big data and
cognitive computing

Article

Big Data Analytics with the Multivariate Adaptive Regression Splines to Analyze Key Factors Influencing Accident Severity in Industrial Zones of Thailand: A Study on Truck and Non-Truck Collisions

Manlika Seefong [1], Panuwat Wisutwattanasak [2], Chamroeun Se [2], Kestsirin Theerathitichaipa [1], Sajjakaj Jomnonkwao [1], Thanapong Champahom [3], Vatanavongs Ratanavaraha [1] and Rattanaporn Kasemsri [4,*]

[1] School of Transportation Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand; d6500580@g.sut.ac.th (M.S.); d6500573@g.sut.ac.th (K.T.); sajjakaj@g.sut.ac.th (S.J.); vatanavongs@g.sut.ac.th (V.R.)
[2] Institute of Research and Development, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand; panuwat.w@g.sut.ac.th (P.W.); chamroeun.s@g.sut.ac.th (C.S.)
[3] Department of Management, Faculty of Business Administration, Rajamangala University of Technology Isan, 744 Sura Narai Rd, Nai Mueang, Mueang Nakhon Ratchasima District, Nakhon Ratchasima 30000, Thailand; thanapong.ch@rmuti.ac.th
[4] School of Civil Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand
* Correspondence: kasemsri@sut.ac.th

Citation: Seefong, M.; Wisutwattanasak, P.; Se, C.; Theerathitichaipa, K.; Jomnonkwao, S.; Champahom, T.; Ratanavaraha, V.; Kasemsri, R. Big Data Analytics with the Multivariate Adaptive Regression Splines to Analyze Key Factors Influencing Accident Severity in Industrial Zones of Thailand: A Study on Truck and Non-Truck Collisions. *Big Data Cogn. Comput.* **2023**, *7*, 156. https://doi.org/10.3390/bdcc7030156

Academic Editor: Jenq-Haur Wang

Received: 10 August 2023
Revised: 4 September 2023
Accepted: 18 September 2023
Published: 21 September 2023

Abstract: Machine learning currently holds a vital position in predicting collision severity. Identifying factors associated with heightened risks of injury and fatalities aids in enhancing road safety measures and management. Presently, Thailand faces considerable challenges with respect to road traffic accidents. These challenges are particularly acute in industrial zones, where they contribute to a rise in injuries and fatalities. The mixture of heavy traffic, comprising both trucks and non-trucks, significantly amplifies the risk of accidents. This situation, hence, generates profound concerns for road safety in Thailand. Consequently, discerning the factors that influence the severity of injuries and fatalities becomes pivotal for formulating effective road safety policies and measures. This study is specifically aimed at predicting the factors contributing to the severity of accidents involving truck and non-truck collisions in industrial zones. It considers a variety of aspects, including roadway characteristics, underlying assumptions of cause, crash characteristics, and weather conditions. Due to the fact that accident data is big data with specific characteristics and complexity, with the employment of machine learning in tandem with the Multi-variate Adaptive Regression Splines technique, we can make precise predictions to identify the factors influencing the severity of collision outcomes. The analysis demonstrates that various factors augment the severity of accidents involving trucks. These include darting in front of a vehicle, head-on collisions, and pedestrian collisions. Conversely, for non-truck related collisions, the significant factors that heighten severity are tailgating, running signs/signals, angle collisions, head-on collisions, overtaking collisions, pedestrian collisions, obstruction collisions, and collisions during overcast conditions. These findings illuminate the significant factors influencing the severity of accidents involving trucks and non-trucks. Such insights provide invaluable information for developing targeted road safety measures and policies, thereby contributing to the mitigation of injuries and fatalities.

Keywords: big data analysis; severity of accidents; trucks; non-trucks; road safety; multivariate adaptive regression splines; industrial zones; Thailand

1. Introduction

Road safety remains a critical global concern [1]. As per the Road Safety Situation Report by Road Safety for All, road accidents annually result in approximately 1.35 million deaths and 50 million injuries [2]. Disturbingly, 93% of these fatalities occur in low to middle-income countries. In this context, middle-income developing nations like Thailand face serious issues concerning road accidents [3]. World Health Organization (WHO) data reveal Thailand as having the ninth highest number of road accident fatalities globally, making it the leading country in Asia and the ASEAN regions. The mortality rate stands at approximately 32.7 deaths per 100,000 population, amounting to an average of 22,491 deaths annually or roughly 60 deaths per day [4].

Throughout the preceding year, the prevalence of road accidents in Thailand has been notably concentrated within provinces classified as industrial zones, as visually depicted in Figure 1. These zones encompass a diverse range of spatial categories, encompassing industrial areas, industrial estate parks, and comprehensive industrial zones. Delving further into the accident data for the industrial province regions during the period spanning 2020 to 2022, a striking finding emerges, indicating that injuries and fatalities collectively averaged a substantial 22.11% [5]. This statistical revelation underscores the inherent challenges of navigating through complex driving conditions in densely populated areas, which inherently magnify the inherent risk of accidents. Complex driving conditions in densely populated areas significantly escalate the risk of accidents. Notably, collisions involving trucks pose a higher threat than those not involving trucks, largely due to the trucks' size and weight impeding swift braking in emergencies [6]. In 2021, data categorized by vehicle type indicated that truck-related accidents constituted 12.41% of all accidents [7]. When assessing the proportion of injuries and fatalities from truck-involved collisions in industrial zones, the figures are markedly higher compared to collisions not involving trucks (Figure 2). Consequently, the rate of injuries and fatalities from truck accidents ranks second in comparison to other vehicle types [5]. Given this significance, a detailed study of factors contributing to the severity of truck accident injuries and fatalities is essential for enhancing road safety.

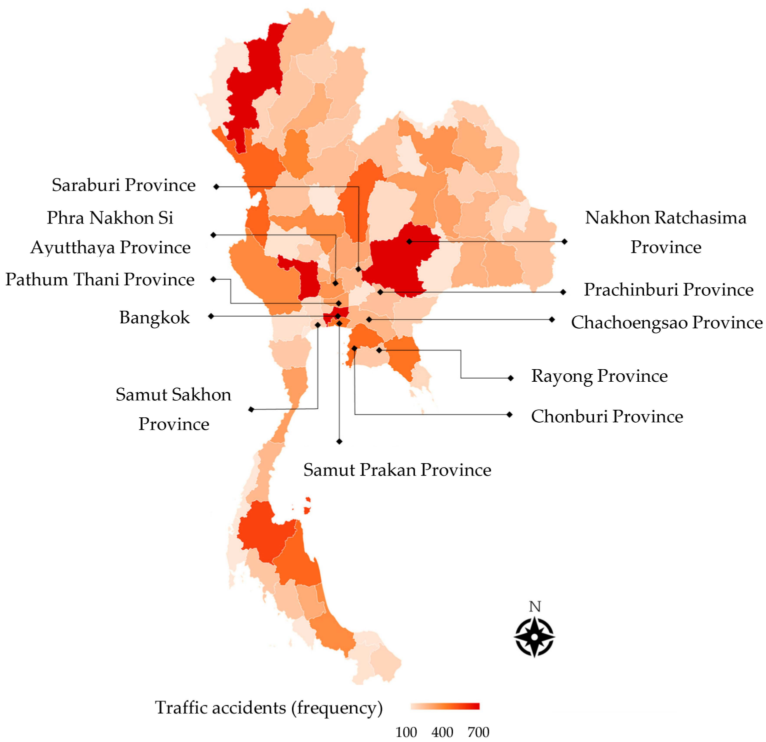

Figure 1. Road Traffic Accidents frequency in Thailand by Provinces from 2020–2022.

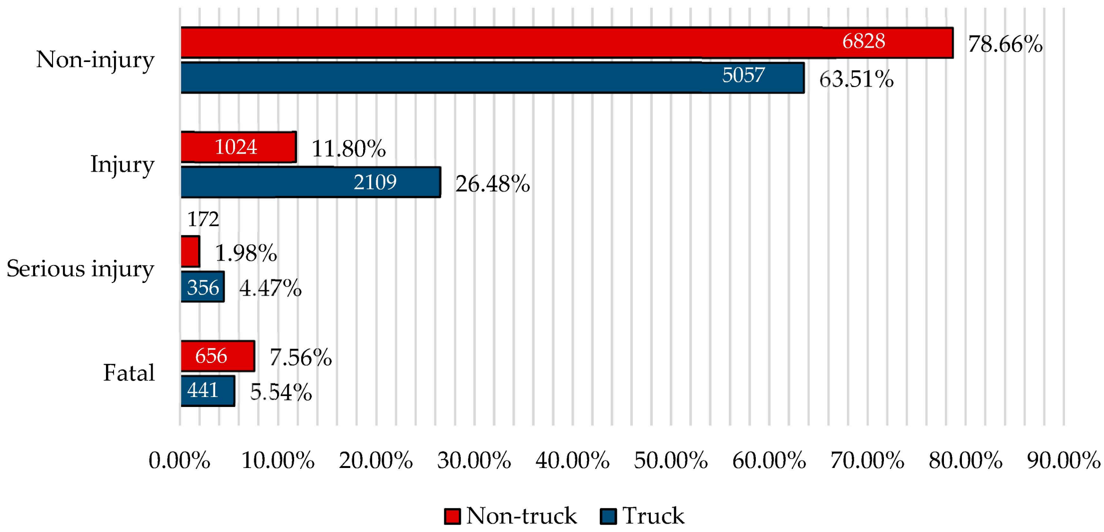

Figure 2. Injury severity distribution of non-truck and truck-involved crashes in the industrial zones of Thailand from 2020 to 2022 [5].

To effectively mitigate road accidents, a comprehensive understanding of their causes and a capability to predict potential accidents are necessary [1]. This understanding enables the implementation of effective preventive strategies and measures. In recent years, substantial attention has been paid to studying factors that contribute to road accident severity. Examples include predictions related to accident severity on expressways [8], urban roads [9], and signalized intersections [10], factors influencing injury severity in car accidents [11] as well as studies on truck collisions [12–17]. In several studies, the focus has been on analyzing big data through high-efficiency platforms to analyze accidents, which enables the discovery of new insights and a deeper understanding of the problem [18–21]. Parameter-free techniques, such as Multivariate Adaptive Regression Splines (MARS), are gaining traction for their efficacy in discerning factors contributing to accident severity [22] and in the field of transportation [23]. The Multivariate Adaptive Regression Spline (MARS) model presents a blend of distinct advantages and disadvantages. On the positive side, its remarkable capability to unravel intricate nonlinear relationships and detect interactions among variables makes it an invaluable asset in tackling intricate data patterns that defy traditional linear regression approaches. MARS sets itself apart from other well-known parametric linear regression techniques by offering a heightened degree of flexibility in investigating nonlinear relationships between input and response variables [24]. MARS operates autonomously in selecting pertinent features and offers insights into the pivotal variables, thereby enhancing its interpretability. Notably, MARS rigorously explores all potential levels of interaction, effectively unveiling a comprehensive spectrum of interactions among variables. By thoroughly considering all interactions and functional shapes inherent in input variables, the approach excels at unveiling latent connections within high-dimensional datasets and capturing intricate structures apparent within data points [25]. However, there is a slight risk of limited adaptability in feature partitioning due to the model's weakness a potential lack of continuity and difficulty in capturing straightforward relationships like linear, additive or interactions with lower orders [26]. The inherent complexity of MARS poses challenges, particularly the risk of overfitting, which looms large when dealing with expansive datasets or an extensive array of variables. Furthermore, MARS models are notably sensitive to noise in the data, potentially incorporating irrelevant patterns that can compromise predictive accuracy when applied to previously unseen data instances (unobserved heterogeneity). While MARS retains a higher level of interpretability compared to some intricate models, comprehending its behavior becomes progressively intricate as the model's complexity grows. The application of Multivariate Adaptive Regression Splines (MARS) has been predominantly used in existing studies for investigating driver behavior, notably lane changing acceptance behavior [23], and developing crash modification factors for freeway interchange areas in urban environments [27]. It has also been used in predicting rear-end collisions [24,28] and studying the safety impacts of wider shoulders on rural multilane highways [29]. However, it is crucial to recognize that there is a notable gap in research specifically examining the factors influencing the severity of accidents involving trucks in industrial zones, particularly using this machine learning technique. Omitting areas prone to truck accidents from such study parameters may result in significant challenges when aiming to effectively reduce the number of severe injuries and fatalities stemming from these crashes. Therefore, it is vital to expand the application of MARS to such specific and high-risk contexts. This approach would facilitate a more comprehensive understanding of road safety, particularly in areas dominated by industrial traffic.

This research is novel as it prioritizes collisions involving trucks and non-trucks in industrial zones, utilizing a promising new approach in safety research—the Multivariate Adaptive Regression Splines (MARS) methodology. The primary objective is to identify significant factors contributing to injury and fatality severity. The findings will provide valuable reference data for policymaking and safety measures aimed at effectively reducing injuries and fatalities. Utilizing accident data from Thailand, a country grappling with unique road safety challenges, serves as the basis for this investigation.

2. Materials and Methods

2.1. Method

The superiority of parameter-free techniques over parameter-based models stems from their capability in making accurate predictions and the absence of predefined assumptions. These techniques are capable of modeling complex relationships, including nonlinearity, and can simultaneously manage a substantial number of explanatory variables [23]. Considering these strengths, this study has selected to utilize Multivariate Adaptive Regression Splines (MARS), a parameter-free technique proposed by Friedman [26]. This model serves to identify key factors influencing the severity of accidents involving both trucks and non-trucks. MARS offers critical advantages in accurately capturing and predicting such data. Moreover, it provides flexibility in exploring nonlinear relationships between independent and dependent variables [30]. Therefore, it can construct a model that effectively captures the complex interrelationships among various variables. This approach delivers in-depth insights into the critical factors influencing the severity of accidents involving trucks and non-trucks with high precision. The fundamental form of the MARS model is represented by Equation (1) [29]:

$$\hat{y} = \exp\left(b_0 + \sum_{m=1}^{M} b_m B_m(x)\right) \tag{1}$$

where

$\hat{y}$ = predicted response variable,
b_0 = coefficient of the constant basis function,
b_m = coefficient of the mth basis function,
M = number of nonconstant basis functions, and
$B_m(x)$ = mth basis functions.

The process of curve fitting using the Multivariate Adaptive Regression Splines (MARS) model encompasses three primary steps [31]. The initial step involves constructing the model by integrating predictor and response variables and assigning weights to these variables to derive the MARS model. Subsequently, the pruning phase takes place, addressing overfitting issues within the MARS curve fitting model. The final step involves selecting the most suitable MARS model, which can then be assessed for predictive performance using the MARS curve fitting technique.

In the first phase of constructing a curve-fitting model with the MARS method, continuous basic functions are added to the MARS base model. These basic functions could comprise single splines or multiple splines, each yielding different predictive outcomes. A "two-at-a-time" strategy is implemented during this addition, whereby the optimal pair of spline functions is chosen to enhance the model. Each pair consists of one left function and one right function, divided by knots as illustrated in Equations (2) and (3) respectively. Following this, the positions of the knots are iteratively optimized until the location that maximizes the model's efficiency is selected. Additionally, after each iteration, the model is continuously examined and adjusted as necessary. Equations (2) and (3) can be defined as follows:

$$[-(x-t)^q] = \begin{cases} (t-x)^q\,;\ x < t \\ 0\,;\text{otherwise} \end{cases} \tag{2}$$

$$[+(x-t)^q] = \begin{cases} (x-t)^q\,;\ x > t \\ 0\,;\text{otherwise} \end{cases} \tag{3}$$

where

x = independent variable

t = constant denoting knot

q = the order of the spline and the subscript indicates the positive part of the argument.

The second stage in this process is the pruning step, which employs a "one-at-a-time" approach to eliminate basic functions contributing minimally to the model. The pruning process adheres to the Generalized Cross-Validation (GCV) criterion, in which a lower GCV value tends to result in a more parsimonious model. Equation (4) below showcases the GCV criterion:

$$\mathrm{GVC}(M) = \frac{1}{N}\frac{\sum_{i=1}^{N}(y_i-\hat{y})^2}{(1-C(M)/N)^2} \tag{4}$$

where

N is number of observations

y_i is observation i

y is predicted response for observation i

C(M) is complexity penalty function

The final stage involves choosing the best fitting spline-based model utilizing the Multivariate Adaptive Regression Splines (MARS) method. This decision is based on the evaluation of the predictive performances of the various spline-based models developed using the MARS method. Figure 3 illustrates the process of the Multivariate Adaptive Regression Splines (MARS) model.

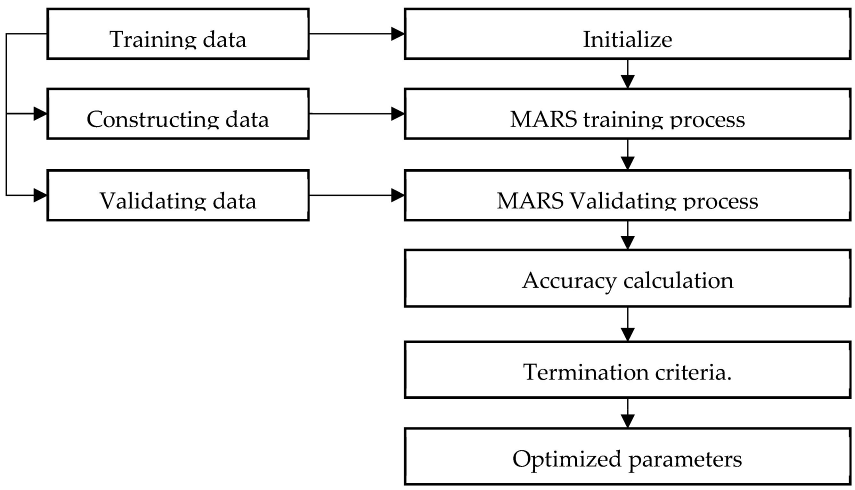

Figure 3. The process of Multivariate Adaptive Regression Splines (MARS) model [31].

2.2. Measures for Performance Evaluation

In this study, the accuracy (ACC), sensitivity (SNS), specificity (SP), precision (PRC), F1-score, and AUC were used as performance metrics for the prediction model of MARS.

These metrics can be calculated from the confusion matrix, as shown in Figure 4. The confusion matrix consists of four components, the count of true positives (TP), count of true negatives (TN), count of false positives (FP) and count of false negatives (FN) [32].

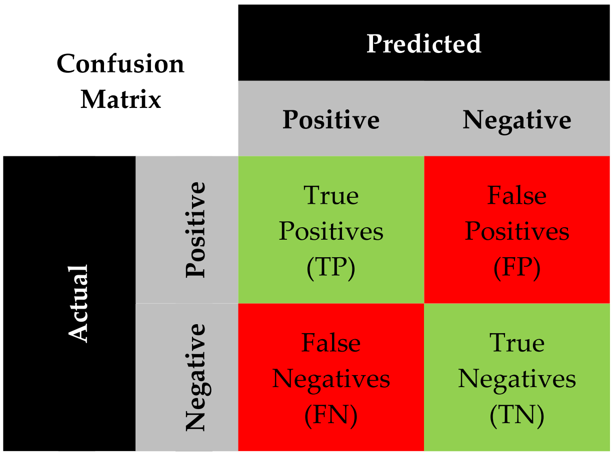

Figure 4. Confusion Matrix.

When the confusion matrices were obtained, the four classifier performance metrics can be calculated as [33,34]:

$$\text{ACC} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \tag{5}$$

$$\text{SNS} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{SP} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}$$

$$\text{PRC} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{8}$$

$$\text{F}_1 = 2 \times \frac{\text{SNS} \times \text{PRC}}{\text{SNS} + \text{PRC}} \tag{9}$$

$$\text{AUC} = \frac{1}{2}(\text{SNS} + \text{SP}) \tag{10}$$

Among the previously mentioned evaluation criteria, "Accuracy" stands as a comprehensive measure of a classifier's overall effectiveness. "Sensitivity" assesses the classifier's ability to correctly identify positive labels, while "Specificity" measures its capacity to accurately recognize negative labels. The "F-score" provides insight into the relationship between the actual positive labels in the dataset and those identified by the classifier. To further enhance the evaluation process, the "AUC" metric, which represents the area under the receiver operating characteristic curve, sheds light on the classifier's capability to minimize erroneous classifications.

2.3. Data Collection

This research used the most recent accident data from the 2020–2022 period, obtained from the Ministry of Transport, with a specific focus on crashes occurring within industrial zones in Thailand. The study used the accumulated data to generate two models aimed at identifying the critical factors influencing the severity of collisions involving trucks and non-trucks. The collected data revealed 7963 truck-involved collision cases, resulting in 797 Severe/Fatal cases. Conversely, there were 8680 non-truck involved collision cases, leading to 828 Severe/Fatal cases. Influential factors were categorized into four main groups: (1) Roadway Characteristics, (2) Cause of Assumption, (3) Crash Characteristics, and (4) Weather Conditions. The total extracted risk factors for each case were 38 explanatories. Each variable was coded 1 = "Yes", 0 = "Otherwise". Table A1 summarizes all the influencing factors, categorized according to the severity levels of injuries, for both trucks and non-truck vehicles, using two levels of injury severities, namely, PDO/minor injury and severe/fatal injury [35].

2.4. Model Evaluation

From the results of the analysis of the performance metrics of the MARS prediction model in Table 1, it was found that the non-truck involved crashes model and the Truck-involved crashes model exhibit high prediction accuracies of 91.05% and 90.32%, respectively, which is relatively higher as compared to previous studies that utilized the big data analysis approach [33,36]. The F1-Scores of 0.242 and 0.133 suggest that there is a trade-off between precision and sensitivity, indicating that the model might not be performing well in both aspects simultaneously. This phenomenon is likely attributable to a substantial disparity in the number of instances across classes, causing the model to exhibit a preference for the majority class (i.e., PDO/minor injury, in this case). This preference subsequently results in reduced sensitivity and, consequently, a lower F1 score. However, when measures the model's ability to distinguish between positive and negative classes across different probability thresholds, the AUC values of 0.773 and 0.774 suggest that the model has a relatively higher capabilities to distinguish between the two classes, as compared to the findings of the previous studies [33,37,38]. Hence, the outcomes derived from the MARS models could be deemed acceptable for the purpose of valid model interpretation.

Table 1. Goodness of fit for the truck and non-truck crash severity model.

	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC
Non-truck involved crashes	91.05%	0.629	0.917	0.150	0.242	0.773
Truck-involved crashes	90.32%	0.641	0.906	0.074	0.133	0.774

3. Result and Discussion

3.1. Roadway Characteristics Factor

Table 2 presents an in-depth analysis of roadway characteristics concerning truck-involved collisions. The study found that attributes such as Interchange Roads/Ramps and Expressways significantly contribute to reducing injuries. Interchange Roads/Ramps, designed to minimize traffic conflicts and enhance junction safety, naturally decrease injury occurrences. Similarly, Expressways, due to their facilitation of consistent speeds and uninterrupted traffic flow, mitigate the potential for accidents and subsequent injuries. Straight roads also contribute to injury reduction, given their flat surface and increased visibility, which allows for swift driver responses to unforeseen circumstances [39]. These findings underscore the role of road attributes, including Interchange Roads/Ramps, Expressways, and Straight Roads, in injury reduction within truck-involved accidents. Additionally, there is a surprising finding suggesting that the characteristic of a wide curved road leads to decreased injury occurrences. This contradicts the findings of previous studies that indicated collisions on curved road segments resulted in increased injuries [40]. Nevertheless, this variable might be contingent on the width of the lanes, The statement aligns with the findings of previous studies indicating that an increased lane width could potentially help reduce the risks of collisions and injuries. This is because a wider lane provides drivers with a greater separation from traffic, promoting a heightened sense of safety [41,42].

Table 2. Estimation results for the truck crash severity model.

Model	Variable	Coefficients
Truck	Intercept	0.290
	Roadway Characteristics Factor	
	Interchange road/Ramps	−0.159
	Wide curved road	−0.162
	Expressway	−0.138
	Straight road	−0.045
	Cause of Assumption Factor	
	Darting in front of a vehicle	0.058
	Malfunctioning equipment	−0.074
	Crash Characteristics Factor	
	Head-on collision	0.227
	Pedestrian collision	0.529
	Sideswipe collision	−0.120
	Rear-end collision	−0.135
	Curved-road rollover	−0.233
	Straight-road rollover	−0.188
	Weather Conditions Factor	
	Rain	−0.031

For collisions not involving trucks, as displayed in Table 3, the study discerned that Straight Roads, due to their extended visibility, were associated with a reduction in injuries. Previous research has identified road characteristics significantly influencing accident severity as typically being intersections with conflicting points and shortened visibility [43,44]. Furthermore, road sections with curves and steep slopes, which inherently have reduced visibility, were found to elevate injury rates [45,46].

Table 3. Estimation results for the non-truck crash severity model.

Model	Variable	Coefficients
Non-Truck	Intercept	0.135
	Roadway Characteristics Factor	
	Straight road	−0.060
	Cause of Assumption Factor	
	Tailgating.	0.369
	Running signs/signals	0.310
	Obstruction	−0.172
	Crash Characteristics Factor	
	Angle collision	0.246
	Head-on collision	0.386
	Overtaking collision	0.358
	Pedestrian collision	0.598
	Obstruction Collision	0.126
	Weather Conditions Factor	
	Rain	−0.031
	Overcast	0.414

3.2. Cause of Assumption Factor

Table 2 displays a comprehensive analysis of factors contributing to truck-involved collisions. The study found that attribute malfunctioning equipment, which traditionally exacerbates injury rates, had a decreasing effect on injuries within this specific context. High traffic congestion, impeding high-speed driving, combined with defective vehicle equipment, could lead to more cautious driving and prompt vehicle management, thus reducing the likelihood of injuries. Conversely, collisions involving vehicles darting in front of trucks, which allow for short braking distances, were found to increase injury rates. This finding aligns with earlier studies showing that sudden lane changes often result in more severe injuries and fatalities in truck-involved collisions [47,48].

In accidents unrelated to trucks (Table 3), the presence of road obstacles or barriers helps reduce the impact of injuries, consistent with previous research. Obstructions or roadblocks, which typically serve as safety measures for traffic regulation, play a role in decreasing injury consequences [49,50]. However, tailgating as a cause of collisions and running signs and signals both increased injury rates. Previous studies have identified the violation of traffic signals and signs as significant contributors to accidents [48,51,52]. Moreover, closely following another vehicle with a short braking distance was found to be a critical factor impacting injuries [53].

3.3. Crash Characteristics Factor

Table 2 presents an analysis of crash characteristics in truck-involved collisions. Rear-end collisions were found to reduce injury rates, presumably because these accidents often occur in areas where the speed differential between vehicles is minimal [54]. The characteristics of rollover collisions, whether on straight or curved roads also had a decreasing effect on injuries. The nature of rollovers generally leads to avoidance behavior or less forceful impacts with other vehicles, thus reducing the number of injuries. Moreover, sideswipe collisions also result in reduced injuries. This aligns with the findings of a previous study which revealed that collisions within the same direction tend to involve less severe impacts, particularly for large trucks colliding with each other [55]. It is possible that the skill of truck drivers in controlling the steering wheel in the same direction contributes to mitigating the severity of injuries in lateral collision scenarios. Conversely, head-on collisions amplified the impact on injuries, a finding consistent with studies on truck collision characteristics [56,57]. The substantial force generated when trucks collide head-on or at an angle with other vehicles escalates injury severity. Likewise, collisions with pedestrians were found to increase the impact on injuries [6,58]. Developed countries often have safer pedestrian infrastructure, while developing countries like Thailand grapple with safety issues, such as poorly maintained pedestrian paths and the lack of protective equipment. This lack of protection, combined with the direct collision between trucks and pedestrians, markedly raises injury severity.

For collisions not involving trucks (Table 3), angle collisions resulted in an increased impact on injuries. These accidents occur when vehicles collide at a perpendicular angle, as observed in sideswipe or T-bone collisions. This finding is congruent with various studies that found sideswipe collisions, particularly in the same direction, tended to cause severe injuries [54]. Head-on collisions also had a more substantial impact on injuries compared to collisions in the same direction, corroborating previous research findings [59,60]. Furthermore, overtaking maneuvers were linked to increased injury impact. High acceleration rates during these maneuvers can lead to poor situational awareness and an increased probability of erroneous driver decisions, thereby increasing the likelihood of injuries [61,62]. Pedestrian collisions lead to an increase in injuries. This finding is consistent with previous research that found pedestrians without protective equipment in pedestrian areas had a high tendency to suffer severe injuries and fatalities when directly hit by vehicles [63,64]. Important studies have also revealed that pedestrian accidents primarily occur in areas near schools and industrial zones [65]. Furthermore, obstruction collisions on roads result in an increased likelihood of injuries, especially when colliding with concrete barriers. This is supported by multiple prior studies. Obstructions have a higher structural rigidity compared to vehicles, resulting in less energy absorption during the collision. As a result, vehicles sustain greater damage from the impact [66–68].

Therefore, direct collisions with obstructions have an elevated propensity for increased injuries [39].

3.4. Weather Conditions Factor

Table 2 presents an analysis of weather factors in truck-involved collisions revealing that rainy conditions have a diminishing effect on injury rates, aligning with the study conducted by Li et al. (2020). Nevertheless, this result contradicts several previous studies that found an increased risk of injuries under adverse weather conditions, especially during rainfall [42]. It is hypothesized that decreased visibility and slippery road conditions during rainy weather contribute to decreased situational awareness and a need for increased driving caution and a decrease in driving speed resulting in reduced collision severity.

The analysis of weather factors influencing non-truck collisions revealed that rainy conditions have a diminishing effect on injury rates (Table 3). This can be attributed to the reduced visibility and slippery road conditions during rainfall, which tend to induce more cautious driving and lower vehicle speeds. Therefore, rainy weather indirectly contributes to a decrease in collision severity. In contrast, collisions occurring under overcast conditions were found to escalate the severity of collisions, as indicated by the coefficient value of 0.414. This aligns with existing literature which suggests that the decreased visibility associated with overcast conditions can exacerbate the severity of collisions [39,54,69–71].

4. Conclusions

Given the high fatality rate of truck-related accidents in Thailand's industrial zones, where they rank second when compared to other vehicles, it is essential to identify the factors contributing to the severity of injuries and fatalities in both truck and non-truck related crashes. This understanding is crucial for developing effective road safety policies and measures.

Our current study uses accident data from Thailand between 2020 and 2022, comprising large and complex datasets. We applied machine learning in conjunction with the Multivariate Adaptive Regression Splines (MARS) technique. This method identifies influential factors affecting the severity of injuries and fatalities in both truck and non-truck related accidents without relying on predefined parameters. These factors encompass roadway characteristics, cause of assumption, crash characteristics, and weather conditions.

The analysis considers two levels of injury severity namely, PDO/minor injury and severe/fatal injury. Upon examining truck-related accidents within Thailand's industrial zones, we discovered that darting in front of a vehicle, head-on collisions, and pedestrian collisions all enhance the severity of injuries. Conversely, non-truck related crashes in these industrial zones revealed that tailgating, running signs/signals, angle collisions, head-on collisions, overtaking collisions, pedestrian collisions, obstruction collisions, and collisions during overcast conditions also increase injury severity.

A comparison of the two models highlighted that head-on collisions and pedestrian collisions significantly increase injury severity in both truck and non-truck accidents. However, the influencing factors differ between accidents involving trucks and those not involving trucks. Hence, it is vital that road safety policies and measures are appropriately tailored without neglecting any specific factor to improve road safety in Thailand effectively.

Following our statistical analysis, we proposed several road safety policies and measures aimed at reducing the severity of injuries and fatalities in both truck and non-truck related accidents. Our recommendations are informed by crucial variables identified within our models (Table 4), and the key guidelines are as follows:

Table 4. Appropriate strategies based on such findings.

Variables	Truck	Non-Truck	Guidelines
Roadway Characteristics Factor			
Interchange road/Ramps	(−)		Designing the characteristics of an interchange road/ramp for intersections with conflicts and high accident rates
Wide curved road	(−)		Increasing the number of lanes for curved sections of the road where there is a higher risk
Expressway	(−)		Designing an expressway-like road layout to shorten travel distances and reduce the risk of accidents
Straight road	(−)	(−)	Designing a straight road layout to increase visibility and reduce points of risk that lead to accidents
Cause of Assumption Factor			
Darting in front of a vehicle	(+)		(1) Install advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance. (2) Configure lower speed limits to reduce the severity of injuries in emergency situations.
Tailgating.		(+)	(1) Install advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance. (2) Install road markings to guide drivers and help them maintain a safe following distance.
Malfunctioning equipment	(−)		Promoting consistent safe driving behavior in emergency situations.
Running signs/signals		(+)	Installing cameras to monitor red-light signals at all intersections to mitigate unsafe driving behavior.
Obstruction		(−)	Installing obstruction devices at high-risk points, such as curved or sharp-angle sections.
Crash Characteristics Factor			
Angle collision		(+)	(1) Promote awareness among drivers about risky scenarios that can lead to increased injuries, such as angled collisions and head-on collisions. (2) Advocate for the use of seatbelts for both drivers and passengers to minimize the severity of injuries. (3) Install Automatic Emergency Braking (AEB) systems to reduce the severity of injuries by automatically applying brakes in emergency situations. (4) Install airbag systems within vehicles to mitigate the severity of injuries.
Head-on collision	(+)	(+)	
Sideswipe collision	(−)		Promote awareness among drivers about risky scenarios that can lead to decreased injuries, such as sideswipe collisions and rear-end collisions.
Rear-end collision	(−)		
Overtaking collision		(+)	Design roads to enhance safety during overtaking maneuvers and mitigate the risk of collisions during passing.
Pedestrian collision	(+)	(+)	(1) Install safety devices for pedestrians. (2) Configure lower speed limits in situations involving pedestrians.
Obstruction Collision		(+)	Install impact-absorbing barriers designed to reduce the severity of accidents without causing significant damage to vehicles, such as barriers made from Polyethylene plastic.
Curved-road rollover	(−)		Promoting skill training for truck drivers to effectively control the steering wheel in the same direction during emergency situations can significantly reduce the severity of injuries resulting from accidents.
Straight-road rollover	(−)		
Weather Conditions Factor			
Rain	(−)	(−)	Promoting responsible driving behavior in continuous rainy weather conditions.
Overcast		(+)	Install roadside conveniences or additional lighting systems to enhance road safety.

+: Indicates an increase in the estimated likelihood for severe injuries. −: Indicates a decrease in the estimated likelihood for severe injuries.

Policies and safety measures for trucks: First, road design should focus on enhancing traffic safety. This could involve designing intersections or upgrading them into interchange roads/ramps to minimize conflict points at junctions. especially at T-junctions, which are commonly implicated in severe injury or fatality-involved accidents with trucks [72–75].

Because of the reasons mentioned, it is critical to design intersections with a minimal number of conflict points and align these with typical driver behavior to mitigate accident risks. Furthermore, this approach includes designing an expressway-like road layout to shorten travel distances and reduce the risk of accidents, designing a straight road layout to increase visibility and reduce points of risk that lead to accidents and increasing the number of lanes for curved sections of the road where there is a higher risk. Such measures coincide with this study's findings that these road characteristics can influence a reduction in injury severity.

Enforcing speed limits for trucks is an approach intended to reduce the risk of accidents caused by darting in front of a vehicle and pedestrian collisions, all of which heighten the likelihood of injuries. This includes installing advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings, ensuring a safe following distance.

Promoting educational policies for truck drivers to minimize collision risk should encompass training on diverse collision types, such as angle collision, rear-end, single-vehicle, and head-on collisions [54]. Special emphasis should be placed on head-on collisions, given their significant contribution to the severity of accidents. Furthermore, this approach includes promoting skill training for truck drivers to effectively control the steering wheel in the same direction during emergency situations and can significantly reduce the severity of injuries. The study suggests that the Department of Land Transport integrate topics on collision types into driver's license training. By gaining a comprehensive understanding of the causes and consequences of different collision types, truck drivers can cultivate increased awareness and promote safer driving practices.

Installing safety devices for both drivers and road users should encompass provisions for pedestrians, such as Pedestrian Crosswalks, Raised Crosswalks, and pedestrian-specific traffic signals. The aim is to stimulate driver awareness, mitigate injuries resulting from unforeseen accidents, and bolster overall road safety.

Lastly, promoting consistent safe driving behavior in emergency situations is crucial (Malfunctioning equipment), as it can significantly reduce the severity of injuries. Encouraging drivers to remain composed, activate hazard lights, and safely navigate their vehicles to the side of the road or a suitable stopping point is essential.

Policy and safety measures for general vehicles: Specifically, designing roads with a focus on traffic safety should give priority to creating straight road sections. These sections offer extended visibility and have been linked to a decrease in the occurrence of injuries. This includes designing roads to reduce the severity of overtaking collisions, another crucial consideration. Overtaking collisions primarily occur on roads where overtaking is permitted, particularly in areas without designated passing zones [61]. Therefore, integrating knowledge of safe passing zones into road design is an important strategy for improving overall roadway safety and effectiveness.

Installing safety devices for both drivers and road users is important. This includes installing safety devices for pedestrians. Implementing impact-absorbing barriers designed to mitigate accident severity without inflicting significant vehicular damage, including barriers crafted from polyethylene plastic, is also key. Additionally, the installation of red-light cameras at all intersections is an approach that should be strongly considered to reduce the risk of collisions resulting from red light running and traffic signal violations. These violations are notable contributors to increased injury risks. Red-light cameras, as a crucial component of the transportation infrastructure, facilitate more effortless enforcement of traffic laws. This approach aligns with studies conducted in the United States, which found that the implementation of red-light cameras can reduce injuries resulting from signal violations by up to 29% [76]. Installing advanced V2V (Vehicle to Vehicle) devices within vehicles to provide rear-end collision warnings from tailgating is another crucial approach. This includes installing road markings to guide drivers and help them maintain a safe following distance is equally important. Furthermore, installing obstruction devices at high-risk points, such as curved or sharp-angle sections, has been shown by the study's findings to effectively reduce injuries. As a final guideline for installing safety devices for both drivers and road users, focusing on reducing the risk of collisions during dark and low-light conditions should entail conducting assessments of areas at high risk for accidents. Following these assessments, the installation of enhanced visibility devices for drivers, such as streetlights, should be prioritized. However, this initiative must be executed within the constraints of the available budget and timeframe. The study recommends prioritizing the installation of streetlights in areas with low-light conditions, especially at high risk for accidents, as these factors significantly increase the likelihood of injuries and fatalities.

Promoting educational policies for drivers to minimize collision risk should encompass training in various collision types, including angle collisions, rear-end collisions, single-vehicle collisions, and head-on collisions [54]. For general vehicle drivers, special emphasis should be placed on preventing head-on collisions and angle collisions, as they have a significant impact on the severity of accidents. Lastly, promoting responsible driving behavior in continuous rainy weather conditions is essential; such proactive measures not only decrease the likelihood of accidents but also play a crucial role in minimizing the severity of injuries.

5. Limitations and Further Research

This study, while providing valuable insights, is not devoid of limitations. As it primarily concentrates on industrial areas, the enforcement and implementation of the proposed safety policies and measures must be carefully executed, particularly when extrapolating them to regions outside of the industrial zone. Additionally, due to data constraints, the study might not encompass all pertinent factors. Thus, further considerations are needed to account for other potentially influential variables. These may include driver demographics such as gender and age, roadway attributes like the number of lanes, and traffic characteristics, such as volume, etc.

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

Funding: This work was supported by Suranaree University of Technology (SUT), Thailand Science Research and Innovation (TSRI), and National Science, Research, and Innovation Fund (NSRF) (NRIIS number 179277).

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Ethics Committee of Suranaree University of Technology (COE No.94/2565, 08 November 2022).

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available on request due to privacy restrictions.

Acknowledgments: The authors express their gratitude to the Suranaree University of Technology (SUT), Thailand Science Research and Innovation (TSRI), and National Science, Research and Innovation Fund for their support in doing this research. In addition, the authors gratefully acknowledge the accident data provided by the Ministry of Transport.

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

Appendix A

Table A1. Data description of the truck and non-truck crash severity model.

Variables	Truck				Non-Truck			
	Severe/Fatal		PDO/Minor		Severe/Fatal		PDO/Minor	
	Freq	%	Freq	%	Freq	%	Freq	%
Roadway Characteristics Factor								
(1) Interchange road/Ramps (1 If crash occurred on interchange road/ramps, 0 Otherwise)	1	1.28	77	98.72	0	0.00	0	0.00
(2) Access road (1 if crash occurred on access road, 0 Otherwise)	0	0.00	0	0.00	6	27.27	16	72.73
(3) Wide curved road (1 if crash occurred on wide curved road, 0 Otherwise)	0	0.00	35	100.00	0	0.00	0	0.00
(4) Curved road (1 if crash occurred on curved road, 0 Otherwise)	33	10.68	276	89.32	60	15.15	336	84.85
(5) Curved slope road (1 if crash occurred on curved slope road, 0 Otherwise)	23	13.53	147	86.47	21	15.79	112	84.21
(6) Sharp curve road (1 if crash occurred on sharp curve road, 0 Otherwise)	0	0.00	0	0.00	4	28.57	10	71.43
(7) Expressway (1 if crash occurred on expressway, 0 Otherwise)	9	2.43	362	97.57	0	0.00	0	0.00
(8) Straight road (1 if crash occurred on straight road, 0 Otherwise)	596	9.69	5554	90.31	716	8.91	7319	91.09
(9) Gradient road (1 If crash occurred on gradient road, 0 Otherwise)	24	21.05	90	78.95	7	15.22	39	84.78
(10) T-junction (1 if crash occurred at the T-junction, 0 Otherwise)	3	60.00	2	40.00	14	41.18	20	58.82
(11) Y-junction (1 if crash occurred on Y-junction, 0 Otherwise)	0	0.00	11	100.00	0	0.00	0	0.00
(12) 4-leg intersection (1 if crash occurred on 4-leg intersection, 0 Otherwise)	5	35.71	9	64.29	0	0.00	0	0.00
Cause of Assumption Factor								
(13) DUI (1 if driver was under influence of alcohol, 0 Otherwise)	8	23.53	26	76.47	15	23.81	48	76.19
(14) Illegal overtaking (1 if driver made an illegal overtaking, 0 Otherwise)	0	0.00	0	0.00	6	24.00	19	76.00
(15) Unfamiliar route (1 if driver was not familiar with the route, 0 Otherwise)	0	0.00	0	0.00	1	7.69	12	92.31
(16) Exceeding the speed limit (1 if driver exceeded the speed limit, 0 Otherwise)	663	10.20	5837	89.80	681	8.92	6952	91.08
(17) Tailgating (1 if driver tailgated the vehicle in front, 0 Otherwise)	0	0.00	0	0.00	9	56.25	7	43.75
(18) Wrong direction (1 if driver drove in the wrong direction/against the traffic, 0 Otherwise)	0	0.00	0	0.00	7	41.18	10	58.82
(19) Darting in front of a vehicle (1 if cause was due to darting in front of a vehicle, 0 Otherwise)	58	22.22	203	77.78	59	14.43	350	85.57
(20) Overloading (1 if the vehicle was overloaded, 0 Otherwise)	1	4.35	22	95.65	0	0.00	0	0.00
(21) Running signs/signals (1 if driver conducted a running signs/signal, 0 Otherwise)	22	32.35	46	67.65	21	50.00	21	50.00

Table A1. *Cont.*

Variables	Truck				Non-Truck			
	Severe/Fatal		PDO/Minor		Severe/Fatal		PDO/Minor	
	Freq	%	Freq	%	Freq	%	Freq	%
(22) Obstruction (1 if obstruction on the road, 0 Otherwise)	0	0.00	0	0.00	0	0.00	34	100.00
(23) Doze Off (1 if driver dozed off, 0 Otherwise)	23	9.20	227	90.80	21	10.50	179	89.50
(24) Malfunctioning equipment (1 if the vehicle had malfunctioning equipment, 0 Otherwise)	9	2.81	311	97.19	7	3.15	215	96.85
Crash Characteristics Factor								
(25) Angle collision (1 if crash type was angle collision, 0 Otherwise)	9	25.71	26	74.29	9	45.00	11	55.00
(26) Head-on collision (1 if crash type was head-on collision, 0 Otherwise)	84	48.55	89	51.45	63	48.46	67	51.54
(27) Overtaking collision (1 if crash type was collision while overtaking, 0 Otherwise)	0	0.00	0	0.00	7	50.00	7	50.00
(28) Pedestrian collision (1 if crash involved pedestrian, 0 Otherwise)	24	80.00	6	20.00	77	68.14	36	31.86
(29) Sideswipe collision (1 if crash type was sideswipe collision, 0 Otherwise)	4	4.26	90	95.74	0	0.00	0	0.00
(30) Rear-end collision (1if crash type was rear-end collision, 0 Otherwise)	412	10.50	3511	89.50	278	7.32	3522	92.68
(31) Obstruction Collision (1 if the crash was against the obstruction on the road, 0 0therwise)	46	25.56	134	74.44	46	23.23	152	76.77
(32) Curved-road rollover (1 if crash type was rollover on a curved road, 0 Otherwise)	20	4.58	417	95.42	57	12.93	384	87.07
(33) Straight-road rollover (1 if crash type was rollover on a straight road, 0 Otherwise)	138	4.86	2704	95.14	291	7.34	3673	92.66
Weather Conditions Factor								
(34) Fine weather (1 if crash occurred under fine weather, 0 Otherwise)	716	10.70	5973	89.30	751	9.79	6923	90.21
(35) Rain (1 if crash occurred during rain, 0 Otherwise)	79	6.25	1186	93.75	58	5.99	911	94.01
(36) Storm/flooding (1 if crash occurred under Storm/flooding, 0 Otherwise)	0	0.00	0	0.00	0	0.00	2	100.00
(37) Fog/smoke/dust (1 if crash occurred during fog, smoke or dust, 0 Otherwise)	0	0.00	0	0.00	0	0.00	3	100.00
(38) Overcast (1 if crash occurred during overcast weather, 0 Otherwise)	0	0.00	0	0.00	16	69.57	7	30.43

References

1. Fernando, C.L.; Yoshii, T.; Tsubota, T. Combining the Deep Neural Network with the K-Means for Traffic Accident Prediction. *Int. J. Comput. Syst. Eng.* **2023**, *17*, 1–8.
2. Vivas Pacheco, H.; Rodríguez-Mariaca, D.; Jaramillo, C.; Fandiño-Losada, A.; Gutiérrez-Martínez, M.I. Traffic Fatalities and Urban Infrastructure: A Spatial Variability Study Using Geographically Weighted Poisson Regression Applied in Cali (Colombia). *Safety* **2023**, *9*, 34. [CrossRef]
3. Road Safety for All | UNECE. Available online: https://unece.org/transport/publications/road-safety-all (accessed on 15 May 2023).
4. Global Status Report on Road Safety. Available online: https://www.who.int/publications/i/item/WHO-NMH-NVI-18.20 (accessed on 17 May 2023).

5. Ministry of Transport. Accidents on the Road Network of the Ministry of Transport—MOT Data Catalog. Available online: https://datagov.mot.go.th/dataset/roadaccident (accessed on 20 May 2023).
6. Chen, M.; Zhou, L.; Choo, S.; Lee, H. Analysis of Risk Factors Affecting Urban Truck Traffic Accident Severity in Korea. *Sustainability* **2022**, *14*, 2901. [CrossRef]
7. Department of Land Transport. Transport Statistics. Available online: https://web.dlt.go.th/statistics/ (accessed on 1 March 2023).
8. Kunt, M.; Aghayan, I.; Noii, N. Prediction for traffic accident severity: Comparing the artificial neural network, genetic algorithm, combined genetic algorithm and pattern search methods. *Transport* **2011**, *26*, 353–366. [CrossRef]
9. Astarita, V.; Haghshenas, S.S.; Guido, G.; Vitale, A. Developing new hybrid grey wolf optimization-based artificial neural network for predicting road crash severity. *Transp. Eng.* **2023**, *12*, 100164. [CrossRef]
10. 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. [CrossRef]
11. Delen, D.; Tomak, L.; Topuz, K.; Eryarsoy, E. Investigating injury severity risk factors in automobile crashes with predictive analytics and sensitivity analysis methods. *J. Transp. Health* **2017**, *4*, 118–131. [CrossRef]
12. Behnood, A.; Mannering, F. Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. *Anal. Methods Accid. Res.* **2019**, *23*, 100102. [CrossRef]
13. Zou, W.; Wang, X.; Zhang, D. Truck crash severity in New York city: An investigation of the spatial and the time of day effects. *Accid. Anal. Prev.* **2017**, *99*, 249–261. [CrossRef]
14. Zheng, Z.; Lu, P.; Lantz, B. Commercial truck crash injury severity analysis using gradient boosting data mining model. *J. Saf. Res.* **2018**, *65*, 115–124. [CrossRef]
15. Uddin, M.; Huynh, N. Factors influencing injury severity of crashes involving HAZMAT trucks. *Int. J. Transp. Sci. Technol.* **2018**, *7*, 1–9. [CrossRef]
16. Zhu, X.; Srinivasan, S. A comprehensive analysis of factors influencing the injury severity of large-truck crashes. *Accid. Anal. Prev.* **2011**, *43*, 49–57. [CrossRef]
17. Kim, J.-K.; Ulfarsson, G.F.; Shankar, V.N.; Kim, S. Age and pedestrian injury severity in motor-vehicle crashes: A heteroskedastic logit analysis. *Accid. Anal. Prev.* **2008**, *40*, 1695–1702. [CrossRef] [PubMed]
18. Ait-Mlouk, A.; Gharnati, F.; Agouti, T. Application of big data analysis with decision tree for road accident. *Indian J. Sci. Technol.* **2017**, *10*, 1–10. [CrossRef]
19. Fan, X.; He, B.; Brézillon, P. Context-Aware Big Data Analytics and Visualization for City-Wide Traffic Accidents. In Proceedings of the Modeling and Using Context: 10th International and Interdisciplinary Conference, Paris, France, 20–23 June 2017; Springer: Cham, Switzerland, 2017; pp. 395–405.
20. Feng, M.; Zheng, J.; Ren, J.; Liu, Y. Towards Big Data Analytics and Mining for UK Traffic Accident Analysis, Visualization & Prediction. In Proceedings of the 12th International Conference on Machine Learning and Computing, Shenzhen, China, 19–21 June 2020; pp. 225–229.
21. Huang, L.; Wu, C.; Wang, B.; Ouyang, Q. A new paradigm for accident investigation and analysis in the era of big data. *Process Saf. Prog.* **2018**, *37*, 42–48. [CrossRef]
22. Champahom, T.; Wisutwattanasak, P.; Chanpariyavatevong, K.; Laddawan, N.; Jomnonkwao, S.; Ratanavaraha, V. Factors affecting severity of motorcycle accidents on Thailand's arterial roads: Multiple correspondence analysis and ordered logistics regression approaches. *IATSS Res.* **2022**, *46*, 101–111. [CrossRef]
23. Das, A.; Khan, M.N.; Ahmed, M.M. Nonparametric Multivariate Adaptive Regression Splines Models for Investigating Lane-Changing Gap Acceptance Behavior Utilizing Strategic Highway Research Program 2 Naturalistic Driving Data. *Transp. Res. Rec. J. Transp. Res. Board* **2020**, *2674*, 223–238. [CrossRef]
24. Zhang, Y.; Jiang, X.; Haghani, A.; Huang, B. Exploring Piecewise Linear Effects of Crash Contributing Factors with a Novel Poisson–Mixed Multivariate Adaptive Regression Splines Model. *Transp. Res. Rec.* **2015**, *2515*, 17–25. [CrossRef]
25. Naser, A.H.; Badr, A.H.; Henedy, S.N.; Ostrowski, K.A.; Imran, H. Application of Multivariate Adaptive Regression Splines (MARS) approach in prediction of compressive strength of eco-friendly concrete. *Case Stud. Constr. Mater.* **2022**, *17*, e01262. [CrossRef]
26. Friedman, J.H. Multivariate adaptive regression splines. *Ann. Stat.* **1991**, *19*, 1–67. [CrossRef]
27. Haleem, K.; Gan, A.; Lu, J. Using multivariate adaptive regression splines (MARS) to develop crash modification factors for urban freeway interchange influence areas. *Accid. Anal. Prev.* **2013**, *55*, 12–21. [CrossRef] [PubMed]
28. Haleem, K.; Abdel-Aty, M.; Santos, J. Multiple Applications of Multivariate Adaptive Regression Splines Technique to Predict Rear-End Crashes at Unsignalized Intersections. *Transp. Res. Rec.* **2010**, *2165*, 33–41. [CrossRef]
29. Park, J.; Abdel-Aty, M. Safety Effects of Widening Shoulders on Rural Multilane Roads: Developing Crash Modification Functions with Multivariate Adaptive Regression Splines. *Transp. Res. Rec.* **2016**, *2583*, 34–41. [CrossRef]
30. Chang, L.-Y.; Chu, H.-C.; Lin, D.-J.; Lui, P. Analysis of Freeway Accident Frequency Using Multivariate Adaptive Regression Splines. *Procedia Eng.* **2012**, *45*, 824–829. [CrossRef]
31. Put, R.; Xu, Q.; Massart, D.; Vander Heyden, Y. Multivariate adaptive regression splines (MARS) in chromatographic quantitative structure–retention relationship studies. *J. Chromatogr. A* **2004**, *1055*, 11–19. [CrossRef] [PubMed]

32. Yao, D.; Yang, J.; Zhan, X. A Novel Method for Disease Prediction: Hybrid of Random Forest and Multivariate Adaptive Regression Splines. *J. Comput.* **2013**, *8*, 170–177. [CrossRef]
33. 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. [CrossRef]
34. Sokolova, M.; Lapalme, G. A systematic analysis of performance measures for classification tasks. *Inf. Process. Manag.* **2009**, *45*, 427–437. [CrossRef]
35. 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. [CrossRef]
36. 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. [CrossRef]
37. Banerjee, S.; Khadem, N.K. Factors influencing injury severity in alcohol-related crashes: A neural network approach using HSIS crash Data. *ITE J.* **2019**, *2019*, 89.
38. Jamal, A.; Umer, W. Exploring the injury severity risk factors in fatal crashes with neural network. *Int. J. Environ. Res. Public Health* **2020**, *17*, 7466. [CrossRef] [PubMed]
39. 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. [CrossRef]
40. Islam, M.B.; Hernandez, S. Modeling Injury Outcomes of Crashes Involving Heavy Vehicles on Texas Highways. *Transp. Res. Rec.* **2013**, *2388*, 28–36. [CrossRef]
41. Zegeer, C.V.; Deen, R.C.; Mayes, J.G. *The Effect of Lane and Shoulder Widths on Accident Reductions on Rural, Two-Lane Roads*; Division of Research Bureau of Highways Department of Transportation Commonwealth of Kentucky: Somerset, KY, USA, 1980.
42. Li, J.; Liu, J.; Liu, P.; Qi, Y. Analysis of Factors Contributing to the Severity of Large Truck Crashes. *Entropy* **2020**, *22*, 1191. [CrossRef]
43. Rezaie Moghaddam, F.; Afandizadeh, S.; Ziyadi, M. Prediction of accident severity using artificial neural networks. *Int. J. Civ. Eng.* **2011**, *9*, 41–48.
44. Mussone, L.; Ferrari, A.; Oneta, M. An analysis of urban collisions using an artificial intelligence model. *Accid. Anal. Prev.* **1999**, *31*, 705–718. [CrossRef]
45. Chang, F.; Li, M.; Xu, P.; Zhou, H.; Haque, M.M.; Huang, H. Injury severity of motorcycle riders involved in traffic crashes in Hunan, China: A mixed ordered logit approach. *Int. J. Environ. Res. Public Health* **2016**, *13*, 714. [CrossRef]
46. Se, C.; Champahom, T.; Jomnonkwao, S.; Ratanavaraha, V. Driver injury severity in single-vehicle run off road crash on 2-lanes and 4-lanes highway in Thailand. *Eng. Appl. Sci. Res.* **2020**, *47*, 393–400.
47. Knipling, R.R. IVHS technologies applied to collision avoidance: Perspectives on six target crash types and countermeasures. In Proceedings of the 1993 Annual Meeting of IVHS America: Surface Transportation: Mobility, Technology, and Society, Washington, DC, USA, 14–17 April 1993; pp. 249–259.
48. Shawky, M. Factors affecting lane change crashes. *IATSS Res.* **2020**, *44*, 155–161. [CrossRef]
49. Prenzler, T. Towards Prevention: A Situational Study of Police Deaths on Duty in Queensland. *Curr. Issues Crim. Justice* **2006**, *18*, 147–164. [CrossRef]
50. World Road Association. Recommendations for Road Authority Action at the Scene of Road Traffic Accidents. Available online: https://www.piarc.org/ (accessed on 1 March 2023).
51. Moffis, K.T.; Martinez, J.A.; Choi, H. Investigating Crash Risks and Driving Performance Among the Oil and Gas Industry Workers. *Proc. Hum. Factors Ergon. Soc. Annu. Meet.* **2022**, *66*, 1476–1480. [CrossRef]
52. Penmetsa, P.; Pulugurtha, S.S. Risk drivers pose to themselves and other drivers by violating traffic rules. *Traffic Inj. Prev.* **2017**, *18*, 63–69. [CrossRef] [PubMed]
53. Begg, D.J.; Langley, J.D. Identifying predictors of persistent non-alcohol or drug-related risky driving behaviours among a cohort of young adults. *Accid. Anal. Prev.* **2004**, *36*, 1067–1071. [CrossRef] [PubMed]
54. Champahom, T.; Jomnonkwao, S.; Banyong, C.; Nambulee, W.; Karoonsoontawong, A.; Ratanavaraha, V. Analysis of crash frequency and crash severity in Thailand: Hierarchical structure models approach. *Sustainability* **2021**, *13*, 10086. [CrossRef]
55. Islam, M.; Hernandez, S. Large truck–involved crashes: Exploratory injury severity analysis. *J. Transp. Eng.* **2013**, *139*, 596–604. [CrossRef]
56. Khattak, A.J.; Targa, F. Injury Severity and Total Harm in Truck-Involved Work Zone Crashes. *Transp. Res. Rec.* **2004**, *1877*, 106–116. [CrossRef]
57. Xu, J.; Wali, B.; Li, X.; Yang, J. Injury Severity and Contributing Driver Actions in Passenger Vehicle–Truck Collisions. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3542. [CrossRef]
58. Verzosa, N.; Miles, R. Severity of road crashes involving pedestrians in Metro Manila, Philippines. *Accid. Anal. Prev.* **2016**, *94*, 216–226. [CrossRef]
59. Jonsson, T.; Ivan, J.N.; Zhang, C. Crash Prediction Models for Intersections on Rural Multilane Highways: Differences by Collision Type. *Transp. Res. Rec.* **2007**, *2019*, 91–98. [CrossRef]

60. Nafis, S.R.; Alluri, P.; Wu, W.; Kibria, B.M.G. Wrong-way driving crash injury analysis on arterial road networks using non-parametric data mining techniques. *J. Transp. Saf. Secur.* **2022**, *14*, 1702–1730. [CrossRef]
61. Richter, T.; Ruhl, S.; Ortlepp, J.; Bakaba, E. Prevention of Overtaking Accidents on Two-Lane Rural Roads. *Transp. Res. Procedia* **2016**, *14*, 4140–4149. [CrossRef]
62. Richter, T.; Ruhl, S.; Ortlepp, J.; Bakaba, E. Causes, consequences and countermeasures of overtaking accidents on two-lane rural roads. *Transp. Res. Procedia* **2017**, *25*, 1989–2001. [CrossRef]
63. Selmoune, A.; Yun, J.; Seo, M.; Kwon, H.; Lee, C.; Lee, J. Development of a Residential Road Collision Warning Service Based on Risk Assessment. *J. Adv. Transp.* **2023**, *2023*, 7496377. [CrossRef]
64. Prato, C.G.; Kaplan, S.; Patrier, A.; Rasmussen, T.K. Considering built environment and spatial correlation in modeling pedestrian injury severity. *Traffic Inj. Prev.* **2018**, *19*, 88–93. [CrossRef]
65. Park, S.-H.; Bae, M.-K. Exploring the Determinants of the Severity of Pedestrian Injuries by Pedestrian Age: A Case Study of Daegu Metropolitan City, South Korea. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2358. [CrossRef] [PubMed]
66. Rzepczyk, S.; Majer, J.; Obst, M. Road Safety Barriers and the Safety of Road users—The Analysis of the Situation in Poland. *Logist. Transp.* **2022**, *55–56*, 19–36. [CrossRef]
67. Russo, B.J.; Savolainen, P.T. A comparison of freeway median crash frequency, severity, and barrier strike outcomes by median barrier type. *Accid. Anal. Prev.* **2018**, *117*, 216–224. [CrossRef] [PubMed]
68. Hu, W.; Donnell, E.T. Median barrier crash severity: Some new insights. *Accid. Anal. Prev.* **2010**, *42*, 1697–1704. [CrossRef]
69. Lenguerrand, E.; Martin, J.L.; Laumon, B. Modelling the hierarchical structure of road crash data—Application to severity analysis. *Accid. Anal. Prev.* **2006**, *38*, 43–53. [CrossRef]
70. Behnood, A.; Mannering, F.L. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: Some empirical evidence. *Anal. Methods Accid. Res.* **2015**, *8*, 7–32. [CrossRef]
71. Wang, Z.; Yue, Y.; Li, Q.; Nie, K.; Tu, W.; Liang, S. Analyzing risk factors for fatality in urban traffic crashes: A case study of Wuhan, China. *Sustainability* **2017**, *9*, 897. [CrossRef]
72. Haq, M.T.; Zlatkovic, M.; Ksaibati, K. Occupant injury severity in passenger car-truck collisions on interstate 80 in Wyoming: A Hamiltonian Monte Carlo Markov Chain Bayesian inference approach. *J. Transp. Saf. Secur.* **2022**, *14*, 498–522. [CrossRef]
73. Khattak, A.; Schneider, R.; Targa, F. Risk factors in large truck rollovers and injury severity: Analysis of single-vehicle collisions. In Proceedings of the 82nd Annual Meeting, Washinghton, DC, USA, 12–16 January 2002.
74. Lemp, J.D.; Kockelman, K.M.; Unnikrishnan, A. Analysis of large truck crash severity using heteroskedastic ordered probit models. *Accid. Anal. Prev.* **2011**, *43*, 370–380. [CrossRef]
75. Islam, M.; Hosseini, P.; Jalayer, M. An analysis of single-vehicle truck crashes on rural curved segments accounting for unobserved heterogeneity. *J. Saf. Res.* **2022**, *80*, 148–159. [CrossRef] [PubMed]
76. Retting, R.A.; Kyrychenko, S.Y. Reductions in injury crashes associated with red light camera enforcement in Oxnard, California. *Am. J. Public Health* **2002**, *92*, 1822–1825. [CrossRef]