase involves building an AdaBoost classifier using the training data while specifying critical hyperparameters such as the number of boosting iterations and the choice of weak learner.

3.4.3. XGBoost

The XGBoost model represents a potent and versatile machine learning algorithm, falling under the purview of ensemble learning techniques. XGBoost employs a gradient boosting framework, a sequential approach that iteratively builds Decision Trees to correct errors made by preceding trees [95]. This iterative refinement enables XGBoost to capture intricate patterns and relationships within data, resulting in superior predictive performance. Mathematically, boosting can be defined as follows [27]:

- Step 1: Model F_0 is initialized to predict the response variable y . This model will relate to a residual $(y - F_0)$.
- Step 2: A new model h_1 will then be overlaid on the residuals from the preceding step.
- F_0 and h_1 will then be integrated to give F_1 , which will be the optimized or boosted version of F_0 . The loss function from F_1 will be better than that from F_0 :

$$f_1(x) \leftarrow f_0(x) + h_1(x) \quad (10)$$

To enhance the performance of F_1 , the residuals of F_1 can be modeled to create a new model F_2 :

$$f_2(x) \leftarrow f_1(x) + h_2(x) \quad (11)$$

This is repeated for m iterations, until such a time that the residuals are reduced as much as possible:

$$f_m(x) \leftarrow f_{m-1}(x) + h_m(x) \quad (12)$$

In gradient boosting, as an alternative to fitting $h_m(x)$ on the residuals, $h_m(x)$ is fitted on the gradient of the loss function. Gradient descent assists in reducing any differentiable function [96]. One of the key strengths of XGBoost lies in its regularization techniques, which help prevent overfitting. It achieves this by incorporating penalties for complex models, thus promoting simpler and more interpretable models. In the practical application of XGBoost, we initiate the process by using the essential R packages “xgboost” (version 2.1.0) package for model construction [97].

3.4.4. Random Forest

The Random Forest model stands as a formidable and versatile machine learning algorithm, firmly situated within the ensemble learning realm. Firstly, it constructs each Decision Tree through the utilization of a random subset of the training data, a process known as bootstrapping [98,99]. This introduction of diversity inherently mitigates overfitting concerns. Secondly, during the tree-building process, Random Forest randomly selects a subset of features for each split [32]. This deliberate diversity injection forestalls any single dominant feature from unduly overshadowing others. These individual Decision Trees collectively coalesce into a “forest,” and their outputs converge through voting (for classification) or averaging (for regression) to yield the final prediction. These attributes have solidified their prominence across diverse machine

learning applications. This study utilized the essential R package “randomForest” (version 4.7-1.2) for the Random Forest model construction [100]. In the Model Training phase, we forge a Random Forest classifier using the training data, specifying the number of trees (ntree) and other hyperparameters as required. The study also delves into hyperparameter tuning, optimizing performance by adjusting parameters such as the number of trees (ntree) or the maximum depth of the trees (max_depth).

3.4.5. Model Training Configuration and Validation Strategy

To ensure reproducibility and robust model evaluation, this subsection describes the data partitioning strategy, cross-validation approach, hyperparameter optimization, and class imbalance treatment applied across all machine learning models.

The dataset containing 8346 crash records was randomly divided into training and validation sets using an 80:20 split ratio, resulting in 6677 observations for training and 1669 observations for validation. Stratified sampling was employed to maintain consistent proportions of crash severity categories across both sets. A 10-fold cross-validation procedure was implemented during the training phase to obtain reliable performance estimates and minimize overfitting. In each iteration, the training data was partitioned into ten equal subsets, with nine subsets used for model fitting and the remaining subset reserved for performance evaluation. The final performance metrics represent the average across all ten folds.

Grid search optimization was conducted to identify optimal hyperparameter configurations for each machine learning model. For the MLP model, the number of hidden layers was varied from 1 to 3, with neurons per layer tested at 32, 64, and 128, while learning rates of 0.001, 0.01, and 0.1 were evaluated, and the activation function was set to ReLU for hidden layers and SoftMax for the output layer. For AdaBoost, the number of boosting iterations was tested at 50, 100, 200, and 500, learning rates of 0.01, 0.1, 0.5, and 1.0 were examined, and Decision Trees with maximum depths of 1, 2, and 3 served as base estimators. For XGBoost, the number of estimators was evaluated with 100, 200, 300, and 500, maximum tree depth was tested with 3, 5, 7, and 10, learning rates of 0.01, 0.05, 0.1, and 0.2 were examined, the minimum child weight parameter was varied between 1, 3, and 5, and the subsample ratio was tested at 0.7, 0.8, and 1.0. For Random Forest, the number of trees was tested at 100, 200, 300, and 500; maximum depth values of 10, 20, 30, and unlimited were evaluated; the minimum samples required for splitting was tested at 2, 5, and 10; and minimum samples per leaf was examined at 1, 2, and 4. The optimal hyperparameters were selected based on the highest average accuracy obtained from cross-validation results.

Given the imbalanced distribution of crash severity categories in the dataset (PDO: 23.8%, minor injury: 45.2%, severe/fatal: 31.0%), the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training data [101]. SMOTE generates synthetic samples for minority classes by interpolating between existing minority class instances and their nearest neighbors. This technique was applied only to the training set to prevent data leakage, while the validation set retained its original distribution to ensure unbiased performance evaluation. The SMOTefamily package (version 1.4.0) in R was utilized for SMOTE implementation [102].

3.5. Model Evaluations

Prior to model evaluation, the dataset was partitioned into training and validation sets, class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE), and hyperparameters were optimized through grid search procedures as detailed in Section 3.4.5. To assess the model performance of the estimated

models, since these are the multi-class classification problems, the following criteria were recommended for model evaluations, based on the confusion matrix in Table 3 [103,104]:

Table 3. Confusion matrix of the crash injury severity.

Actual Injury Severity	Predicted Injury Severity	
	<i>i</i> th Injury Severity	Not <i>i</i> th Injury Severity
<i>i</i> th injury severity	True Positive (TP_s)	False Negative (FN_s)
Not <i>i</i> th injury severity	False Positive (FP_s)	True Negative (TN_s)

$$\text{Accuracy} = \frac{TP_s + TN_s}{TP_s + FN_s + TP_s + TN_s} \quad (13)$$

$$\text{Recall (Sensitivity)} = \frac{TP_s}{TP_s + FN_s} \quad (14)$$

$$\text{Precision} = \frac{TP_s}{TP_s + FP_s} \quad (15)$$

$$\text{F-Score} = \frac{2TP_s}{2TP_s + FN_s + FP_s} \quad (16)$$

Another direct approach to compare the model performance of each model is a comparing the performance of predictability by injury severity level and then compute the total scores for comparison. That is, two measurements, i.e., the prediction accuracy rate (PAR) and false positive rate (FPR), are employed to evaluate the performance of different crash injury severity levels [34,105]:

$$PAR_s = \frac{TP_s}{TP_s + FN_s} \quad (17)$$

$$FPR_s = \frac{FP_s}{FP_s + TN_s} \quad (18)$$

$$\text{Summary score } (C) = \sum PAR - FPR \quad (19)$$

4. Results and Discussion

This section presents a comprehensive model comparison examining prediction accuracy, overall performance, and other pertinent metrics. Additionally, it discusses the significant variables identified within each analysis model employed in the research, including the best-performing machine learning model and the RPOLHM. Furthermore, this section provides a rigorous interpretation of the significance of the results obtained through these analyses.

4.1. The Comparison of Model Prediction Accuracy

Table 4 presents a comparison of different machine learning models based on various performance metrics, including accuracy, recall, precision, F-score, and AUC (Area Under the Curve). These metrics are crucial for evaluating the effectiveness of each model in solving a particular problem and provide insights into how well each model performs in classifying data.

Table 4. Model fit comparisons.

Model	Data	Accuracy	Recall	Precision	F-Score	AUC
Unobserved heterogeneity model						
RPOLHM	Total	49.6%	47.1%	52.8%	48.5%	48.0%
Machine Learning models						
MLP	Training	64.9%	58.6%	58.2%	58.3%	58.3%
	Validating	58.0%	64.1%	65.5%	64.5%	64.3%
Adaboost	Training	72.8%	71.4%	72.7%	72.0%	72.0%
	Validating	71.8%	70.3%	71.5%	70.8%	70.9%
RF	Training	78.2%	77.3%	79.3%	77.9%	77.6%
	Validating	76.8%	76.0%	77.7%	76.4%	76.2%
XGBoost	Training	85.1%	85.0%	85.2%	85.0%	85.0%
	Validating	83.8%	83.7%	83.9%	83.7%	83.7%

Note: AUC = Area Under the Curve (macro-averaged across all three severity classes, calculated as the unweighted mean of class-specific AUC values).

These metrics collectively provide a comprehensive evaluation framework consistent with established practices in machine learning model assessment [106]. Table 4 presents aggregate performance metrics including Accuracy, Recall, Precision, F-score, and AUC, while Table 5 disaggregates model performance by injury severity category through the prediction accuracy rate (PAR) and false positive rate (FPR). The PAR metric is equivalent to class-specific recall (or sensitivity), representing the proportion of actual cases in each severity category that are correctly predicted, while FPR indicates the proportion of cases not belonging to a severity category that are incorrectly classified into that category. These class-specific metrics convey equivalent information to confusion matrices, as they are directly derived from the true positive, false negative, false positive, and true negative counts constituting confusion matrix cells. The combination of aggregate and class-specific performance metrics enables thorough evaluation of each model's classification capability across all severity categories.

Table 5. Model fit comparison by injury severity.

Model	Data	Performance by Driver Injury Severity						Summary Score
		PDO		MI		SF		
		PAR	FPR	PAR	FPR	PAR	FPR	
Unobserved heterogeneity model								
RPOLHM	Total	37.3%	11.4%	60.2%	57.9%	43.7%	28.4%	43.6%
Machine Learning models								
MLP	Training	67.2%	14.0%	71.0%	36.2%	54.2%	15.1%	127.0%
	Validating	66.0%	19.1%	58.8%	38.1%	50.9%	23.0%	95.5%
Adaboost	Training	59.3%	13.1%	75.3%	27.1%	79.6%	7.6%	166.4%
	Validating	58.2%	13.7%	74.4%	27.8%	78.2%	8.2%	161.1%
RF	Training	80.4%	8.6%	84.5%	24.0%	67.1%	6.0%	193.5%
	Validating	78.7%	9.3%	83.1%	25.1%	66.2%	6.8%	186.8%
XGBoost	Training	88.4%	5.8%	87.0%	13.8%	79.6%	5.8%	229.7%
	Validating	86.7%	6.4%	86.2%	14.8%	78.2%	6.4%	223.7%

Note: PDO = property damage only; MI = minor injury; SF = severe/fatal injury.

MLP (Multilayer Perceptron) demonstrates reasonable performance on both the training and validation datasets, with accuracy ranging from 58% to 64.9%. However, its precision and F-score are relatively lower, indicating difficulty in correctly identifying positive cases while maintaining precision. The AUC is also in the middle range,

suggesting moderate discrimination ability. AdaBoost (Adaptive Boosting) exhibits better accuracy, recall, and precision than MLP on both training and validation sets, with values around 71.8% to 72.8%. This suggests that AdaBoost is more effective at correctly classifying positive cases while maintaining precision. The AUC is also relatively high, indicating good discrimination ability. RF (Random Forest) demonstrates the highest accuracy among the models, with values around 76.8% to 78.2% for both training and validation. It also shows good recall, precision, and F-score values. The AUC is reasonably high, indicating strong discrimination ability. RF appears to be a strong performer in this context. XGBoost outperforms all other models in terms of accuracy, with values around 83.8% to 85.1% on both training and validation sets. It also exhibits excellent recall, precision, F-score, and AUC values. XGBoost appears to be the most robust and accurate model among those tested. RPOLHM (Random Parameter Ordered Logit with Heterogeneity in Means) performs the poorest among all models, with accuracy at 49.6% and relatively low values for recall, precision, F-score, and AUC. It appears to be the least suitable model for this problem based on these metrics. This subpar performance may be attributed to the inherent limitations of ordered models employed in this study, characterized by fixed thresholds. These fixed thresholds limit the model's adaptability in analyzing crash severity, as they do not accommodate the simultaneous increase or decrease in the effects of extreme categories, as discussed in Mannering and Bhat [107]. Future research may explore alternatives such as a random thresholds random parameters hierarchical ordered probit model or a random parameter generalized ordered model. These alternatives offer greater flexibility by allowing thresholds to vary both as a function of estimated parameters (reflecting unobserved heterogeneity) and across observations (capturing threshold heterogeneity) [108–111].

Examining predictive performance by driver injury severities in Table 5, it becomes evident that XGBoost (220%) and RF (190%) excel, demonstrating the highest scores, followed by AdaBoost with moderate performance (160%). Furthermore, despite yielding a lower score than the AdaBoost model, MLP (60%) still outperforms the random parameters ordered logit approach significantly, which only achieves a score of 43%. RPOLHM consistently exhibits the lowest performance across all metrics, aligning with findings from Yu et al. [105], who found that various machine learning models (Neural Network, Convolutional Neural Network, and Fusion Convolutional Neural Network), with scores ranging between 107% and 152%, significantly outperform the random parameters model, which scores only 59%. Based on Mannering et al. [36], although data-driven approaches have low causality or inference capability, they often provide good big data analysis suitability and the best predictive capability.

The summary score presented in Table 5 provides a comprehensive measure of model performance across all injury severity categories. This metric is calculated by summing the differences between the Prediction Accuracy Rate (PAR) and False Positive Rate (FPR) for each severity class: $\text{Summary Score} = (\text{PAR_PDO} - \text{FPR_PDO}) + (\text{PAR_MI} - \text{FPR_MI}) + (\text{PAR_SF} - \text{FPR_SF})$. A higher summary score indicates better overall model performance, reflecting the model's ability to correctly identify cases within each severity category (high PAR) while minimizing incorrect classifications (low FPR). The theoretical maximum score is 300% (achieved when PAR equals 100% and FPR equals 0% for all three categories), while a score of 0% would indicate performance no better than random classification. In practical terms, the XGBoost model's summary score of 223.7% substantially exceeds that of RPOLHM (43.6%), demonstrating markedly superior discriminative capability across all severity levels.

4.2. Machine Learning Models

Given that the XGBoost model outperformed RF, AdaBoost, and MLP models, a variable importance analysis was conducted using the XGBoost model as the basis, as

illustrated in Figure 2. The variable importance was calculated using the gain metric, which quantifies the average improvement in model accuracy (reduction in loss function) contributed by each variable across all splits where that variable is utilized. Higher gain values indicate greater contribution to the model's predictive performance. Within this analysis, several key factors emerged as significant contributors to crash severity. Notably, the type of vehicle involved, specifically motorcycles, had the highest importance score, signifying its predominant impact. Additionally, the timing of crashes in relation to festivals or holidays played a pivotal role, with pre-festival incidents significantly affecting severity. Adequate road lighting and vehicle type, including cars and pickup trucks, also had substantial influence. Furthermore, road infrastructure characteristics, such as four-lane roads, and driver behaviors like speeding, substantially influenced crash outcomes. Urban settings and the nature of the crash, particularly single-vehicle crashes, ranked among the top ten factors impacting crash injury severity. These findings underscore the multifaceted nature of crash severity, encompassing diverse elements such as vehicle attributes, road conditions, temporal factors, and driver actions, highlighting the importance of tailored interventions and policies to improve road safety.

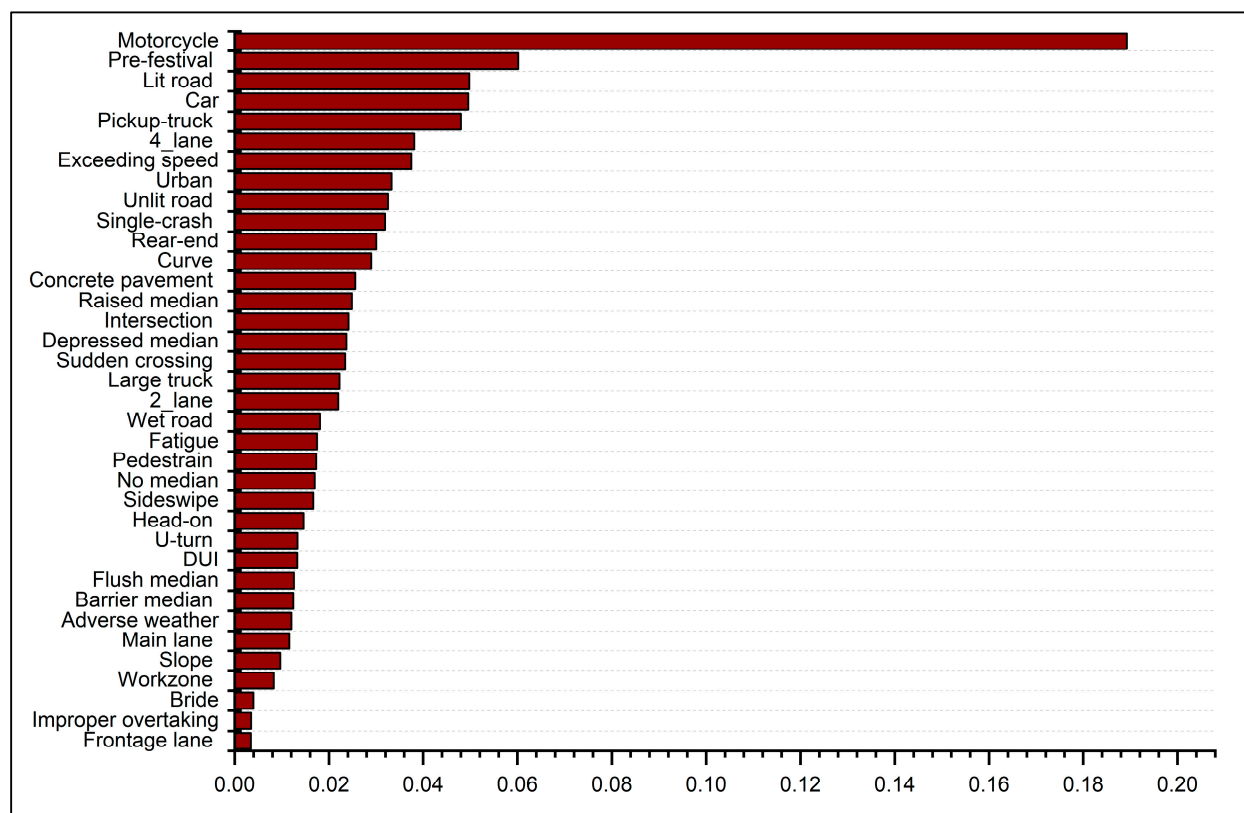


Figure 2. Variable importance for XGBoost model based on gain metric. Note: Importance values represent the average contribution to model accuracy improvement across all tree splits utilizing each variable. Font sizes have been enlarged for improved legibility.

4.3. Results of Random Parameters Ordered Logit with Heterogeneity in Means

It is important to note that in this study, heterogeneity in the means of the random parameters was identified through the systematic specification search procedure described in Section 3.3, but no statistically significant heterogeneity in variances was found despite comprehensive testing across all explanatory variables. As a result, the final model specification reverted to RPOLHM rather than the full heterogeneity in means and variances specification.

4.3.1. Factors Affecting Festival Crash Injury Severity

The study's model revealed the statistical significance of specific non-random (fixed) factors pertaining to crash severity. These factors encompassed characteristics such as road type (two and four lanes), median type (raised, depressed, barrier), road surface material (concrete), road curvature, presence of U-turns, adverse weather conditions, lighting conditions (both lit and unlit roads), and various driving behaviors like speeding, drunk driving, fatigue, sudden crossing, improper overtaking, and rear-end collisions, as well as crash types (pedestrian-involved, sideswipe, single-crash, head-on collisions). Furthermore, the model identified the involvement of motorcycles and pedestrians as factors more likely to result in higher injury severity levels for victims. These findings are consistent with the results of Farid and Ksaibati [112] and Dzinyela et al. [113], which demonstrated that motorcycle crashes were more likely to result in high severity rates compared to other vehicle types. Similarly, pedestrians are categorized as vulnerable road users, akin to motorcyclists. Shrinivas et al. [114] reported that when pedestrians were involved in crashes, it often led to higher injury severity. Additionally, the factor of fatigue, referring to drivers who fall asleep while driving and subsequently cause collisions, was identified. Such incidents can lead to higher fatality rates due to loss of control over vehicles, resulting in increased severity. This observation aligns with the findings of Li et al. [115]. Conversely, adverse weather emerged as the most influential factor with a negative association with crash injury severity. This result corresponds with the findings of Wei et al. [116], Ebrahimi Darkhaneh et al. [117] and Se et al. [43], who indicated that rainy or adverse weather conditions can make driving difficult, causing a decrease in driving speed and, consequently, reducing injury severity.

It is important to acknowledge that the negative association between adverse weather and crash injury severity observed in this study may appear counterintuitive, as some previous research has reported positive relationships between adverse weather conditions and crash severity [118,119]. This apparent discrepancy can be reconciled by distinguishing between crash frequency and crash severity effects. While adverse weather conditions such as rain may increase the overall likelihood of crash occurrence due to reduced visibility and compromised road surface friction, the severity of crashes that do occur under such conditions may be attenuated by compensatory driver behaviors. Specifically, drivers tend to reduce speeds, increase following distances, and exercise heightened caution during inclement weather, resulting in lower impact energies when collisions occur [120]. Furthermore, traffic volumes typically decrease during adverse weather as discretionary trips are postponed, reducing exposure to high-severity multi-vehicle collisions. The finding in this study is consistent with research conducted in similar Southeast Asian contexts, where the relationship between weather and crash severity has been shown to differ from patterns observed in temperate climates due to differences in driver adaptation behaviors, road infrastructure design, and rainfall characteristics [69]. Nevertheless, this finding should not be interpreted as suggesting that adverse weather conditions are inherently safer; rather, it highlights the complex interplay between environmental conditions and human behavioral responses in determining crash outcomes.

The elevated crash frequency during pre-festival periods (51% of crashes occurred before official festival dates) warrants further examination from behavioral and enforcement perspectives. This pattern may be attributable to several interconnected factors. First, enforcement efforts during Thai festival periods are traditionally concentrated during the officially designated “7-Day Danger” periods, with heightened police presence, sobriety checkpoints, and speed enforcement commencing on the first day of the official monitoring period. Consequently, the days immediately preceding this intensified enforcement window may experience relatively lower enforcement intensity, potentially encouraging riskier driving behaviors among travelers who depart early to avoid anticipated traffic congestion. Second, driver behavior during pre-festival periods may reflect a combination of time pressure to reach destinations before the holiday and reduced perceived risk due to the absence of visible enforcement activities. Third, workplace schedules and leave patterns often result in concentrated departure times during pre-festival days, generating traffic volumes that approach or exceed festival-period levels without corresponding safety interventions. These findings suggest that extending the enforcement window to commence several days before the traditional 7-Day Danger period could effectively address this temporal displacement of crash risk. Public awareness campaigns highlighting the elevated risks during pre-festival travel, combined with advance notification of extended enforcement periods, may encourage more cautious driving behaviors throughout the entire holiday travel window.

4.3.2. Distribution of Model’s Random Parameters and Heterogeneity in Means

The RPOLHM model has the capability to account for data variation and revealed two potential factors represented by random parameters: personal cars and pickup trucks. Crashes involving personal cars and pickup trucks exhibited a lower proportion of serious injuries or fatalities. This observation is logical because vulnerable road users (motorcyclists, pedestrians, and cyclists) tend to result in higher injury severity than larger vehicles (such as large trucks or trailers). Table 6 also indicates the presence of unobserved characteristics among crashes, with the main lane, roads without a median, and roads with a flush median being the sources of unobserved heterogeneity in the model. These factors have the potential to either decrease (main lane of frontage road) or increase (no median and flush median) the injury severity of the model’s random parameters.

Table 6. Model results of RPOLHM.

Variables	Estimates	S.E.	t-Stat	p-Value	Marginal Effect		
					PDO	Minor	Severe/Fatal
Constant	−0.069	0.167	−0.41				
Non-random parameters							
Frontage lane	−0.033	0.208	−0.16		0.0049	0.0000	−0.0048
Work zone	0.175	0.158	1.11		−0.0244	−0.0032	0.0276
2_lane	0.498	0.114	4.37	***	−0.0698	−0.0080	0.0778
4_lane	0.272	0.072	3.78	***	−0.0396	−0.0013	0.0409
Raised median	0.352	0.109	3.23	***	−0.0484	−0.0076	0.0560
Depressed median	0.353	0.109	3.24	***	−0.0489	−0.0069	0.0558
Barrier median	0.27	0.136	1.99	**	−0.0368	−0.0065	0.0433
Concrete pavement	−0.315	0.08	−3.94	***	0.0499	−0.0065	−0.0434
Curve	−0.268	0.072	−3.72	***	0.0418	−0.0041	−0.0377
Slope	−0.092	0.123	−0.75		0.0139	−0.0005	−0.0134
Intersection	−0.039	0.082	−0.48		0.0058	−0.0000	−0.0058
U-turn	0.278	0.098	2.84	***	−0.0377	−0.0070	0.0447
Bridge	0.175	0.212	0.83		−0.0243	−0.0032	0.0276

Wet road	−0.011	0.19	−0.06		0.0016	0.0000	−0.0016
Adverse weather	−0.486	0.186	−2.61	***	0.0802	−0.0161	−0.0641
Lit road	0.38	0.053	7.17	***	−0.0530	−0.0066	0.0596
Unlit road	0.693	0.071	9.76	***	−0.0858	−0.0347	0.1204
Exceeding speed limit	0.254	0.09	2.82	***	−0.0380	0.0008	0.0372
Sudden crossing	0.496	0.106	4.68	***	−0.0654	−0.0167	0.0820
Improper overtaking	0.909	0.228	3.99	***	−0.0990	−0.0741	0.1732
DUI	0.316	0.12	2.63	***	−0.0425	−0.0089	0.0513
Fatigue	1.105	0.12	9.21	***	−0.1180	−0.0953	0.2132
Pedestrian	1.382	0.134	10.31	***	−0.1323	−0.1506	0.2828
Rear-end	−0.345	0.099	−3.48	***	0.0534	−0.0044	−0.0490
Sideswipe	−0.245	0.108	−2.27	**	0.0382	−0.0036	−0.0346
Single crash	−0.183	0.094	−1.95	*	0.0271	0.0000	−0.0271
Head-on	0.693	0.137	5.06	***	−0.0827	−0.0413	0.1240
Motorcycle	2.162	0.072	30.03	***	−0.3070	−0.0346	0.3416
Large truck	0.314	0.083	3.78	***	−0.0461	−0.0008	0.0469
Urban	−0.315	0.068	−4.63	***	0.0497	−0.0058	−0.0439
Pre-festival	0.039	0.045	0.87		−0.0058	−0.0000	0.0059
Random parameters							
Car	−0.248	0.079	−3.14	***	0.0372	−0.0010	−0.0362
Standard deviation	1.38	0.045	30.67	***			
Pickup truck	−0.219	0.079	−2.77	***	0.0325	−0.0002	−0.0323
Standard deviation	1.247	0.042	29.69	***			
Heterogeneity in means							
Car: Main lane	−0.327	0.17	−1.92	*			
Car: No median	0.487	0.108	4.51	***			
Car: Flush median	0.922	0.177	5.21	***			
Pickup truck: No median	0.537	0.102	5.26	***			
Pickup truck: Flush median	0.847	0.163	5.2	***			
Threshold; Mu(01)	3.023	0.05	60.46	***			

Model statistics: Halton draw = 1000; N = 8346; AIC = 15,422.7; R² = 0.1364; ***, **, * Significance at 1%, 5%, 10% level, respectively.

5. Conclusions and Implications

This study investigated factors contributing to crash injury severity during the Western New Year and Songkran festival holidays from 2017 to 2019 in Thailand. A total of 8346 crash records were analyzed using both the Random Parameters Ordered Logit Model with Heterogeneity in Means (RPOLHM) and four machine learning approaches including Multilayer Perceptron (MLP), Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost), and Random Forest. The analysis incorporated 36 explanatory variables encompassing driver behavior, roadway characteristics, environmental conditions, and crash attributes, with crash severity categorized into three levels: property damage only (PDO), minor injury, and severe/fatal injury.

The comparative analysis of prediction accuracy revealed substantial differences in model performance. The XGBoost model demonstrated superior predictive capability with accuracy rates of 85.1% for training and 83.8% for validation datasets, significantly outperforming all other approaches. Random Forest achieved the second-highest performance with 78.2% training and 76.8% validation accuracy, followed by AdaBoost at 72.8% and 71.8%, and MLP at 64.9% and 58.0% for training and validation respectively. The RPOLHM exhibited the lowest prediction accuracy at 49.6%. When evaluated using the summary score metric combining prediction accuracy rate and false positive rate

across all severity categories, XGBoost achieved 223.7%, followed by Random Forest at 186.8%, AdaBoost at 161.1%, MLP at 95.5%, and RPOLHM at 43.6%. These findings indicate that ensemble-based machine learning methods, particularly gradient boosting algorithms, offer substantially better predictive capability for crash severity classification compared to traditional econometric approaches.

Despite the lower prediction accuracy, the RPOLHM provided valuable insights into the directional effects of contributing factors on crash severity. The marginal effects analysis revealed that motorcycle involvement exhibited the largest positive effect on severe/fatal injury probability, with a marginal effect of 0.3416, indicating that crashes involving motorcycles increase the probability of severe/fatal outcomes by 34.16 percentage points compared to crashes not involving motorcycles. Pedestrian involvement demonstrated the second-largest effect with a marginal effect of 0.2828, followed by driver fatigue at 0.2132, improper overtaking at 0.1732, and head-on collisions at 0.1240. Conversely, adverse weather conditions exhibited a negative association with severe/fatal injury probability (marginal effect of -0.0641), suggesting that inclement weather may induce more cautious driving behavior, resulting in reduced speeds and consequently lowering injury severity.

The variable importance analysis from the XGBoost model corroborated these findings, identifying motorcycle involvement as the most influential factor, followed by pre-festival timing, lit road conditions, personal car involvement, pickup truck involvement, four-lane roads, exceeding speed, urban areas, unlit roads, and single-vehicle crashes as the top ten contributing factors. The consistency between the XGBoost variable importance rankings and the statistically significant variables in the RPOLHM strengthens confidence in the robustness of these findings across different analytical paradigms.

The identification of heterogeneity in means revealed that the effects of personal car and pickup truck involvement on crash severity vary systematically depending on roadway characteristics. Specifically, crashes involving personal cars on roads without medians or with flush medians exhibited increased severity compared to roads with other median configurations, with heterogeneity coefficients of 0.487 and 0.922 respectively. Similar patterns were observed for pickup trucks, with heterogeneity coefficients of 0.537 for roads without medians and 0.847 for roads with flush medians. These findings suggest that the protective effects of enclosed vehicles are diminished on roadways lacking physical separation between opposing traffic flows, likely due to increased exposure to head-on collision risks.

Based on these empirical findings, several policy implications can be derived for relevant stakeholders. For law enforcement agencies, the significant positive effects of exceeding speed (marginal effect of 0.0372), driving under the influence (0.0513), and driver fatigue (0.2132) on severe/fatal crash probability underscore the critical importance of intensified enforcement during festival periods. Given that fatigue demonstrated the third-largest marginal effect among all contributing factors, enforcement strategies should extend beyond traditional alcohol checkpoints to include fatigue detection measures. The establishment of mandatory rest stops at regular intervals along major highways and the deployment of mobile fatigue screening units at strategic locations could effectively address this risk factor. Additionally, considering that 62% of crashes in the dataset were attributed to speeding, enhanced speed enforcement through automated speed cameras and increased patrol frequency during the 7-Day Danger periods warrants prioritization.

For highway engineers and transportation infrastructure planners, the findings regarding median configurations present actionable insights. The heterogeneity analysis demonstrated that crashes on roads without medians and roads with flush medians resulted in elevated injury severity, particularly for crashes involving personal cars and

pickup trucks. Consequently, infrastructure improvements prioritizing the installation of physical median barriers on high-volume corridors during festival periods could yield substantial safety benefits. Furthermore, the significant positive effect of U-turn locations on crash severity (marginal effect of 0.0447) supports the implementation of temporary U-turn closures during peak festival travel periods, particularly at locations with documented crash histories. The finding that unlit roads exhibited a larger marginal effect on severe/fatal injury probability (0.1204) compared to lit roads (0.0596) highlights the importance of adequate roadway illumination, suggesting that temporary lighting installations at high-risk unlit segments during festival periods could reduce injury severity.

For public health authorities and emergency medical services, the substantial marginal effects associated with motorcycle involvement (0.3416) and pedestrian involvement (0.2828) indicate that vulnerable road users constitute the highest-priority target population for injury prevention interventions. Public awareness campaigns specifically addressing motorcycle safety during festival periods, combined with enhanced helmet enforcement, could substantially reduce severe injury outcomes. The pre-positioning of emergency medical resources along corridors with high motorcycle traffic volumes during festival periods would facilitate rapid response and potentially mitigate injury severity through timely medical intervention.

For transportation policymakers, the finding that pre-festival periods exhibited elevated crash frequency (51% of crashes occurred before the official festival dates) suggests that safety interventions should commence prior to the officially designated danger periods. Extending the monitoring and enforcement window to encompass several days before the traditional 7-Day Danger period could capture a larger proportion of at-risk travel. Additionally, the urban area variable demonstrated a negative association with severe/fatal injury probability (marginal effect of -0.0439), likely attributable to lower travel speeds and proximity to medical facilities. This finding supports strategies encouraging travelers to utilize routes passing through urban areas rather than isolated rural highways where emergency response times may be prolonged.

From a methodological perspective, this study demonstrates that machine learning and econometric approaches offer complementary strengths for crash severity analysis. While XGBoost and other ensemble methods provide superior predictive accuracy suitable for real-time crash severity prediction systems and resource allocation optimization, the RPOLHM offers interpretable coefficient estimates and marginal effects essential for understanding causal mechanisms and formulating evidence-based policies. Consequently, the concurrent application of both analytical paradigms is recommended for comprehensive crash severity investigations, with machine learning methods serving prediction-oriented objectives and random parameters models addressing inference and policy evaluation needs.

Several limitations should be acknowledged when interpreting these findings. The use of crash data from 2017 to 2019 represents a constraint, as more recent data could not be obtained due to restricted access to the HAIMS database and the significant disruption to normal travel patterns during the COVID-19 pandemic from 2020 to 2022, which resulted in atypical crash characteristics unsuitable for understanding typical festival travel behavior. Nevertheless, the 2017 to 2019 dataset remains valuable as it represents the most recent period of normal pre-pandemic festival travel conditions with consistent data collection practices and comprehensive variable coverage. The 8346 crash records across six festival periods provide a sufficient sample size to identify stable patterns in crash severity determinants. The identified risk factors encompassing human behaviors such as speeding, drunk driving, and fatigue, along with road environment characteristics, represent fundamental contributors to crash severity that are unlikely to

have fundamentally changed. Additionally, the fixed threshold specification in the RPOLHM may limit model flexibility, and future research could explore random threshold specifications or generalized ordered logit models to address this limitation. Future research should validate these findings with post-pandemic data when normal travel patterns have stabilized and comprehensive data becomes accessible, and should consider incorporating additional variables such as vehicle safety features, driver demographics, and real-time traffic conditions to further enhance model explanatory power.

Author Contributions: Conceptualization, T.C. and S.U.; methodology, S.U. and P.W.; software, T.C. and P.W.; validation, S.J., and V.R.; formal analysis, P.W. and C.S.; investigation, C.S.; resources, T.C.; data curation, S.U. and P.W.; writing—original draft preparation, T.C. and S.U.; writing—review and editing, T.C. and S.J.; visualization, T.C.; supervision, V.R.; project administration, S.J. and V.R. funding acquisition, S.J. and V.R. All authors have read and agreed to the published version of the manuscript.

Funding: This project is funded by the National Research Council of Thailand, grant number: N33A650760.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to receiving an exemption from the Institutional Review Board of Suranaree University of Technology.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy.

Acknowledgments: The authors would like to thank the Road Safety Center in Nakhon Ratchasima Province, Department of Disaster Prevention and Mitigation of the Ministry of Interior, Thailand, for providing road traffic accident data. We are also grateful for the insightful suggestions and recommendations from the anonymous reviewers whose comments substantially increased the quality and lucidity of the paper.

Conflicts of Interest: The authors declare no conflicts of interest.

References

- Islam, M.; Shirani, N. Investigating the factors behind cellphone-distracted crashes: Assessing injury severity among distracted drivers in states with and without cell phone bans. *J. Saf. Res.* **2025**, *92*, 192–206.
- World Health Organization. *Global Status Report on Road Safety 2015*; World Health Organization: Geneva, Switzerland, 2015.
- Georgiev, K. Aviation safety training methodology. *Heliyon* **2021**, *7*, e08511.
- Department of Disaster Prevention and Mitigation. *Thailand National Status Report on Road Safety 2018*; Department of Disaster Prevention and Mitigation: Bangkok, Thailand, 2018.
- Jomnonkwao, S.; Wisutwattanasak, P.; Ratanavaraha, V. Factors influencing willingness to pay for accident risk reduction among personal car drivers in Thailand. *PLoS ONE* **2021**, *16*, e0260666.
- Prencipe, L.P.; De Bartolomeo, S.; Caggiani, L.; Ottomannelli, M. An injury severity-based methodology for assessing priority areas for shared micromobility accident risk mitigation. *Travel Behav. Soc.* **2025**, *39*, 100962.
- Semple, T.; Fountas, G. Twelve years of evidence: Modelling the injury severity of single-vehicle collisions pre- and post-20mph (32 km/h) implementation in Edinburgh and Glasgow. *Accid. Anal. Prev.* **2025**, *221*, 108183.
- Senanayake, H.; Kanitpong, K. Assessment of a two-way motorcycle lane to reduce traffic conflicts and their severity: A case study of Phaholyothin road, Thailand. *IATSS Res.* **2025**, *49*, 93–103.
- Santos, K.; Dias, J.P.; Amado, C. A literature review of machine learning algorithms for crash injury severity prediction. *J. Saf. Res.* **2022**, *80*, 254–269.

10. Bae, J.; Pani, A.; Balla, S.N.; Oh, S. Machine Learning Approach for Ex-Post Evaluation of Road Traffic Collision Severity Trends. *Transp. Res. Rec.* **2025**, 2679, 924–938.
11. Sarkar, A.; Sarkar, S. Comparative Assessment Between Statistical and Soft Computing Methods for Accident Severity Classification. *J. Inst. Eng. (India) Ser. A* **2020**, 101, 27–40.
12. Wahab, L.; Jiang, H. Severity prediction of motorcycle crashes with machine learning methods. *Int. J. Crashworthiness* **2020**, 25, 485–492.
13. Shanthi, S.; Ramani, R.G. Feature Relevance Analysis and Classification of Road Traffic Accident Data through Data Mining Techniques. In Proceedings of the World Congress on Engineering and Computer Science, San Francisco, CA, USA, 24–26 October 2012.
14. El Ferouali, S.; Elamrani Abou Elasad, Z.; Qassimi, S.; Abdali, A. From Baseline to Best Practice: An Advanced Feature Selection, Feature Resampling and Grid Search Techniques to Improve Injury Severity Prediction. *Appl. Artif. Intell.* **2025**, 39, 2452675.
15. Champahom, T.; Jomnonkwao, S.; Chatpattananan, V.; Karoonsoontawong, A.; Ratanavaraha, V. Analysis of Rear-End Crash on Thai Highway: Decision Tree Approach. *J. Adv. Transp.* **2019**, 2019, 2568978.
16. Chen, M.-M.; Chen, M.-C. Modeling Road Accident Severity with Comparisons of Logistic Regression, Decision Tree and Random Forest. *Information* **2020**, 11, 270. <https://doi.org/10.3390/info11050270>.
17. Rezapour, M.; Mehrara Molan, A.; Ksaibati, K. Analyzing injury severity of motorcycle at-fault crashes using machine learning techniques, decision tree and logistic regression models. *Int. J. Transp. Sci. Technol.* **2020**, 9, 89–99.
18. Arhin, S.A.; Gatiba, A. Predicting crash injury severity at unsignalized intersections using support vector machines and naïve Bayes classifiers. *Transp. Saf. Environ.* **2020**, 2, 120–132.
19. Hosseinzadeh, A.; Moeinaddini, A.; Ghasemzadeh, A. Investigating factors affecting severity of large truck-involved crashes: Comparison of the SVM and random parameter logit model. *J. Saf. Res.* **2021**, 77, 151–160.
20. Li, Z.; Liu, P.; Wang, W.; Xu, C. Using support vector machine models for crash injury severity analysis. *Accid. Anal. Prev.* **2012**, 45, 478–486.
21. Tariq, A.-M.; Xiao, H.; Jean Pierre, N.; Eshrak Naji, A.; Ibrahim, A. Exploiting Machine Learning Algorithms for Predicting Crash Injury Severity in Yemen: Hospital Case Study. *Appl. Comput. Math.* **2020**, 9, 155–164.
22. Lee, J.; Yoon, T.; Kwon, S.; Lee, J. Model Evaluation for Forecasting Traffic Accident Severity in Rainy Seasons Using Machine Learning Algorithms: Seoul City Study. *Appl. Sci.* **2020**, 10, 129.
23. Labib, M.F.; Rifat, A.S.; Hossain, M.M.; Das, A.K.; Nawrine, F. Road Accident Analysis and Prediction of Accident Severity by Using Machine Learning in Bangladesh. In Proceedings of the 2019 7th International Conference on Smart Computing & Communications (ICSCC), Sarawak, Malaysia, 28–30 June 2019; pp. 1–5.
24. Jafari, M.; Persaud, B. Application of a novel hybrid multigroup statistical approach to investigate the factors affecting crash severity. *Accid. Anal. Prev.* **2025**, 214, 107985.
25. Qi, Z.; Yao, J.; Zou, X.; Pu, K.; Qin, W.; Li, W. Investigating Factors Influencing Crash Severity on Mountainous Two-Lane Roads: Machine Learning Versus Statistical Models. *Sustainability* **2024**, 16, 7903.
26. Al Mamlook, R.E.; Kwayu, K.M.; Alkasisbeh, M.R.; Frefer, A.A. Comparison of Machine Learning Algorithms for Predicting Traffic Accident Severity. In Proceedings of the 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), Amman, Jordan, 9–11 April 2019; pp. 272–276.
27. Mokoatle, M.; Marivate, D.V.; Bukohwo, P.M.E. Predicting Road Traffic Accident Severity using Accident Report Data in South Africa. Presented at the 20th Annual International Conference on Digital Government Research, Dubai, United Arab Emirates, 18–20 June 2019. <https://doi.org/10.1145/3325112.3325211>.
28. Umer, M.; Sadiq, S.; Ishaq, A.; Ullah, D.S.; Saher, N.; Madni, H. Comparison Analysis of Tree Based and Ensembled Regression Algorithms for Traffic Accident Severity Prediction. *arXiv* **2020**, arXiv:2010.14921.
29. Samerei, S.A.; Aghabayk, K. Exploring interacting effects of risk factors on run-off-road crash severity: An interpretable machine learning model joint with latent class clustering. *IATSS Res.* **2024**, 48, 261–274.
30. Aghayan, I.; Hosseinlou, M.H.; Kunt, M.M. Application of Support Vector Machine for Crash Injury Severity Prediction: A Model Comparison Approach. *J. Civ. Eng. Urban.* **2015**, 5, 193–199.
31. Abdelwahab, H.T.; Abdel-Aty, M.A. Development of Artificial Neural Network Models to Predict Driver Injury Severity in Traffic Accidents at Signalized Intersections. *Transp. Res. Rec.* **2001**, 1746, 6–13.
32. Wahab, L.; Jiang, H. A comparative study on machine learning based algorithms for prediction of motorcycle crash severity. *PLoS ONE* **2019**, 14, e0214966.

33. Lin, C.; Wu, D.; Liu, H.; Xia, X.; Bhattarai, N. Factor Identification and Prediction for Teen Driver Crash Severity Using Machine Learning: A Case Study. *Appl. Sci.* **2020**, *10*, 1675.
34. Se, C.; Champahom, T.; Jomnonkwao, S.; Ratanavaraha, V. Motorcyclist injury severity analysis: A comparison of Artificial Neural Networks and random parameter model with heterogeneity in means and variances. *Int. J. Inj. Control. Saf. Promot.* **2022**, *29*, 500–515.
35. Champahom, T.; Se, C.; Watcharamaisakul, F.; Jomnonkwao, S.; Karoonsoontawong, A.; Ratanavaraha, V. Tree-based approaches to understanding factors influencing crash severity across roadway classes: A Thailand case study. *IATSS Res.* **2024**, *48*, 464–476.
36. Mannering, F.; Bhat, C.R.; Shankar, V.; Abdel-Aty, M. Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. *Anal. Methods Accid. Res.* **2020**, *25*, 100113.
37. Champahom, T.; Jomnonkwao, S.; Watthanaklang, D.; Karoonsoontawong, A.; Chatpattananan, V.; Ratanavaraha, V. Applying hierarchical logistic models to compare urban and rural roadway modeling of severity of rear-end vehicular crashes. *Accid. Anal. Prev.* **2020**, *141*, 105537.
38. Chen, C.; Zhang, G.; Tian, Z.; Bogus, S.M.; Yang, Y. Hierarchical Bayesian random intercept model-based cross-level interaction decomposition for truck driver injury severity investigations. *Accid. Anal. Prev.* **2015**, *85*, 186–198.
39. Huang, H.; Chin, H.C.; Haque, M.M. Severity of driver injury and vehicle damage in traffic crashes at intersections: A Bayesian hierarchical analysis. *Accid. Anal. Prev.* **2008**, *40*, 45–54.
40. Ye, F.; Cheng, W.; Wang, C.; Liu, H.; Bai, J. Investigating the severity of expressway crash based on the random parameter logit model accounting for unobserved heterogeneity. *Adv. Mech. Eng.* **2021**, *13*, 16878140211067278.
41. Singh, D.; Das, P.; Ghosh, I. Conflict-Based safety evaluations at unsignalized intersections using surrogate safety measures. *Heliyon* **2024**, *10*, e27665.
42. Fu, C.; Sayed, T. Random-Parameter Bayesian Hierarchical Extreme Value Modeling Approach with Heterogeneity in Means and Variances for Traffic Conflict-Based Crash Estimation. *J. Transp. Eng.* **2022**, *148*, 04022056.
43. Se, C.; Champahom, T.; Jomnonkwao, S.; Wisutwattanasak, P.; Laphrom, W.; Ratanavaraha, V. Temporal Instability and Transferability Analysis of Daytime and Nighttime Motorcyclist-Injury Severities Considering Unobserved Heterogeneity of Data. *Sustainability* **2023**, *15*, 4486.
44. Olson, P.L.; Dewar, R.E. *Human Factors in Traffic Safety*; Lawyers & Judges Pub.: Tucson, AZ, USA, 2002. (In English)
45. Effati, M.; Ramezanpoor, A. Examining the role of random parameters and unobserved heterogeneity in the frequency-severity of rural freeway run-off-road and fixed-object crashes: A Bayesian hierarchical-geospatial approach. *Accid. Anal. Prev.* **2025**, *215*, 108005.
46. Mohan, D.; Tiwari, G.; Khayesi, M.; Nafukho, F.M. *Road Traffic Injury Prevention: Training Manual*; World Health Organization: Geneva, Switzerland, 2006.
47. Connor, J.; Norton, R.; Ameratunga, S.; Robinson, E.; Civil, I.; Dunn, R.; Bailey, J.; Jackson, R. Driver sleepiness and risk of serious injury to car occupants: Population based case control study. *BMJ J.* **2002**, *324*, 1125.
48. Haghi, A.; Ketabi, D.; Ghanbari, M.; Rajabi, H. Assessment of Human Errors in Driving Accidents; Analysis of the Causes Based on Aberrant Behaviors. *Life Sci. J.* **2014**, *11*, 414–420.
49. Cho, J.; Lee, S.; Park, J. Investigation of injury severity level in truck-related crashes at school zones using mixed generalized ordered models. *PLoS ONE* **2025**, *20*, e0318725.
50. Zhang, G.; Yau, K.K.W.; Chen, G. Risk factors associated with traffic violations and accident severity in China. *Accid. Anal. Prev.* **2013**, *59*, 18–25.
51. Liu, G.; Chen, S.; Zeng, Z.; Cui, H.; Fang, Y.; Gu, D.; Yin, Z.; Wang, Z. Risk factors for extremely serious road accidents: Results from national Road Accident Statistical Annual Report of China. *PLoS ONE* **2018**, *13*, e0201587.
52. Harith, S.H.; Mahmud, N.; Doulatbadi, M. Environmental Factor and Road Accident: A Review Paper. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Bangkok, Thailand, 5–7 March 2019; pp. 3409–3418.
53. Anvari, M.B.; Kashani, A.T.; Rabieyan, R. Identifying the Most Important Factors in the At-Fault Probability of Motorcyclists by Data Mining, Based on Classification Tree Models. *Int. J. Civ. Eng.* **2017**, *15*, 653–662.
54. Chen, C.; Zhang, G.; Tarefder, R.; Ma, J.; Wei, H.; Guan, H. A multinomial logit model-Bayesian network hybrid approach for driver injury severity analyses in rear-end crashes. *Accid. Anal. Prev.* **2015**, *80*, 76–88.
55. Pervez, A.; Jamal, A.; Haider Khan, S. Analyzing injury severity of three-wheeler motorized rickshaws: A correlated random parameters approach with heterogeneity in means. *Accid. Anal. Prev.* **2024**, *204*, 107651.

56. Copsey, S.; Christie, N.; Drupsteen, L.; Kampen, J.V.; Kuijt-Evers, L.; Schmitz-Felten, E.; Verjans, M. *A Review of Accidents and Injuries to Road Transport Drivers*; European Agency for Safety and Health at Work (EU-OSHA): Luxembourg, 2010; p. 59.
57. Bachani, A.M.; Peden, M.; Gururaj, G.; Norton, R.; Hyder, A.A. Road Traffic Injuries. In *Injury Prevention and Environmental Health*; The World Bank: Washington, DC, USA, 2017; pp. 35–54.
58. Kim, S.; Song, T.-J.; Roupail, N.M.; Aghdashi, S.; Amaro, A.; Gonçalves, G. Exploring the association of rear-end crash propensity and micro-scale driver behavior. *Saf. Sci.* **2016**, *89*, 45–54.
59. Se, C.; Champahom, T.; Jomnonkwo, S.; Ratanavaraha, V. Risk factors affecting driver severity of single-vehicle run off road crash for Thailand highway. *Eng. J.* **2020**, *24*, 207–216.
60. Abdulazeez, M.U.; Khan, W.; Abdullah, K.A. Predicting child occupant crash injury severity in the United Arab Emirates using machine learning models for imbalanced dataset. *IATSS Res.* **2023**, *47*, 134–159.
61. Mahajan, N.; Kaur, B.P. Analysis of Factors of Road Traffic Accidents using Enhanced Decision Tree Algorithm. *Int. J. Comput. Appl.* **2016**, *135*, 1–3.
62. Klinjun, N.; Kelly, M.; Praditsathaporn, C.; Petsirasan, R. Identification of Factors Affecting Road Traffic Injuries Incidence and Severity in Southern Thailand Based on Accident Investigation Reports. *Sustainability* **2021**, *13*, 12467.
63. Uchida, N.; Kawakoshi, M.; Tagawa, T.; Mochida, T. An investigation of factors contributing to major crash types in Japan based on naturalistic driving data. *IATSS Res.* **2010**, *34*, 22–30.
64. Kumar Pathivada, B.; Banerjee, A.; Haleem, K. Impact of real-time weather conditions on crash injury severity in Kentucky using the correlated random parameters logit model with heterogeneity in means. *Accid. Anal. Prev.* **2024**, *196*, 107453.
65. Wang, C.; Abdel-Aty, M.; Han, L. Tunnel crash severity and congestion duration joint evaluation based on cross-stitch networks. *Accid. Anal. Prev.* **2025**, *213*, 107942.
66. Asare, I.O.; Mensah, A.C. Crash severity modelling using ordinal logistic regression approach. *Int. J. Inj. Control. Saf. Promot.* **2020**, *27*, 412–419.
67. Somchainuck, O.; Taneerananon, P.; Jaritngam, S. An In-Depth Investigation of Roadside Crashes on Thai National Highways. *Eng. J.* **2013**, *17*, 63–74.
68. Li, Z.; Wang, W.; Chen, R.; Liu, P. Conditional inference tree-based analysis of hazardous traffic conditions for rear-end and sideswipe collisions with implications for control strategies on freeways. *IET Intell. Transp. Syst.* **2014**, *8*, 509–518.
69. Sangkharat, K.; Thornes, J.E.; Wachiradilok, P.; Pope, F.D. Determination of the impact of rainfall on road accidents in Thailand. *Heliyon* **2021**, *7*, e06061.
70. Bullard, C.; Jones, S.; Adanu, E.K.; Liu, J. Crash severity analysis of single-vehicle rollover crashes in Namibia: A mixed logit approach. *IATSS Res.* **2023**, *47*, 318–324.
71. Solah, M.S.; Ariffin, A.H.; Md Isa, M.H.; Wong, S.V. In-depth crash investigation on bus accidents in Malaysia. *J. Soc. Transp. Traffic Stud.* **2013**, *3*, 22–31.
72. Ulak, M.B.; Ozguven, E.E.; Vanli, O.A.; Dulebenets, M.A.; Spainhour, L. Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations. *Accid. Anal. Prev.* **2018**, *121*, 1–13.
73. Al-Ghamdi, A.S. Using logistic regression to estimate the influence of accident factors on accident severity. *Accid. Anal. Prev.* **2002**, *34*, 729–741.
74. Lardelli-Claret, P.; Luna-del-Castillo, J.D.; Jiménez-Moleón, J.J.; Femia-Marzo, P.; Moreno-Abril, O.; Bueno-Cavanillas, A. Does Vehicle Color Influence the Risk of Being Passively Involved in a Collision? *Epidemiology* **2002**, *13*, 721–724.
75. Lankarani, K.B.; Heydari, S.T.; Aghabeigi, M.R.; Moafian, G.; Hoseinzadeh, A.; Vossoughi, M. The impact of environmental factors on traffic accidents in Iran. *J. Inj. Violence Res.* **2014**, *6*, 64–71.
76. Pervaz, S.; Bhowmik, T.; Eluru, N. Examining driver injury severity in motor vehicle crashes: A copula-based approach considering temporal heterogeneity in a developing country context. *Accid. Anal. Prev.* **2024**, *206*, 107721.
77. Ismail, A.; Aram, A.; Aminzadeh, R.; Rahmat, R.A.O.K. Crashes and Effective Safety Factors within Interchanges and Ramps on Urban Freeways and Highways. *Aust. J. Basic Appl. Sci.* **2011**, *5*, 397–404.
78. Zhao, Z.; Liu, T.; Zhang, L.; Xie, S.; Jin, H. Enhancing autonomous vehicle safety: An Integrated Ensemble Learning-Logit Model for accident severity prediction and analysis. *Int. J. Transp. Sci. Technol.* **2025**, in press.
79. Xiao, D.; Zuo, D.; Xu, X.; Yuan, Q. Geospatial and econometric approaches to older driver safety: Analysis of crash injury severity of regional highways. *PLoS ONE* **2025**, *20*, e0307927.
80. Fiorentini, N.; Losa, M. Handling imbalanced data in road crash severity prediction by machine learning algorithms. *Infrastructures* **2020**, *5*, 61.

81. Byrne, J.P.; Mann, N.C.; Dai, M.; Mason, S.A.; Karanickolas, P.; Rizoli, S.; Nathens, A.B. Association between emergency medical service response time and motor vehicle crash mortality in the United States. *JAMA Surg.* **2019**, *154*, 286–293.
82. Savolainen, P.T.; Mannering, F.L.; Lord, D.; Quddus, M.A. The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accid. Anal. Prev.* **2011**, *43*, 1666–1676.
83. Sum, S.; Wisutwattanasak, P.; Champahom, T.; Jomnonkwao, S.; Ratanavaraha, V. A Comparative Study of a Series of Supervised Learning Models for Motorcycle Crash Injury Severity Prediction. *Civ. Eng. J.* **2025**, *11*, 4246–4261.
84. Washington, S.; Karlaftis, M.; Mannering, F.; Anastasopoulos, P. *Statistical and Econometric Methods for Transportation Data Analysis*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2020.
85. Xin, C.; Guo, R.; Wang, Z.; Lu, Q.; Lin, P.-S. The effects of neighborhood characteristics and the built environment on pedestrian injury severity: A random parameters generalized ordered probability model with heterogeneity in means and variances. *Anal. Methods Accid. Res.* **2017**, *16*, 117–132.
86. Agüero-Valverde, J.; Jovanis, P.P. Analysis of road crash frequency with spatial models. *Transp. Res. Rec.* **2008**, *2061*, 55–63.
87. Se, C.; Champahom, T.; Jomnonkwao, S.; Karoonsoontawong, A.; Ratanavaraha, V. Temporal stability of factors influencing driver-injury severities in single-vehicle crashes: A correlated random parameters with heterogeneity in means and variances approach. *Anal. Methods Accid. Res.* **2021**, *32*, 100179.
88. Zhang, W.; Zhou, Z.; Li, L.; Huang, R. Identifying Significant Injury Severity Risk Factors in Traffic Accidents Based on the Machine Learning Methods. In Proceedings of the CICTP 2019, Nanjing, China, 6–8 July 2019, pp. 3759–3770.
89. Ramchoun, H.; Amine, M.; Idrissi, J.; Ghanou, Y.; Ettaouil, M. Multilayer Perceptron: Architecture Optimization and Training. *Int. J. Interact. Multimed. Artif. Intell.* **2016**, *4*, 26–30.
90. Popescu, M.-C.; Balas, V.E.; Perescu-Popescu, L.; Mastorakis, N. Multilayer perceptron and neural networks. *WSEAS Trans. Circuits Syst.* **2009**, *8*, 579–588.
91. Günther, F.; Fritsch, S. Neuralnet: Training of neural networks. *R J.* **2010**, *2*, 30.
92. Kuhn, M. Building predictive models in R using the caret package. *J. Stat. Softw.* **2008**, *28*, 1–26.
93. Wang, R. AdaBoost for Feature Selection, Classification and Its Relation with SVM, A Review. *Phys. Procedia* **2012**, *25*, 800–807.
94. Alfaro, E.; Gamez, M.; García, N. adabag: An R Package for Classification with Boosting and Bagging. *J. Stat. Soft.* **2013**, *54*, 1–35.
95. Chen, T.; Guestrin, C. XGBoost: A Scalable Tree Boosting System. Presented at the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016. <https://doi.org/10.1145/2939672.2939785>.
96. Liao, X.; Cao, N.; Li, M.; Kang, X. Research on Short-Term Load Forecasting Using XGBoost Based on Similar Days. In Proceedings of the 2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), Changsha, China, 12–13 January 2019; pp. 675–678.
97. Chen, T.; He, T.; Benesty, M.; Khotilovich, V. Package ‘xgboost’. *R Version* **2019**, *90*, 40.
98. Lin, Y.; Jeon, Y. Random Forests and Adaptive Nearest Neighbors. *J. Am. Stat. Assoc.* **2006**, *101*, 578–590.
99. Suthaharan, S. *Machine Learning Models and Algorithms for Big Data Classification*; Springer Nature: Berlin/Heidelberg, Germany, 2016.
100. RColorBrewer, S.; Liaw, M.A. *Package ‘Randomforest’*; University of California, Berkeley: Berkeley, CA, USA, 2018.
101. Adeel, M.; Khattak, A.J.; Mishra, S.; Thapa, D. Enhancing work zone crash severity analysis: The role of synthetic minority oversampling technique in balancing minority categories. *Accid. Anal. Prev.* **2024**, *208*, 107794.
102. Kotb, M.H.; Ming, R. Comparing SMOTE family techniques in predicting insurance premium defaulting using machine learning models. *Int. J. Adv. Comput. Sci. Appl.* **2021**, *12*, 621–629.
103. Sokolova, M.; Lapalme, G. A systematic analysis of performance measures for classification tasks. *Inf. Process. Manag.* **2009**, *45*, 427–437.
104. Mokhtarimousavi, S.; Anderson, J.C.; Azizinamini, A.; Hadi, M. Factors affecting injury severity in vehicle-pedestrian crashes: A day-of-week analysis using random parameter ordered response models and Artificial Neural Networks. *Int. J. Transp. Sci. Technol.* **2020**, *9*, 100–115.
105. Yu, H.; Li, Z.; Zhang, G.; Liu, P.; Ma, T. Fusion convolutional neural network-based interpretation of unobserved heterogeneous factors in driver injury severity outcomes in single-vehicle crashes. *Anal. Methods Accid. Res.* **2021**, *30*, 100157.
106. Sum, S.; Se, C.; Champahom, T.; Jomnonkwao, S.; Sinha, S.; Ratanavaraha, V. A random forest and SHAP-based analysis of motorcycle crash severity in Thailand: Urban-rural and day-night perspectives. *Transp. Eng.* **2025**, *21*, 100369.

107. Mannering, F.L.; Bhat, C.R. Analytic methods in accident research: Methodological frontier and future directions. *Anal. Methods Accid. Res.* **2014**, *1*, 1–22.
108. Eluru, N.; Bhat, C.R.; Hensher, D.A. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accid. Anal. Prev.* **2008**, *40*, 1033–1054.
109. Fountas, G.; Anastasopoulos, P.C. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. *Anal. Methods Accid. Res.* **2017**, *15*, 1–16.
110. Yasmin, S.; Eluru, N.; Pinjari, A.R. Analyzing the continuum of fatal crashes: A generalized ordered approach. *Anal. Methods Accid. Res.* **2015**, *7*, 1–15.
111. Shaffiee Haghshenas, S.; Guido, G.; Shaffiee Haghshenas, S.; Astarita, V. Predicting the level of road crash severity: A comparative analysis of logit model and machine learning models. *Transp. Eng.* **2025**, *20*, 100323.
112. Farid, A.; Ksaibati, K. Modeling severities of motorcycle crashes using random parameters. *J. Traffic Transp. Eng.* **2021**, *8*, 225–236.
113. Dzinyela, R.; Dadashova, B.; Westfall, G.; Das, S.; Silvestri-Dobrovolsky, C.; Adanu, E.K.; Lord, D. Analysis of motorcyclists crash severity using cluster correspondence and hierarchical binary logit models. *Multimodal Transp.* **2025**, *4*, 100197.
114. Shrinivas, V.; Bastien, C.; Davies, H.; Daneshkhah, A.; Hardwicke, J. Parameters influencing pedestrian injury and severity—A systematic review and meta-analysis. *Transp. Eng.* **2023**, *11*, 100158.
115. Li, Y.; Yamamoto, T.; Zhang, G. The effect of fatigue driving on injury severity considering the endogeneity. *J. Safe. Res.* **2018**, *64*, 11–19.
116. Wei, F.; Cai, Z.; Liu, P.; Guo, Y.; Li, X.; Li, Q. Exploring Driver Injury Severity in Single-Vehicle Crashes under Foggy Weather and Clear Weather. *J. Adv. Transp.* **2021**, *2021*, 9939800.
117. Ebrahimi Darkhaneh, M.; Effati, M.; Arabani, M. Factors affecting the injury severity of head-on crashes on undivided rural roads under different weather conditions. *Int. J. Transp. Sci. Technol.* **2025**, *in press*.
118. Naik, B.; Tung, L.-W.; Zhao, S.; Khattak, A.J. Weather impacts on single-vehicle truck crash injury severity. *J. Safe. Res.* **2016**, *58*, 57–65.
119. Champahom, T.; Se, C.; Laphrom, W.; Watthanaklang, D.; Jomnonkwao, S.; Ratanavaraha, V. Empirical comparison of the effects of other party's vehicle type on motorcyclists' injury severity. *J. Traffic Transp. Eng.* **2025**, *12*, 180–200.
120. Hao, W.; Daniel, J. Driver injury severity related to inclement weather at highway–rail grade crossings in the United States. *Traffic Inj. Prev.* **2016**, *17*, 31–38.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.